Springer Tracts on Transportation and Traffic

Anastasia Loukaitou-Sideris
Alexandre M. Bayen
Giovanni Circella
R. Jayakrishnan *Editors*

# Pandemic in the Metropolis

## Transportation Impacts and Recovery

Springer

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*We dedicate this book to the memory of our colleague, mentor, friend, and former director of the University of California Institute of Transportation Studies*
*Martin Wachs (1942–2021)*


Photo Courtesy of Helen Wachs

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# Introduction

**Anastasia Loukaitou-Sideris**

**Abstract** This introductory chapter discusses the book's scope and structure and gives a brief summary of the 20 chapters that follow. The COVID-19 pandemic brought urban life all over the world at a standstill. It dramatically affected mobility and had ripple effects on the economy, environment, and safety of urban areas. But not all urban residents were affected equally. The chapter introduces the major research topics and questions, which are addressed collectively by the book's contributors. These include (1) the impacts of the pandemic on vulnerable populations; (2) the impacts on the transportation industry and other sections of the economy that rely on the transportation sector; (3) the impacts on alternative forms of work, shopping, and travel; (4) the impacts on environmental quality and traffic safety; and (5) the lessons that the phenomena observed during the pandemic may entail for policymakers and transportation planners.

Mobility—the ability to move from one place to another smoothly, quickly, and without impediment—has been the epitome of modernity. Mobility has been valued as it is associated with accessibility—the ability to access and take advantage of urban amenities such as schools, hospitals, supermarkets, or parks, but also jobs, which are distributed across a metropolitan landscape. For this reason, physical mobility is often linked to opportunities for the achievement and enjoyment of a better life in cities. Mobility is bolstered by the availability and smooth integration of multiple transportation modes, including opportunities for walking and biking. Indeed, great cities are also characterized by high levels of mobility among their residents and by good transportation networks.

But what happens when urban mobility is greatly disrupted by a catastrophic event—an event that comes unexpectedly and lasts for multiple months or even years? This dystopic scenario is exactly what happened in cities around the world during the COVID-19 pandemic. Emerging first in Wuhan, China in the waning days of 2019, the pandemic proceeded to spread fast throughout the globe, partly facilitated

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by inter- and intra-urban and long-distance travel. No corner of the world, no matter how remote, remained unaffected or untouched. Certainly, the most significant and sober impact of the pandemic can be measured in the millions of lives that have been lost. But the pandemic also brought cities and urban life as we know it at a standstill. Physical distancing and shelter-in-place mandates and lockdown orders, issued by governments around the world, along with people's fears about the transmission of the disease, curtailed mobility and travel, but have also had ripple effects on the economy, the environment, and on safety in cities and metropolitan areas. The pandemic affected different urban groups differently, often exacerbating pre-existing inequalities and vulnerabilities.

This book explores the impact of the pandemic on mobility and transportation. It examines both its direct impacts on travel and mobility but also the side effects of altered or disrupted travel patterns. Thus, it also explores some of the by-products of diminished mobility—such as the proliferation of telecommuting and e-commerce, reduction of greenhouse gas emissions, and decreased traffic crashes. It collectively aims to address the following questions.

- How has the pandemic impacted vulnerable populations in cities differently?
- What have been the impacts of the pandemic on the transportation industry (in particular public transit) but also on other industries of the economy that rely on transportation (such as freight trucking, retail, and food industries, or the gig-economy)?
- How has the pandemic affected automobile traffic and associated air quality and traffic safety?
- How has the pandemic bolstered alternative forms of work (telecommuting), shop (e-retail), and travel (walking and cycling), and are the altered patterns likely to persist?
- Importantly, what have been some positive responses to the transportation and mobility challenges? What lessons can policymakers, planners, and transportation officials learn from the pandemic? Can the condition of and reaction to the pandemic spur positive changes in urban transport?

## 1 Book Organization

The book is a compilation of 19 chapters, in addition to Introduction and Conclusion. The chapters are arranged in two parts: Impacts and Responses. The impacts are further divided into four sections: Vulnerable Populations, Economy, Environment and Safety, Mobility and Travel. All chapters represent empirical, data-driven, and original research work. The authors are affiliated with the University of California Institute of Transportation Studies (ITS) (https://www.ucits.org/)—a flagship multi-campus research institute on transportation and policy in the United States and in the world. ITS spans the UC Berkeley, UC Davis, UC Irvine, and UCLA campuses and other affiliated universities of the University of California system. While a number of chapters focus particularly on California, the largest and most diverse U.S. state and the largest state economy in the United States, other chapters also draw information from other geographic contexts. The concluding chapter builds on the previous chapters to summarize the collective wisdom and major findings and extrapolate lessons for cities and metropolitan areas, as well as for future research and policy.

## 2 Summary of Contributions

The economic fallout of the pandemic has hit low-income families the hardest. One of the consequences is delinquent car loans, as families who have seen their household income decrease cannot make car payments. In Chap. 2, Evelyn Blumenberg, Fariba Siddiq, Samuel Speroni, and Jacob L. Wasserman examine this issue in California, drawing on data from the University of California Consumer Credit Panel, a dataset that includes anonymized consumer credit and debt data for all California residents, including data on vehicle debt and loan delinquency. They compare the impacts of the Great Recession in the United States (from 2007 to 2009) with the impacts of the COVID-19 pandemic (2020–2021) on car loan delinquencies and analyze their data across neighborhoods by income and race. They find that the crisis affected low-income, minority households the most, as these households saw their automobile burden grow. Loans to buy a car slowed down in California during the pandemic, and the burden of automobile debt decreased overall. Nevertheless, the lower rates of automobile borrowing were offset by rising automobile prices, especially for used vehicles. This represented a true hardship for economically vulnerable populations, many of whom are essential workers, who cannot afford to stop working but also cannot afford their cars. The chapter points to the need for policies to better support the transportation needs of lower-income households, especially under shocks such as the one caused by the pandemic.

As homeless shelters reduced their capacity to uphold physical distancing requirements, unhoused individuals were most hardly hit by the pandemic. Many of them had no other places to go to than bus stops, station platforms, and transit vehicles. In Chap. 3, Anastasia Loukaitou-Sideris, Jacob L. Wasserman, Ryan Caro, and Hao Ding inquire about the impact of the pandemic on homelessness in the transit environments of the United States and Canada, and how transit agencies in these two countries have responded to it. They present the results of a survey of 115 transit agencies, finding that the vast majority of these agencies perceive that homelessness has increased in their systems during the pandemic. As most transit riders shunned using buses and trains out of the fear of getting infected, the unhoused riders became more visible. Most transit agencies responded by adopting a range of measures, some positive for their unhoused riders but some also punitive toward them. The chapter points to the importance of outreach strategies that offer help and services (for example free transportation) to unhoused individuals and uphold the social role of transit in cities. It also underlines the need for external public funding for agencies that could help them put in place outreach strategies.

Low-wage workers of the gig-economy represent a vulnerable group, as they receive few (if any) employee benefits and have to work for low wages. The pandemic forced some gig economy workers to shift from driving people in ride-hailing operations to delivering food and groceries for Uber Eats, Instacart, Grubhub, or DoorDash, without access to personal protective equipment. In Chap. 4, Amelia Regan and Nicola Christie review the recent academic and gray literature to examine the impact of the pandemic on the gig economy and its workers—especially the labor, safety, and environmental impacts. Despite the importance of food delivery and other delivery services during the pandemic, many transportation workers in the gig economy made less than the minimum wage. The outcome of labor issues in some countries, such as the prospect of gig worker unionization or the gig industries' efforts to classify their workers as independent contractors, does not necessarily relate to the pandemic but will affect gig workers' welfare in the future. The safety of transportation gig workers also is a concern as the pressure to complete rides in tight schedules often leads to higher rates of crashes. Lastly, the environmental impacts of the transportation gig economy are mixed. There are demonstrated positive environmental impacts of food delivery services, and pooled ridesharing would result in less vehicle miles traveled (VMT) overall, but the pandemic made people reluctant to use shared ride-hailing services.

Turning to transportation-related economic effects of the pandemic, Hannah King, Natalie Amberg, Jacob L. Wasserman, Brian Taylor, and Martin Wachs examine in Chap. 5 the pandemic's impacts on California's Local Option Sales Tax (LOST), a tax that is levied on the price of all goods and services that are subject to sales taxes (including fuel purchases). Many counties around the United States employ such a tax as a revenue source for funding transportation infrastructure and services (i.e., roadways, bikeways, transit services, transportation services for elderly and disabled people). But unexpected revenue shortages can inhibit the capacity of counties and cities to provide some of these services. The authors find that revenues from LOST fell during the initial stages of the pandemic in all California counties. LOST revenues increased again after the initial months but with variations across counties. Counterintuitively, counties with higher-income households and concentrations of employment in information and professional services, arts, and recreation, lost more revenues from decreased LOST. Not surprisingly, where unemployment rose, LOST revenue fell. This chapter points to the need for policymakers to incorporate uncertainty in revenue projections from taxes such as LOST and prioritize transportation infrastructure and projects, which are typically funded from such revenue sources. The chapter also underlines the importance of federal stimulus funding, which partly covered the lost tax revenues.

Decreases in physical mobility meant that shopping from brick-and-mortar establishments would also fall. In Chap. 6, Miguel Jaller and Sarah Dennis examine the interrelationship between shopping, and mobility trends in the United States, UK, and France and use data from several sources to track people's mobility, shopping and e-shopping patterns, and time spent at home versus work. They find that in all three countries, shopping-related mobility decreased during the first months of the pandemic, as people started spending more time at their homes, but eventually started catching up pre-pandemic trends. At the same time, e-commerce saw a major boost in all three countries; a trend that has been largely maintained, even if mobility started increasing again. The authors pinpoint to some positive effects of reduced travel (less congestion, cleaner air) but warn that we need clear and deliberate policies and strategies to maintain any mobility benefits experienced during the early months of the pandemic.

In Chap. 7, Jean-Daniel Saphores, Lu Xu, and Bumsub Park also focus on e-commerce for food, analyzing the impacts of the pandemic on how people in California, China, and South Korea shopped for groceries and meals. In contrast to China and South Korea, very few people in California shopped for groceries online, prior to the pandemic. The pandemic changed this trend, with many more Californians ordering groceries online, requesting food deliveries, or using "click-and-pick" to shop groceries. Similarly, China and South Korea, two countries with well-established platforms for e-grocery sales, saw their sales in this sector increase even more as a result of the pandemic and the initiation of innovations such as contactless delivery (dropping packages at designated locations) and livestreaming e-commerce in China, and development of a variety of pre-packaged or instant meal products in South Korea. The authors predict that most e-grocery gains will remain post-pandemic, but their implications for Vehicle Miles Travelled (VMT) are less clear. They recommend zoning changes that would allow e-stores that can fulfill e-orders locally; but also paying attention to equity issues so that poor neighborhoods also receive good e-grocery services.

A surge in e-commerce translates to higher trucking activity. The pandemic affected supply chains globally and created significant bottlenecks in freight movement. In Chap. 8, Yiqiao Li, Andre Tok, Guoliang Feng, and Stephen G. Ritchie investigate the impacts on freight trucking activity in California, looking in particular at changes in drayage, long- and short-haul movement, and payload characteristics. They find that the counts of containers at the Port of Los Angeles initially decreased but later increased, a fact that affected truck activity. Drayage truck movements serving large warehouses increased, while those serving warehouses of smaller businesses decreased. Short-haul truck movements increased significantly, while long-haul truck movements witnessed a small decrease. The pandemic saw a significant increase in full-load tracks and a slight reduction in empty trucks. The authors note that the aforementioned changes are a consequence of changed consumer behavior and needs during the pandemic but also changes in local and foreign policies and supply-chain bottlenecks.

The changes in mobility patterns because of the pandemic have not only brought about economic and social impacts but have also affected air pollution levels. In general, less traffic means less pollution; however, significant disparities were observed in air-pollution levels during the pandemic across neighborhoods, based on their sociodemographic characteristics. In Chap. 9, Shams Tanvir, Dwaraknath Ravichandran, Cesunica Ivey, Matthew Barth, and Kanok Boriboonsomsin explore how the pandemic affected mobility across different communities in Southern California and the associated changes in pollutant concentration. They find that freeway traffic dropped as low as 50% within 6 weeks from California's lockdown, with associated reductions in transportation-related air pollution. However, traffic gradually increased to pre-pandemic levels. The authors note significant differences in traffic volume changes across the region based on neighborhood sociodemographic characteristics, with traffic flows rebounding faster in disadvantaged neighborhoods. Indeed, the more disadvantaged a community, the less traffic reduction and air pollution reduction it experienced. Such disparities accentuate already existing environmental justice concerns in the region. The authors propose the development of telecommuting programs for low-income employees, as well as ensuring that the expansion of warehousing activities (because of e-commerce proliferation) does not further penalize disadvantaged communities.

In Chap. 10, Fraser Shilling expands the inquiry about pandemic-related environmental impacts, estimating the reduction in greenhouse gas (GHG) emissions because of reduction in VMT, as well as the associated change in fuel tax revenue throughout the United States. He finds that, thanks to a 50% reduction in VMT, GHG emissions in the United States were reduced by 4% in total and by 13% from transportation in the 8 weeks following stay-at-home orders. He estimates that this translates to savings of about $5 billion per week to U.S. drivers, but losses of about $0.7 billion per week in states' tax revenues. California's reduction in GHG has been greater than the U.S. average, and the state's travel rates remained reduced by as much as 20% through the spring 2021, compared to 2019. As the author notes, it is clear that human behavior, similar to the one exhibited during the pandemic, can contribute significantly to long-term reduction of GHG emissions. Policymakers and businesses should consider policies that enable, even incentivize, more work from home but do it in ways that do not exacerbate inequity.

The reduced trip frequency and associated changes in traffic volumes observed during the pandemic influenced the incidence of highway crashes. This is the topic examined by Offer Grembek, Praveen Vayalamkuzhi, and SangHyouk Oum in Chap. 11. The authors analyze crash data on California highways from the California Statewide Integrated Traffic Records System (SWITRS) database, as well as exposure data based on Vehicle Miles Traveled (VMT) as provided by the Caltrans Performance Measurement System (PeMS), for 6 weeks before and 7 weeks after California's Stay Home orders. They also collect crash and VMT data for corresponding weeks during 2019. They find that the total number of injury crashes, across all levels of severity, decreased during the pandemic, as compared to 2019. However, while the overall crash frequency dropped, the rates of severe crashes increased, likely because of less traffic on the highways, which allowed for higher speeds. The authors note that their findings suggest some policy implications for traffic operations such as coupling congestion mitigation measures with safety improvements.

The fear of shared transportation modes in enclosed environments, whether justified or not, led to a preference of individual modes during the pandemic. In Chap. 12, Sean McElroy, Dillon Fitch, and Giovanni Circella examine how the pandemic changed walking and biking habits of adults in the United States. Using data from a longitudinal panel, collected during four time periods between 2018 and 2020 from different regions across the United States, the authors find that walking and biking for commuting trips increased during the pandemic, possibly encouraged by many cities that designated Open Streets favoring these two modes. At the same time, however, the mode share of private car also increased during the spring of 2020, as people needing to travel longer distances avoided modes that would bring them into close contact with other travelers. The authors emphasize the need for post-pandemic policies that facilitate the use of active travel modes, such as making Open Streets permanent, developing a pedestrian and cycling infrastructure in cities, and offering incentives for e-biking.

Working from home, or telecommuting, became a viable option for many during the pandemic. Indeed, we can say that the pandemic effectively created two major groups: those who worked from home and those who continued to travel to work. Using data from a cross-sectional survey of 4,045 Southern California residents, Jai Malik, Bailey Affolter, and Giovanni Circella examine in Chap. 13 the differences in sociodemographic characteristics and travel behavior between these two groups. They find that non-teleworkers are mostly non-White, younger, and of lower incomes. The authors note a dramatic increase in telecommuting in the region, finding that only 20% of telecommuters were working from home prior to the pandemic. Both groups experienced decreases in their overall trip frequency and VMT across all transportation modes, and shifted to more individual modes such as private automobiles and active travel modes for non-commute travel. During the same time, transit use and shared mobility options such as e-scooters and ride-hailing declined. The authors point to the importance of making these options safe again, while encouraging non-motorized travel where possible.

In Chap. 14, Michael G. McNally, Rezwana Rafiq, and Md Yusuf Sarwar Uddin also focus on changes in telecommuting during the pandemic and the resulting travel behavior. They merge a number of datasets to examine nine months of data from the four largest U.S. states (California, Florida, New York, and Texas) to identify changes in travel behavior, telecommuting, visits to work and non-work places, and average distance traveled. Similar to the findings of the previous chapter, they find that those who telecommuted were more high-income, White or Asian. In all four states, a sharp decrease was observed during the initial outbreak period for all types of trips; however, visits to grocery stores, pharmacies, and parks were among the first types of trips to recover. The researchers find differentiation among the four states in the extent of telework among their residents. California, in particular, had a higher fraction of people staying home and has experienced higher reductions in work and non-work trips than the other three states. The authors note, that in a post-pandemic world, high levels of telecommuting would help lessen traffic congestion and reduce commuting time and cost. However, changes from the part of both companies and policymakers would need to happen to maintain the gains in telecommuting observed during the pandemic.

The use of public transit witnessed a dramatic reduction during the pandemic because of the public's fear of disease spread and infection within the narrow confines of transit vehicles. But to what extent transit use impacts the transmission of COVID-19 in urban areas? Henry Bernal and David Brownstone seek to respond to this question in Chap. 15 using data on station-level ridership and COVID-19 case counts within Countywide Statistical Areas (CSA) in Los Angeles County. They find no evidence that increased ridership levels or bus trip lengths are associated with higher incidence of COVID-19 at the CSA level in Los Angeles County in the period between June 2020 and January 2021. Indeed, their study suggests that masking and vehicle sanitation measures proved quite effective, and fears of becoming infected because of riding transit may have been exaggerated. However, the authors cautiously note that contact tracing investigations using virus sample genetic sequencing to identify the sources of COVID-19 infections can better confirm if bus ridership does not affect COVID transmission.

While the previous chapters focus more on the mobility-related impacts of the pandemic, the next five chapters focus more on actual or potential responses. The first three of these chapters focus on the transit industry and its responses to the pandemic, using different geographic contexts. Thus, in Chap. 16, Yiduo Huang and Zuojun Max Shen summarize evaluation methodologies, which examine the effectiveness of policies that various transit agencies worldwide have followed in their efforts to prevent COVID-19 transmission in transit environments. They find that if different districts in a city have almost similar infection rates, an effective policy to minimize the spread of the infection in public transportation networks is by reducing the total travel time and crowding levels. On the other hand, if different districts have uneven infection rates, effective policies should seek to reduce the weighted sum of the travel time and crowding levels. They also discuss the impacts on disease spread of reducing bus line capacity or closing lines, as well as of cutting transit budgets. As also discussed in Chap. 15, the authors' models show that the preventive measures against the spread of COVID-19 in U.S. transit environments seem to have been effective.

In Chap. 17, Samuel Speroni, Brian Taylor, and Yu Hong Hwang survey 72 U.S. transit operators to inquire about the pandemic's impact on their agencies and these agencies' response during the initial shock period of three months, a later period of adaptation, and a period of recovery, after March 2021. The authors find that small and large agencies were affected somewhat differently, but overall, they acted fast in response to pandemic mandates and challenges, initiating mandatory masking on vehicles and rear-door vehicle boarding, restricting some seats from use, installing dividers between operators and riders, and practicing extensive cleaning and disinfection. The pandemic increased the visibility of transit's role as social service provider, and many agencies reported developing service and outreach policies targeted toward their more disadvantaged riders. The authors note that while the short-term financial shortfalls of the transit industry were addressed by the federal relief bills, the industry's long-term financial future is rather uncertain.

The woos of the public transit industry had started in the United States well before the pandemic but became further aggravated as ridership dramatically declined during the pandemic. In Chap. 18, Alex Kurzhanskiy and Servet Lapardhaja focus on three transit operators in the Bay Area and describe their responses to the challenges generated by the pandemic. In particular, they discuss issues of service adjustments, fleet management, adjustment of performance metrics, and the ways that these transit agencies have operated paratransit in response to the pandemic.

The last two chapters of the book use scenario planning to offer policymakers a range of possible scenarios for recovery. As discussed in Chap. 5, the pandemic has affected transportation revenue needed to finance transit projects and operations of transit and highway systems. In Chap. 19, Asha Weinstein Agrawal, Hannah King, and Martin Wachs present six different revenue recovery scenarios for a range of possible futures for the State of California. The scenarios represent different combinations of future patterns in travel behavior and fleet composition, discussing high, medium, and low trajectories for each of five key variable inputs: (1) Annual state VMT; (2) light-duty vehicle fleet size; (3) light duty, zero-emission vehicle (ZEV) fleet size; (4) light-duty ZEV fleet values; and (5) Diesel share of the heavy-duty flee. Depending on the scenario, different transportation revenues can be accrued by 2040. Nevertheless, the authors note that, over the long term, structural factors other than the pandemic will have far greater impacts on revenue.

In Chap. 20, Susan Shaheen and Stephen Wong ponder ways that public transit and shared mobility—two industries that were hit hard by the pandemic—can recover. They relate findings from a scenario planning exercise with 36 U.S. transportation experts on ways that these industries can initiate recovery and eventually develop a more "resilient, socially equitable, and environmentally friendly transportation future." They discuss a series of short- and long-term actions, interventions, and policies that transit operators can follow in the areas of innovation and technology, planning and operations, customer focus, and workforce development. They also articulate broader policy strategies for both the public transit and shared mobility sectors in ways that they align with larger social goals (i.e., sustainability, resilience, etc.) and stabilize their funding streams.

Collectively, this book teases out the pandemic's impacts on mobility, accessibility, and transportation in California, other U.S. states, and some other countries. The concluding chapter underlines the book's major findings, summarizes common themes, and offers the editors' reflections on the lessons learned from the pandemic. As devastating as the pandemic has been for human life, it has also triggered responses, adaptability, and adjustments to human behavior. Some travel behavior adjustments have even had positive outcomes for the environment and transit safety. The challenges for scholars and policymakers in the years to come will be to develop policies and strategies to maintain the positives, correct the negatives, and do so in ways that are equitable and sustainable for society.

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# Impacts on Vulnerable Populations

# Can I Borrow [for] Your Car? Income, Race, and Automobile Debt in California

**Evelyn Blumenberg, Fariba Siddiq, Samuel Speroni, and Jacob L. Wasserman**

**Abstract** The COVID-19 crisis elevated the importance of private vehicles. The pandemic drove riders off public transit and spawned additional car-based activities such as drive-through testing and vaccinations and curbside pick-ups. Yet millions of low-income and non-white households do not own vehicles. This chapter draws on a unique credit panel dataset to examine automobile debt and delinquency in California. In particular, we examine whether automobile debt patterns during the pandemic differed from those during and coming out of the Great Recession (December 2007–June 2009). We also analyze the response to the COVID-19 recession across neighborhoods by income and race. Similar to the situation during the Great Recession, we find that the number of automobile loans per borrower declined. While the automobile debt burden (the ratio between total automobile debt and aggregate income) also declined, it fell far less during the pandemic than during the Great Recession. Moreover, automobile loan delinquencies spiked during the Great Recession but instead continued to drop during the pandemic. Finally, the COVID-19 crisis affected consumers differently by both race and income. Automobile debt burden rose in low-income, Latino/a, and Black neighborhoods, a pattern that preceded but continued unabated during the pandemic. The findings suggest that COVID-19 relief may have

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helped some families manage their automobile-related expenditures. However, other factors, such as increasing automobile prices, likely contributed to growing debt burdens, a potential source of financial distress.

## 1 Introduction

Most U.S. metropolitan areas grew alongside the automobile. As a result, most have come to consist of relatively low-density development best suited to vehicle travel. In the United States, about 82% of all trips and 91% of all miles are made in a private vehicle [20]. However, despite the many advantages of driving, more than 18.5 million households did not own a vehicle prior to the pandemic, of which almost 60% were households of color [38]. While some of these households were voluntarily car-free, more than 70% were car-less largely due to income constraints that prevented them from purchasing and operating a vehicle [8].

The crisis caused by the Coronavirus Disease 2019 (COVID-19) elevated the importance of private vehicles. Despite the lack of empirical evidence of transit's role in the transmission of the virus (see Chap. 15 on this topic), many former transit riders avoided buses and trains [28, 32]. Transit ridership plummeted during the pandemic, particularly in higher income, white neighborhoods, where many workers could work from home and most owned automobiles [28, 32]. Vehicle miles of travel (VMT) also dropped, falling 42% from February to April 2020 [24]. While transit ridership remains depressed [10], VMT rebounded quickly and, as of March 2021, was at about 90% of the pre-pandemic levels [24]. Despite stay-at-home orders during the pandemic, some of this vehicle travel was for essential work purposes. The COVID-19 crisis also spawned additional car-based activities, such as drive-through testing and vaccinations, curbside pick-ups, and drive-in church services and entertainment, to name a few [27].

A number of researchers have examined changes in travel behavior during this health crisis with an eye toward predicting future travel and mode use [7, 40]. Far fewer have analyzed the effect of the pandemic on automobile ownership, which is the focus of this chapter. We use a unique dataset—credit panel data—to track changes in automobile debt in California from 2004 to the first quarter of 2021. We track three measures: the ratio of automobile loans to borrowers (automobile borrowing), the ratio of automobile debt to aggregate income (automobile debt burden), and the share of delinquent borrowers (delinquency rate).

We examine whether consumer response during the pandemic differed from that during and coming out of the Great Recession. The federal response to the COVID-19 crisis differed substantially from that during the Great Recession [54]. As of March 2021, 44% of all adults experienced a loss of household employment income; however, almost 40% of this group relied on stimulus payments to cover their expenses [45]. Additionally, some consumers benefited from loan forbearance and other financial relief provided by select financial institutions [13].

Our data show that similar to the Great Recession, automobile borrowing slowed. However, while the automobile debt burden declined, it fell far less during the COVID-19 recession. And while automobile loan delinquencies spiked during the Great Recession, they instead continued to drop during the pandemic. Analyzing the response to the COVID-19 recession across neighborhoods by income and race, we find that the crisis affected different groups of consumers differently. The most apparent trend was the growing automobile debt burden in low income, Latino/a, and Black neighborhoods, a pattern that preceded but continued unabated during the pandemic.

## 2 COVID-19, Consumers, and the Car

In most metropolitan areas, automobiles provide greater access to opportunities within a reasonable travel time than other modes [41]. This access advantage not only explains why so many households own cars but also why studies find positive relationships between automobile ownership and economic outcomes, particularly among low-income and non-white households [33, 36, 42]. Conversely, households without cars can be isolated from opportunities, a disadvantage that has grown in parallel with the continued dispersion of metropolitan areas [30].

As of 2019, almost all U.S. households (94%) had at least one automobile [38]. Automobile ownership rates are high even among low-income households: 80% of households in the bottom income quintile owned at least one vehicle. However, low-income households own fewer vehicles than higher-income households, and Black and Asian households are the least likely to own cars [34, 38].[1]

On average, low-income and non-white households have less automobile debt than higher-income households [51]. Due to a lack of savings, lower-income households might be expected to be more likely than higher-income households to finance their automobile purchases. However, this is not the case. In 2019, low-income households spent an average of $10,000 on a vehicle—45% less than high-income households—and were more likely than higher-income households to purchase their vehicles with cash [34]. In addition to drawing from their savings, low-income households buy automobiles using lump-sum payments such as those from the earned income tax credit [26], as well as targeted revenue generation such as from crowdfunding campaigns [29].

While some consumers prefer to pay cash, others may do so after being denied financing. For example, an analysis of credit bureau records shows that Black and Latino/a applicants had loan approval rates 1.5 percentage points lower than white consumers, even accounting for creditworthiness [11]. Finally, lower-income

[1] Sixty-nine percent of low-income Black households and 74% of low-income Asian households have at least one automobile. Automobile ownership among Latino/a households (81%) is only slightly lower than among non-Latino/a white households (85%) [38].

households own fewer and less expensive vehicles than higher-income households [34, 38].

About a third of all low-income households fully or partially finance the costs of their vehicle purchases; this group spent significantly more on their vehicles than those who paid cash [34]. While this group tends to have less automobile debt than higher-income households, on average they have higher automobile debt *burdens*—automobile debt as a percentage of household income [34, 51]. Indeed, more broadly, among households with cars, low-income households have slightly higher total transportation expenditure burdens than higher-income households [52].

Studies show significant racial discrimination in automobile lending. In a matched pair test of purchases at car dealerships, researchers found that non-white testers received a higher quote for the financing of the exact same vehicle; non-white testers who experienced discrimination would have paid an average of $2,663 more over the life of the loan [37]. Studies drawing on other sources of data find similar results [11, 12].

Lower-income and non-white buyers who finance their vehicles are subject to an array of predatory loan practices including excessive interest rates, false or misleading information about vehicle costs, lending without verification of borrower income, and inflated fees and add-ons [15, 48, 49]. These practices can drive up the costs of vehicle loans and elevate default risks [48, 49]. Emmons and Ricketts [19] find that younger, less-educated, and non-white families are more likely than other families to miss loan payments. Indeed, unanticipated economic shocks, credit constraints, and lack of financial education are the leading causes of higher delinquency risks, each a factor inextricably linked to structural racism and enduring discrimination in credit markets based on racial and ethnic identities [2, 11].

These disparities also map onto neighborhoods by income and race. Residents of majority-non-white and low-income neighborhoods are less likely than residents of other neighborhoods to have automobile loans [6, 31].[2] However, automobile loans comprise a larger share of total debt in lower-income than higher-income neighborhoods, since residents in these neighborhoods are less likely to have mortgages [31]. Moreover, the ratio of automobile debt to income is higher in ZIP codes in the lowest income quintile compared to those in the highest income quintile [1].

Since the Great Recession, total outstanding U.S. automobile debt adjusted for inflation increased significantly, growing by 40% from 2010 to 2019 [21]. Much of this growth was due to a substantial increase (22%) in the percentage of consumers with automobile debt [22]. Increasing median automobile debt played a smaller role, growing by 8% over this period to just under $15,000. Vehicle credit tended to follow the economic cycle, increasing during periods of expansion and contracting during recessions. These trends were magnified among consumers living in low-income neighborhoods [1].

[2] However, this pattern is not consistent across states and counties in the United States. For example, the percentage of the population with automobile loans is the same (28%) in majority-white and majority-non-white neighborhoods in California [6].

As we note above, the COVID-19 pandemic has elevated the importance of driving, largely due to concerns about the health effects of other modes (e.g., transit, etc.) [4]. As evidence of this, one survey found that a high percentage of individuals in zero-vehicle households were contemplating purchasing a vehicle in the near future [3]. Increased demand also contributed to the significant rise in vehicle prices in 2021, particularly for used vehicles [18].[3] Overall, after dipping to nine million vehicles per month in April 2020, vehicle sales rebounded, increasing by 94% by May 2021 [46]. Preliminary analysis also shows that total automobile debt has increased across the United States [44]. Automobile debt trends among low-income and non-white consumers during the pandemic have not yet been studied.

## 3 Data and Methods

For this analysis, we used a 1% random sample of the University of California Consumer Credit Panel (UC-CCP), a dataset from Experian of every loan and every borrower in California, for every quarter from 2004 through the first quarter of 2021. For every loan, the dataset has information on loan type, current balance, whether or not the loan is delinquent on payment, and beginning in 2010, the census tract of the borrower's residential address. The data also include all of the borrowers associated with the loan, some of whom have shared ownership of the asset; to minimize double-counting, we restrict our analysis to only the primary borrower on each loan.

The credit data do not provide income, race, or ethnic identifiers. Therefore, we analyze the debt and delinquency characteristics of consumers across neighborhoods, defined for the purposes of this chapter by the income and racial/ethnic characteristics of the census tract in which they live. We matched UC-CCP data to socio-economic characteristics of census tracts from the U.S. Census Bureau's American Community Survey (ACS) 2015–2019 5-year estimates. We first present statewide trends from 2004 to the first quarter of 2021. These data allow us to compare automobile loan trends between the Great Recession (December 2007 to June 2009) and the COVID-19 recession (February to April 2020), plus their aftermath [35]. Drawing on geographic data from 2010 onward (with more detail available in 2014 and after), we then analyze neighborhoods by quintiles of median household income and race/ethnicity, selecting tracts where at least half of the residents were non-Latino/a white, Black, Asian, or Latino/a.[4]

Our analysis centers on the three metrics included and defined in Table 1: the rate of automobile borrowing, automobile debt burden, and automobile loan delinquencies.

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[3] Production slowdowns due to the shortage of semiconductor chips, along with increased competition from car-hire firms, also contributed to the surge in automobile prices [18].

[4] All but seven tracts in California had records for median household income, and roughly three-quarters of tracts had a race majority; tracts that had no income data or did not have a majority race/ethnicity are excluded from the corresponding analyses but are included in the statewide data. Statewide data also include loans without census tract identifiers (20% of all loans).

**Table 1** Automobile debt measures

| Topic | Questions | Measures |
|---|---|---|
| Automobile borrowing | Did more consumers finance their automobile purchases during the COVID-19 pandemic? | Ratio of automobile loans to number of all borrowers with an active primary credit record |
| Automobile debt burden | Did the automobile debt burden increase during the COVID-19 pandemic? | Relationship between total automobile debt and aggregate income |
| Automobile loan delinquencies | Did the COVID-19 recession affect consumers' ability to retain vehicles they have financed? | Share of automobile borrowers with loans 30+ days in arrears |

# 4 Findings

## *4.1 Automobile Borrowing*

Just how common is automobile borrowing? From 2004 to 2021, California averaged 0.38 automobile loans per individual with a credit record as a primary borrower—in other words, California has one automobile loan for every 2.6 borrowers. As the first graph in Fig. 1 shows, this ratio remained relatively steady from 2004 until the Great Recession. In the recession's wake, automobile loans per borrower declined by 17% from the third quarter of 2007 to the third quarter of 2011, bottoming out at 0.32. The ratio then increased, in all but one quarter, until mid-2018, when it peaked at 0.45—a 40% increase over seven years—after which it remained relatively unchanged until the beginning of the COVID-19 pandemic. While the first quarter of 2020 saw a slight decline, the second quarter of 2020 saw the steepest change of any quarter in the past 17 years, with neighborhoods of all incomes and racial/ethnic majorities experiencing a drop in automobile borrowing.

Few neighborhoods were immune to the effects of the pandemic shock by this measure; however, the lead-up and aftermath to the pandemic nonetheless contoured differently across neighborhoods. We found small but significant differences in the number of automobile loans among neighborhoods by income, particularly beginning in 2018. As the middle panel of Fig. 1 shows, the number of automobile loans among all borrowers leveled off in neighborhoods in the three highest-income quintiles after years of growth and then slightly declined in 2018 and 2019, whereas the number of automobile loans in neighborhoods in the two lower-income quintiles continued to slightly increase during those years. When the pandemic struck, the number of borrowers in all neighborhoods dipped in the second quarter of 2020, as households net shed automobile loans in the period immediately after the first lockdowns.[5] Subsequently, while loans per borrower generally rebounded—the bottom

[5] All neighborhood household income quintiles were significantly different from each other within and between the second quarter of 2019 and the second quarter of 2020.

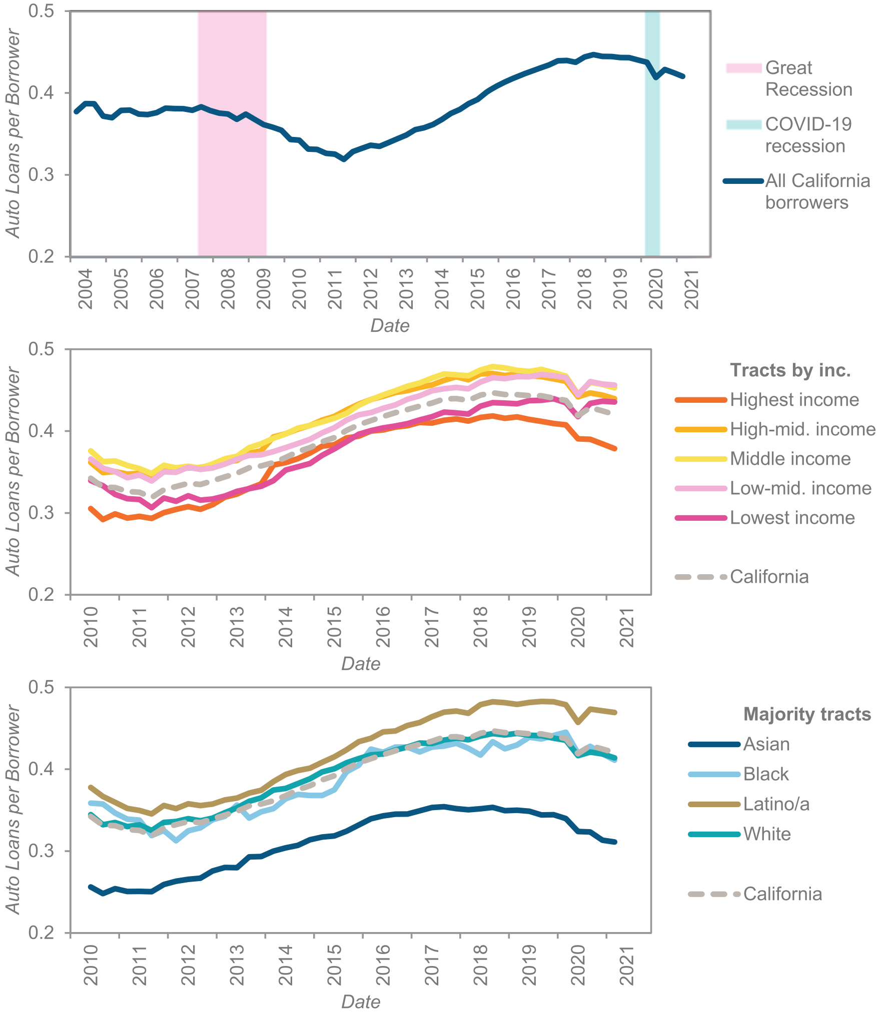


**Fig. 1** Ratio of automobile loans to all borrowers in California. *Supplementary data sources* [35, 47]

four income quintiles averaged a 3% increase—the ratio in the highest-income neighborhoods instead slightly declined. These well-off areas continued to lose automobile loans into the start of 2021, as did middle-income areas; meanwhile, the lowest-income neighborhoods leveled off. All told, while the pandemic caused an initial drop in automobile borrowing, only lower-income neighborhoods shifted back toward pre-pandemic loan patterns thereafter.

In the decade prior to the pandemic and since, trends in loans per borrower were similar across majority-race/ethnicity neighborhoods, but the ratios themselves were more dispersed. Asian-majority neighborhoods averaged 0.31 automobile loans per

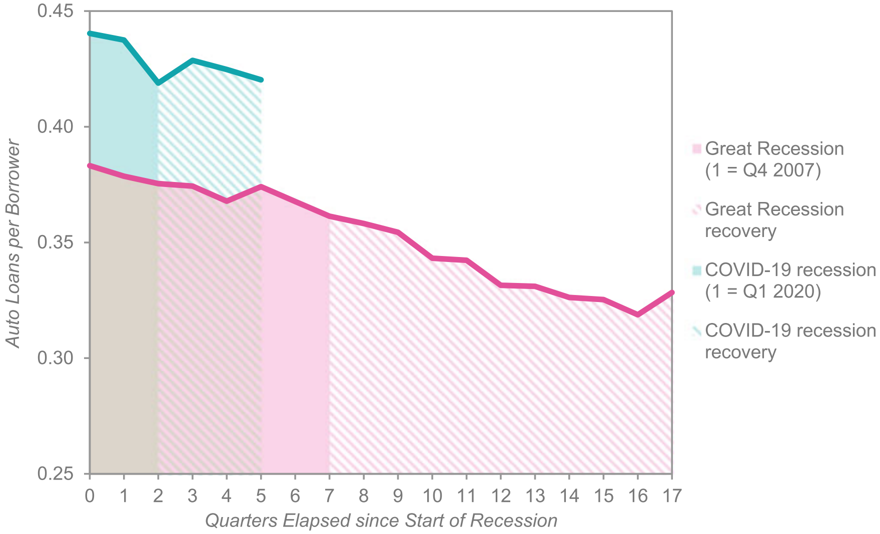


**Fig. 2** Ratio of automobile loans to all borrowers in California during recessions and recoveries. *Supplementary data source* [35]

borrower from 2010 to 2021, a ratio consistently far below that of other groups and the state average. In contrast, Latino/a-majority areas consistently had the most automobile loans per borrower, an average of 0.42 over the same time period. All majority-race/ethnicity neighborhoods experienced a decrease in automobile loans in the second quarter of 2020, but the drop continued thereafter in majority-Asian neighborhoods.[6] In contrast, vehicle lending in Black- and white-majority neighborhoods rebounded in the third quarter of 2020 and since declined, while automobile lending in Latino/a neighborhoods experienced a larger, longer-lasting rebound. These trends represent a continuation of patterns from both prior to and during the pandemic; automobile borrowing in Latino/a neighborhoods was consistently high, while it was consistently low in Asian neighborhoods.

The sudden and substantial decline in automobile borrowing at the start of the COVID-19 recession and the subsequent rebound differs from patterns during the Great Recession. As shown in Fig. 2, automobile borrowing declined gradually for over a year during the Great Recession before beginning to rebound. However, automobile loans per borrower fell a precipitous 4.2% in just the second quarter of 2020, which contained the COVID-19 recession. This was the largest single-quarter change in the dataset. The immediate dip may have been due to the combined effects of initial economic uncertainty, as well as shelter-in-place orders that were associated with an 80% drop in vehicle sales [5]. As we describe below, automobile loan delinquencies

[6] All majority-race/ethnicity neighborhoods were significantly different from each other within and between the second quarter of 2019 and the second quarter of 2020 with one exception: Black-majority neighborhoods.

declined over this same period, suggesting that the decline in borrowing was not due to an increase in automobile loan defaults.

Nonetheless, over the five quarters after the beginning of each recession, the percentage decline was roughly comparable (4.0% drop in loans per borrower in the Great Recession versus 4.6% drop in the pandemic recession). What remains unknown about the COVID-19 recession is how its recovery will proceed. According to economists with the National Bureau of Economic Research, the Great Recession ended after seven quarters; however, the ratio of automobile loans to all borrowers continued to decline for nearly four more years. By the same definition, the COVID-19 recession lasted only 2 months, making it the shortest recession in U.S. history [35]. This is likely because the COVID-19 recession was caused by an external shock, and thus the recovery from this recession may be far faster than from the Great Recession. Other indicators suggest that this might be the case [53].

## *4.2 Automobile Debt Burden*

While trends in the number of automobile loans are telling, not all loans are the same size, nor do they have the same effect on the finances of different households. Thus, we turn next to the burden of automobile debt across California: the ratio of automobile debt to the median neighborhood income.[7]

During the Great Recession, the automobile debt burden declined steeply. This downward trend continued to 2011 and then began to rise, peaking in 2016.[8] The top panel of Fig. 3 shows the average automobile debt burden from 2014 to 2021, which ranged from 0.08 and 0.11. Automobile expenditures are cyclical. Historically, the automobile debt burden is lowest in the first quarter of each year, a seasonal pattern similar to vehicle sales [23]. Typically, consumer spending—including consumer spending on automobiles—falls after the December holidays and then accelerates in the spring, aided by tax refunds and improved weather [26, 43]. The COVID-19 pandemic disrupted this pattern; in 2020, the lowest automobile debt burden occurred during the second quarter, the same quarter as the steep decline in the ratio of automobile loans to borrowers described previously. Overall, the automobile debt burden waned during the pandemic but far less than during the Great Recession.

The second and third panels in Fig. 3 show the automobile debt burden across neighborhoods by income and race. Households in the lowest-income neighborhoods have a higher debt burden compared to households in other neighborhoods, a finding consistent with Amromin and McGranahan's ZIP-code level analysis of data from

[7] We draw neighborhood income data from the middle year of the 5-year ACS estimates and assign that income to all quarters in the year. For instance, we draw the aggregate income in all quarters of 2016 from the 2014–2018 5-year estimates. From 2017 on, we assign the income from the 2015–2019 estimates—the most recent year available—to all quarters, adjusting for inflation.

[8] We begin our analysis in all graphs of Fig. 3 with 2014 due to data limitations inherent in combining UC-CCP data and ACS estimates; the percentage of loans with census tract identifiers in the UC-CCP data increased substantially during 2013.

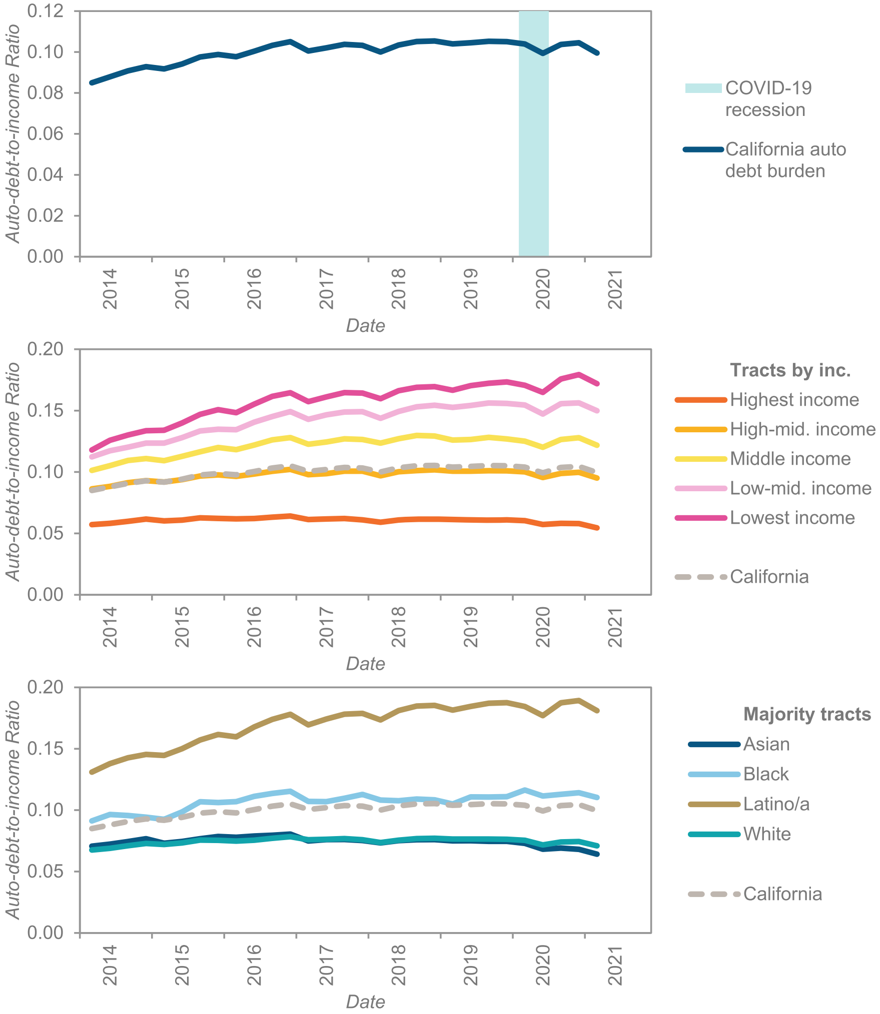


**Fig. 3** Automobile debt burden in California. *Supplementary data sources* [35, 47]

2004 and 2012 [1]. This debt gap widened over time. In 2014, the automobile debt burden in the lowest-income neighborhoods was twice that in the highest-income neighborhoods. By the third quarter of 2020, the differential was more than three to one. The debt burden in higher-income neighborhoods remained relatively stable. Therefore, this trend can be largely explained by the increasing automobile debt burden among households in low-income neighborhoods.

During the COVID-19 pandemic, this diverging trend of debt burden between the lowest-income and the highest-income neighborhoods continued. Between the first quarters of 2019 and 2021, the debt burden in the lowest-income neighborhoods increased by 3%, while it declined by about 11% in the highest-income neighborhoods.[9] Expanded federal benefits may have contributed to the uptick in vehicle sales and the automobile debt burden among households in lower-income neighborhoods.

The bottom panel in Fig. 3 highlights the substantial differences in the automobile debt burden across majority-race/ethnicity neighborhoods. Automobile borrowers in Latino/a-majority neighborhoods had a substantially higher automobile debt burden than the residents of any other majority-race/ethnicity neighborhood, followed by borrowers in Black-majority neighborhoods. Latino/a neighborhoods also experienced the largest increase in automobile debt burden, a 38% increase from 2014 to 2021. The debt burden in Black neighborhoods also increased by 21%, while it remained largely constant in Asian- and white-majority areas. During the pandemic, only Asian neighborhoods experienced a decline in their automobile debt burden, and a slight one at that. In other majority-race/ethnicity neighborhoods, the auto-debt-to-income ratio remained largely unchanged.[10]

### *4.3 Automobile Loan Delinquencies*

Having the financial means to purchase a vehicle is important, but so too is the ability to hold on to a vehicle once it has been purchased. Vehicles that have been financed require regular payments, which can be difficult to manage for individuals with low credit scores, high-risk borrowers who are highly vulnerable to financial shocks [16]. Data from past recessions show that delinquency rates typically follow the unemployment rate and other macroeconomic indicators [17, 50]. However, bucking the trend, automobile loan delinquencies in the United States fell during the COVID-19 economic downturn, even as unemployment rates rose [17].

As the top panel in Fig. 4 shows, vehicle delinquencies rose steeply during the Great Recession, as expected, and then fell over the last decade. Before the Great Recession, between 3% and 4% of California automobile borrowers were delinquent on at least one loan. As economic conditions worsened during the Great Recession, the delinquency rate nearly doubled, peaking at 6% in the last quarter of 2008. The delinquency rate declined coming out of the recession, dropping to below 4% in 2012. Despite seasonal fluctuations, delinquencies remained roughly constant (between 3% and 4%) through 2019, as the economy recovered and grew. However, during the COVID-19 recession, history did not repeat itself. Unlike during the previous recession, the percentage of delinquent borrowers continued to decline. Other studies

[9] Automobile debt burdens were significantly different from each other in neighborhoods by household income quintile in the second quarter of 2019 and in the second quarter of 2020. Between these two time periods, neighborhoods of all income quintiles had significant differences in debt burden.

[10] All majority-race/ethnicity neighborhoods were significantly different from each other within and between the second quarter of 2019 and the second quarter of 2020 with one exception: Black-majority neighborhoods did not have significant differences in their automobile debt burden between second quarter of 2019 and second quarter of 2020.

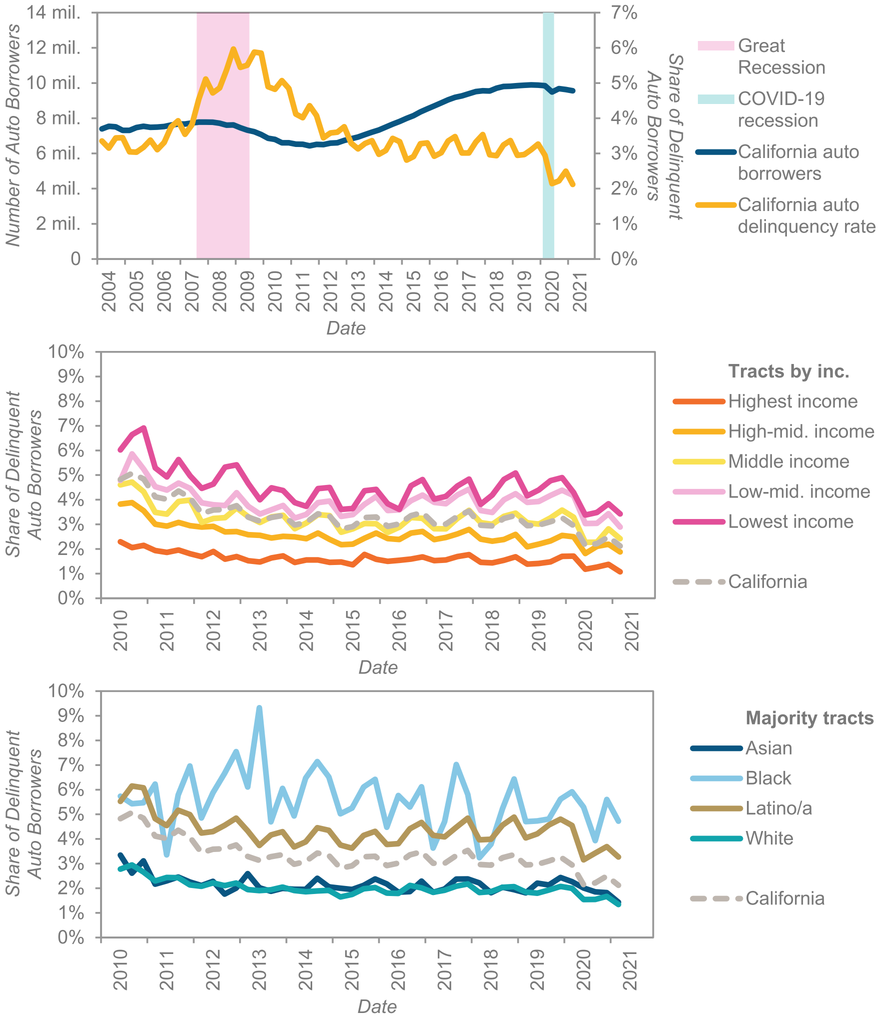


**Fig. 4** Automobile borrower delinquency rates. *Supplementary data sources* [35, 47]

have found declining delinquency rates for automobile loans as well as other loan types (e.g., student loans, mortgages, and credit cards) during the pandemic [17, 39].

As the middle panel in Fig. 4 shows, there is a negative relationship between neighborhood income and delinquency rates. As median income falls, automobile delinquency rates rise. In the highest-income neighborhoods, about 2% of automobile borrowers had delinquent loans a year after the Great Recession, whereas the share in the lowest-income neighborhoods was about 7%. Starting in 2012, the share of delinquent automobile borrowers in the highest-income neighborhoods fell below 2%, where it has remained. Delinquency rates also declined in the lowest-income neighborhoods, but have remained between 3% and 5%. During the pandemic, delinquency rates dropped across all neighborhoods by income, with consumers in the three lowest-income quintile neighborhoods experiencing the steepest decline.[11]

As with the automobile debt burden, there are stark disparities in delinquency rates across majority-race/ethnic neighborhoods. Black-majority neighborhoods had the highest delinquency rate in most quarters, followed by Latino/a neighborhoods. The share of delinquent automobile borrowers in white- and Asian-majority neighborhoods, meanwhile, remained largely between 2.0% and 2.5% during the post-Great-Recession period. During the pandemic, automobile loan delinquency rates again declined across all neighborhoods. The rate of decline was greatest in Asian-majority neighborhoods, followed by white-majority neighborhoods.[12]

## 5 Discussion and Conclusion

Our analysis of automobile debt highlights how consumer response varied between the two most recent recessions. In general, recessions are associated with a decline in automobile loans and debt and an increase in automobile loan delinquencies. Aside from an initial shock, in 2020 and 2021, California experienced a decline in automobile borrowers similar to the Great Recession, though for different reasons. In the early days of the pandemic, many car dealerships were closed [25]. Moreover, increased economic insecurity combined with shifts to remote work likely prevented or delayed automobile purchases among many households. Consequently, both automobile sales as well as purchase intent plummeted during the pandemic [25].

In other respects, the automobile debt patterns during the pandemic differed more noticeably from those during the Great Recession. Although the burden of automobile debt compared to neighborhood income fell during the pandemic, the decline was far less substantial than during the Great Recession, as falling rates of automobile borrowing were potentially offset by rising automobile prices and average amount financed [14, 18]. From February 2020 to February 2021, the price of new automobiles increased by 1.2%. Over this same time period, the price of used vehicles increased by 9.3% and then by another 19.5% from February to May of 2021 [9]. Used car prices spiked, not just because of rising demand (particularly with the lifting of stay-at-home orders), but also because of heightened competition for used vehicles from car rental agencies that sold off their stock during the pandemic, as well

[11] Neighborhoods in all income quintiles were significantly different from each other in terms of share of delinquent borrowers within and between the second quarter of 2019 and the second quarter of 2020.

[12] The share of delinquent borrowers was significantly different across all of the majority-race/ethnicity neighborhoods in both the second quarter of 2019 and the second quarter of 2020. Between these two quarters, the share of delinquent borrowers was significantly different in Latino/a-majority and white-majority neighborhoods.

as a slowdown in the production of new vehicles due to a semiconductor shortage [14, 18].

Despite initial job losses and rising car prices, automobile loan delinquency rates fell during the pandemic. This decline continued pre-pandemic trends since the last quarter of 2009 but differed from patterns during the Great Recession, when delinquencies skyrocketed. We suspect that federal, state, and local policy interventions played a key role in this trend. For instance, payment assistance, income support, and loan forbearances may have helped avert the rise of delinquencies. Income replacement from various policy interventions (e.g., stimulus payments, unemployment insurance expansions, and forgivable loans to small businesses) resulted in a greater rate of support for unemployed workers during the pandemic compared to previous recessions [17]. While temporary economic support may not have motivated households to purchase vehicles, it may have reduced the rate of missed automobile debt payments. Per the U.S. Census Bureau's Household Pulse Survey, 22.5% of California respondents who received a stimulus payment in the previous week used or planned to use at least some of the funds to make vehicle payments [45].

The credit panel data do not allow us to track automobile debt by neighborhood income or race/ethnicity prior to 2010. However, they do highlight income and racial disparities leading up to and during the pandemic. Perhaps most glaring is the increase in automobile debt among consumers in the lowest-income neighborhoods and, even more apparent, in majority-Latino/a neighborhoods. Even prior to the pandemic, automobile ownership among low-income and Latino/a households in California had increased substantially. Consumers in lower-income neighborhoods were also the only group that shifted back to pre-pandemic loan borrowing patterns.

From 2004 to 2019, the average number of household vehicles in Latino/a households increased by more than 15% (from 1.85 to 2.13) [38]. Over this same time period, mean household vehicles among households in the bottom income quintile increased by about 8%. Automobiles may have been particularly important to these two population groups during the pandemic since they were the groups least likely to be able to work from home [45]. They likely saw a greater need for cars during the pandemic (though they needed to borrow to finance them), while consumers in higher-income areas, with higher rates of working from home [25, 38], did not. The trends underscore the importance of subsidies to help low-income households purchase vehicles as well as manage their automobile debt.

Consumer response during the COVID-19 pandemic, while similar across some dimensions, varied from that during the Great Recession, suggesting that federal support may have helped some families purchase vehicles and manage their automobile-related expenditures. However, the growing automobile debt burden in low-income and, particularly, in Latino/a neighborhoods is cause for concern, as it may indicate significant financial distress. The data suggest the ongoing need for financial assistance to support automobile ownership among lower-income households, whose quality of life depends on access to a reliable vehicle. The observed trends—both over time and across neighborhoods by race/ethnicity and income—may be due to other confounding factors, too (e.g., household composition, access to high-quality transit, etc.). Therefore, as the country continues to recover from the pandemic, additional analysis of the underlying causes of these trends is needed to better target policy interventions.

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# Unhoused on the Move: Impact of COVID-19 on Homelessness in Transit Environments

**Anastasia Loukaitou-Sideris, Jacob L. Wasserman, Ryan Caro, and Hao Ding**

**Abstract** More than half a million individuals experience homelessness every single night in the United States. The limited capacity of shelters to meet their needs is forcing many to turn to transit vehicles, bus stops, and transit stations for shelter. The pandemic only exacerbated the homelessness crisis. Fear of infection in shelters and reduced capacity due to physical distancing requirements drove more unhoused people to take shelter on the streets and also in transit settings. Although discussions in the popular media have raised awareness of homelessness in transit environments, the scale of the problem has not been well-documented in scholarly research. This chapter investigates the intersection of the pandemic, transit, and homelessness in U.S. cities, presenting the results of a survey of 115 transit operators on issues of homelessness on their systems, both before and during the coronavirus pandemic. We find that homelessness is broadly present across transit systems though mostly concentrated on larger transit systems and central hotspots, and it has worsened during the pandemic. The challenges of homelessness are deepening, and dedicated funding and staff are rare. Attempting to respond to the needs of homeless riders, some agencies have put forth innovative responses, including hubs of services, mobile outreach, discounted fares, and transportation to shelters.

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## 1 Introduction

With the Coronavirus Disease 2019 (COVID-19) pandemic generating major concerns about the spreading of infection in enclosed and densely occupied environments and forcing a shift to remote work for some employers, transit ridership plummeted in the United States (See Chap. 17). But while many riders with other mobility options sought to avoid the narrow confines of buses and trains, one group of riders, in particular, did not leave transit. Individuals experiencing homelessness have long been a frequent presence in U.S. cities. Since the 1980s and over the last decades, homelessness has continued to grow as a result of the deinstitutionalization of mental healthcare centers, the deregulation and financialization of housing markets, the gutting of many welfare programs, and the drug epidemic [28]. As of January 2020, before the pandemic, the U.S. Department of Housing and Urban Development estimated that over 500,000 people lacked a stable roof over their heads every night [9].

Even prior to the pandemic, transit environments provided common settings for homelessness [2], with people using buses and trains both as shelter and transportation to workplaces, shelters, and social service centers. But as the pandemic brought into sharp relief preexisting inequities and disparities in North American cities, it also made the plight of unhoused riders more visible. Indeed, the pandemic intensified the scale of the homeless crisis and its implications for transit. Anecdotal evidence suggests that the number of people using transit environments for shelter rose. Physical distancing mandates led some homeless shelters to lower their capacity [21], forcing more unhoused Americans to look for shelter in public spaces and transit environments. With affordable housing scarce in U.S. metropolitan areas and the scale of homelessness crisis often surpassing the capacities of existing safety nets, transit operators faced these pressing issues themselves and had to implement policy measures from realms beyond transportation to address them. Additionally, the fear of contagion created public health concerns for transit agencies about the safety of their staff and riders [8, 13, 16].

Although discussions in the popular media have raised awareness of homelessness in transit environments, potential responses have not been studied extensively. Because of the health and safety implications of the pandemic and the anticipated further rise in homelessness from the resulting economic downturn [4], understanding and responding to the needs of these vulnerable riders are critical. To that end, this chapter presents the findings from a survey of U.S. and Canadian public transit operators, conducted during the pandemic, and compares these findings to those of another survey on the same topic conducted by Daniel Boyle in 2016. The chapter also reports insights from a series of in-depth interviews with transit agency staff and their partnering organizations, conducted from November 2020 to April 2021, on particular strategies that some agencies have initiated in response to homelessness. Our survey and interviews occurred prior to the mass distribution of COVID-19 vaccines in the United States and therefore document conditions during the pandemic itself, not the recovery that is ongoing as of this writing.

In the sections that follow, we first give a brief overview of prior research on homelessness in transit environments. We then discuss our research methodology, followed by the findings from our survey and interviews. Drawing from this empirical research, we conclude by offering suggestions on how to address homelessness in transit environments.

## 2 Prior Research

Transit environments represent common settings for individuals experiencing homelessness because of their anonymity, relative publicness, and in the case of transit vehicles and transit stations, microclimate control. Nevertheless, the literature on the intersection of transit and homelessness is rather sparse and primarily concentrated in the United States, where the phenomenon is most acute.[1]

A number of surveys have indicated the frequency of the phenomenon. As early as 1991, a survey by the Port Authority of New York and New Jersey found that all surveyed transit operators and airports viewed homelessness as an issue in their facilities [23]. Twenty years later, Nichols and Cazáres [20] interviewed 49 people sleeping overnight on buses in Santa Clara County in the San Francisco Bay Area, finding that about two thirds of them used the bus as their only or most regular shelter to spend the night. Bassett et al. [1] surveyed 69 staff from departments of transportation in 24 U.S. states and British Columbia, Canada and found that 70 percent regularly encountered people experiencing homelessness in their rights-of-way. More recently, Boyle [5] surveyed staff from 55 transit operators about homelessness on their systems and conducted detailed case studies of six operators' responses. More than 9 out of 10 responding transit agencies characterized transit homelessness as a challenge. In Minnesota, a 2018 survey found that 33% of adults experiencing homelessness used a transit vehicle, bus stop, station, or highway rest area as nighttime shelter at least once in the past year [22].

Researchers have examined the travel patterns of people experiencing homelessness, documenting the important role of transit for their mobility. A systematic literature review found that the primary travel mode for unhoused individuals is public transit [19]—in stark contrast to the low rate of transit ridership among the U.S. general public. In a case study in Long Beach, California by Jocoy and Del Casino [14], over half of the surveyed people experiencing homelessness used transit daily.

[1] Transit homelessness, while particularly common in North America, is also present in other countries of the Global North. In the United Kingdom, Heriot-Watt University researchers estimated that 11,950 people slept in vehicles, transit, or tents in 2017; unfortunately, the research as published does not separate out transit from these other settings [6]. In Berlin, a homeless census counted 154 people sleeping in transit stations—16% of the city's unsheltered individuals and 8% of all people experiencing homelessness [24]. For context, Berlin, with a population of 3.77 million, had 1,976 unhoused individuals just prior to the pandemic in 2020, while the similarly sized City of Los Angeles, with a pre-pandemic population of 3.98 million, had 41,290 unhoused individuals [3, 15, 24, 26].

Interviewing unhoused people in Toronto, Hui and Habib [12] found that healthcare, social service centers, food banks, and visits to friends and families were top travel destinations; most either walked or used transit for these trips. Some studies have sought to understand the obstacles unhoused people face when riding transit, finding that transit fare cost represents a common barrier [10, 14].

What are the characteristics of unhoused individuals riding transit? Two studies that compared unhoused people on transit to unhoused people in other spaces in the city found that the former were more chronically unhoused and structurally disadvantaged; they were more likely to be men, to be Black, and to have been incarcerated, to be addicted to drugs or alcohol, or to suffer from mental illness [20, 27].

A survey of 49 U.S. transit operators in 2018, prepared for the American Public Transportation Association (APTA), found that more than two thirds of these agencies believed they should play a role in addressing homelessness [2]. Nevertheless, transit agencies have often ignored or minimized their social service role[2] and often have conflicting or misdirected goals that "suggest a lack of focus on the needs of transit riders themselves, particularly the poor and transit dependent" [25, p. 347].

In sum, only a limited literature exists on transit homelessness and in particular on agencies' responses to this challenge. Additionally, the existing studies prior to the pandemic do not capture the new and potentially unique challenges of rising homelessness during a public health crisis and the possible adjustments and responses to it. To cast some light to these issues, we turn to our empirical research.

## 3 The Pandemic, Transit Operations, and Homelessness: Survey Findings

We undertook a study of transit operators in the United States to understand how the pandemic has affected homelessness on their systems and what they are doing about it. We sought to answer:

1. How has the pandemic impacted homelessness in transit environments?
2. What has been the response of transit agencies?
3. What strategies are promising for responding to transit homelessness during and after the pandemic?

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[2] Broadly, transit serves a social service role of providing mobility to those who lack other means of transportation, due to poverty, disability, etc. [25]. In the context of public transit and homelessness, this social role entails serving all transit riders, even those who lack the ability to pay a fare or those who use transit for both shelter and mobility, and "treating all individuals with dignity and respect" [2, p. 5].

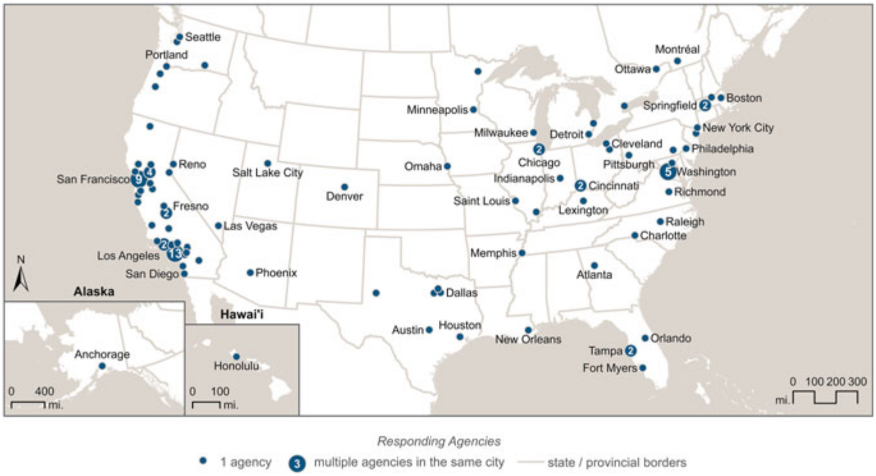


**Fig. 1** Locations of responding transit agencies (n = 115 agencies). *Data source* Authors' survey; *supplemental data source* [11]

## *3.1 Research Design*

To answer the first two questions, we deployed an online survey in late summer 2020 that was sent to 238 transit operators across the United States and Canada (Fig. 1) and yielded responses from 142 staff at 115 agencies (48.3% response) [17].[3] We e-mailed a link to this 37-question survey to all transit operators in the United States that operate 100 or more vehicles in maximum service [7] and all Canadian APTA members. Because California has the highest number of unsheltered individuals [9], we oversampled there, sending the survey to all operators in the California Transit Association. The survey asked about the extent and common settings of homelessness on transit systems, agency policies and procedures for interacting with unhoused riders, challenges and concerns faced by agencies, types or resources and partnerships employed, agency response strategies, and how all of these may have changed as a result of the pandemic. We repeated a number of questions that appeared in Boyle's survey [5] so that we could identify any differences in the responses. We also asked additional questions, many specifically related to the impact of the pandemic. Where appropriate, we calculated the statistical significance of select survey findings using Pearson's chi-squared tests.

[3] For questions asking for perceptions, evaluations, and opinions, we analyzed responses by individual respondent, as employees at the same agency might reasonably differ. For factual questions, the agency instead served as our primary unit of analysis. Boyle's survey [5] only reported a single response per agency, so some comparisons (such as those in Figs. 2 and 3) compare individuals in 2020 to agencies in 2016.

To respond to the third research question, we identified through the survey ten agencies for a deeper study of their response strategies [18].[4] We interviewed relevant staff from these agencies and their partners to learn how each strategy was carried out, its impact, associated challenges (especially during the pandemic), and lessons learned from its implementation. In total, between November 2020 and April 2021, we conducted semi-structured interviews with 26 individuals, each of around 45 min. Our findings were only based on the responses of transit staff and their experiences and perceptions. Due to resource and time limitations, we could not directly collect views of people experiencing homelessness themselves.

## *3.2 Impact on Homelessness in Transit Settings*

The survey revealed homelessness is present on transit systems across the United States and Canada, but its extent varies from one city and one system to another. The majority of agencies reported at least 100 unhoused riders daily. Expectedly, large operators (those operating 200 or more vehicles during maximum service), typically located in large metropolitan areas, reported more homelessness on their systems than small operators. West Coast and some Mountain West agencies reported the highest numbers of unhoused riders. Certain transit modes attracted homelessness more than others: among bus operators, 93% classified their buses as hotspots for homelessness, while light rail (83%), heavy rail (73%), and commuter rail (64%) were each less likely than buses to be cited as settings for homelessness. However, only a few operators indicated taking consistent counts (6%) (e.g., taking annual counts at stations and on transit vehicles); only 17% have access to counts or formal estimates, partial or full, from any source. Thus, many respondents reported perceived estimates.

Sixty-one percent of the responding agencies perceived rising numbers of unhoused individuals on their systems during the pandemic. Large agencies were more likely to report increases than small agencies, and this difference was statistically significant ($p < 0.05$). Multiple factors might have contributed to this rise in visible homelessness, including the pandemic-induced economic downturn and job losses, reduced capacity at some shelters, closure of public libraries (often frequented by unhoused people), and some agencies' suspension of fares and fare enforcement

[4] These agencies were: Metropolitan Transportation Authority, New York City (MTA) in New York City, New York; Los Angeles County Metropolitan Transportation Authority (LA Metro) in Los Angeles, California; Southeastern Pennsylvania Transportation Authority (SEPTA) in Philadelphia, Pennsylvania; San Francisco Municipal Transportation Agency (SFMTA) in San Francisco, California; King County Department of Metro Transit (King County Metro) in Seattle, Washington; San Francisco Bay Area Transit District (BART) in the San Francisco Bay Area, California; Denver Regional Transportation District (Denver RTD) in Denver, Colorado; Tri-County Metropolitan Transportation District of Oregon (TriMet) in Portland, Oregon; Sacramento Regional Transit District (SacRT) in Sacramento, California; and City of Madison Metro Transit (Madison Metro Transit) in Madison, Wisconsin [18].

during the pandemic. Additionally, as overall transit ridership and service fell, and as many housed riders stopped using transit, unhoused riders became more visible as they made up a larger share of riders.

### 3.3 Increasing Challenges and Concerns

Homelessness in transit settings poses a variety of challenges to transit operators, which increased during the pandemic, including a lack of resources, support, and training to address it, and complaints from housed riders about visible homelessness. Among transit agency staff, 53% perceived the challenge of homelessness as worsening during the pandemic, and only 9% thought it had eased. The severity of the challenge seems to have worsened since 2016. As seen at the top of Fig. 2, which compares responses from our survey to questions of the same wording asked by Boyle [5], 38% regarded the extent of homelessness on their system as a major challenge, compared to 26.5% in 2016.[5]

Indeed, almost every concern listed in Fig. 2 was more pronounced in 2020, during the pandemic and after years of worsening homelessness in many areas, than in 2016. Significantly enhanced concerns included the negative perception of housed riders toward unhoused riders, the lack of internal resources to address homelessness, and the lack of government support. Large agencies were more likely than small agencies to characterize several of these issues as severe challenges, including unclear policy ($p < 0.05$), lack of funding ($p < 0.05$), and other riders' concerns ($p < 0.01$).

Homelessness generates concerns among housed riders, which may influence transit policy. The top bar of Fig. 3 shows that 86% of respondents indicated that their agency received complaints related to homelessness. While the prevalence of these concerns remained steady from 2016 to 2020, their perceived severity worsened, as compared to questions of the same wording. This is particularly true for concerns over aggressive behavior by unhoused people and discomfort among housed riders. The pandemic added a new concern: 89% of respondents noted that housed riders fear that unhoused riders may spread disease. Respondents at large operators were statistically significantly more likely to receive complaints about homelessness ($p < 0.01$) and to consider discomfort, fear, aggressive behavior, and personal hygiene as major concerns among housed riders than their peers at small operators. Meanwhile, six out of ten survey respondents perceived that the presence of unhoused riders in transit settings had a negative effect on general ridership, and this perception increased during the pandemic, when 17.3% of survey respondents attributed ridership decline to the larger visibility of homelessness on transit, compared to 6.7% of respondents who made a similar argument in 2016 [5]. We caution that our survey findings

[5] This and similar comparisons are admittedly indicative rather than definitive, because, while there was a significant overlap in the responding agencies, our survey included 115 agencies, while the survey by Boyle [5] included 55.

speak only to perceptions of this effect among staff respondents, not necessarily homelessness' actual effect on ridership numbers.

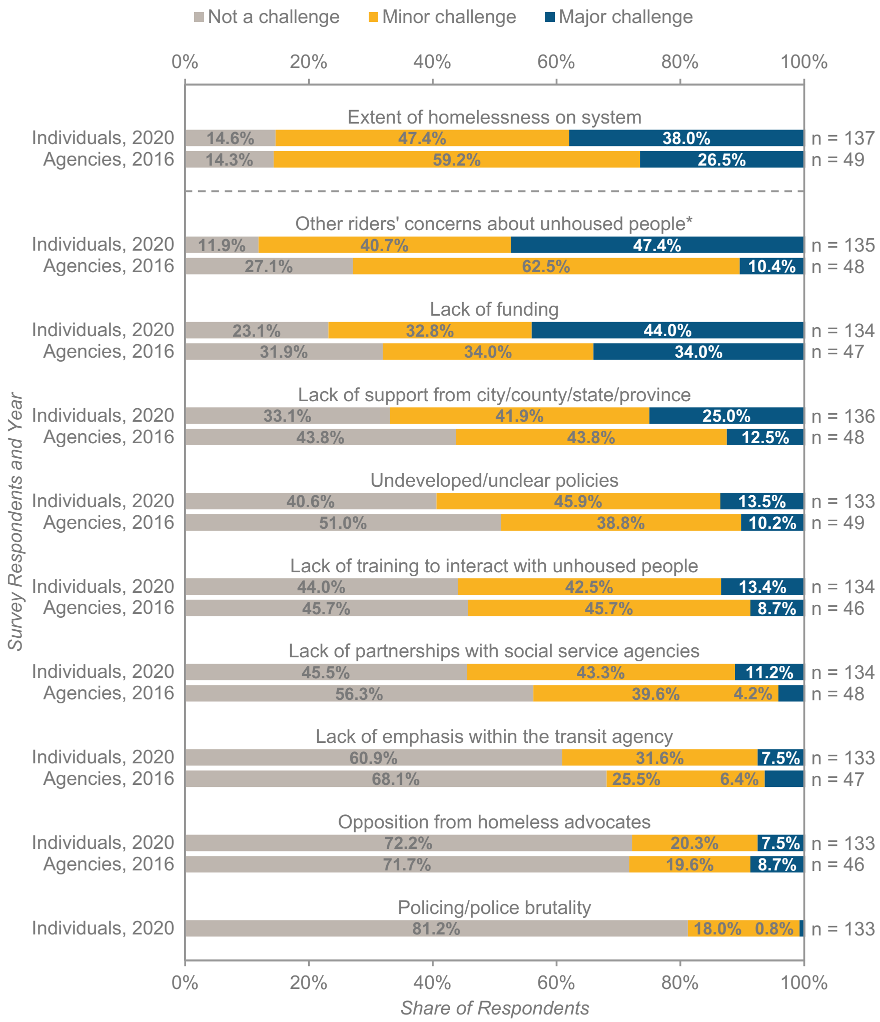


**Fig. 2** Ratings of challenges. *Data source* Authors' survey; *supplemental data source* [5]. *Note* * The 2016 wording was "Balancing customer concerns with humane actions"

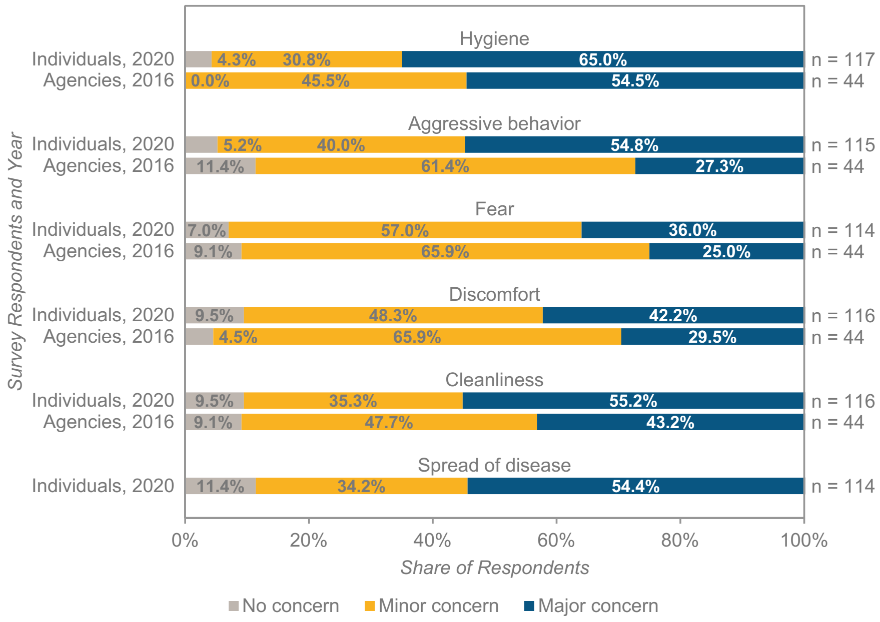


**Fig. 3** Characterization by agency staff of housed riders' concerns about unhoused riders. *Data source* Authors' survey; *supplemental data source* [5]

## *3.4 Responses to Homelessness*

The survey found that only 19% of agencies had formal policies or protocols on how to address homelessness on their systems prior to the pandemic. Additionally, only six agencies received outside funding to address homelessness, and 77 percent did not have dedicated staff or a budgetary line item for this purpose. Nevertheless, the pandemic led a number of agencies to change the way they respond to homelessness, with many increasing their overall efforts. Indeed, more agencies (29%) reported increasing their responses during the pandemic than those that decreased them (5%), underscoring the severity of the homelessness crisis on many transit systems since the onset of the pandemic. In addition to expanding existing efforts, the pandemic led many agencies to develop or rethink their policies on homelessness: 41% of agencies reported creating or altering policies and procedures on interacting with unhoused people because of the pandemic.

Table 1 shows the types of actions that some transit agencies take to respond to homelessness. We classify them into two major categories: (1) enforcement-related actions, which are often punitive toward unhoused individuals, as they seek to enforce anti-loitering laws and expel them from transit spaces, and (2) service- and outreach-related actions, which seek to provide unhoused riders with social services or connect them to housing resources.

**Table 1** Common actions in response to homelessness

| Category | Action | Agencies | |
|---|---|---|---|
| | | # (out of 105) | Percentage |
| Enforcement | Requirement that riders exit the transit vehicle at the last stop or pay an additional fare to re-board | 70 | 66.7 |
| | Installation of structural elements or landscaping to discourage sleeping at stops or stations | 52 | 49.5 |
| | Enforcement of anti-loitering laws | 51 | 48.6 |
| | Clearance of encampments from transit settings | 49 | 46.7 |
| | Sweeps of areas where unhoused people are known to congregate | 44 | 41.9 |
| Services and outreach | Discounted or free fares for unhoused riders or distribution of free or discounted passes to homeless service providers | 33 | 31.4 |
| | Using vehicles or facilities as cooling/heating centers during extreme weather | 25 | 23.8 |
| | Additional service or modified routes connecting to shelters | 23 | 21.9 |
| | Allowing unhoused people to use transit facilities to spend the night | 5 | 4.8 |
| | Discounted or free bike share for unhoused people | 1 | 1.0 |

*Data source* Authors' survey

The most common enforcement practice, undertaken by two-thirds of responding agencies during the pandemic and especially by larger operators, was requiring that all riders exit the transit vehicle at the end of the route, a protocol that disrupted unhoused riders from continually resting on transit vehicles throughout the day. Only 36% of agencies had such a policy in 2016. However, the use of other punitive measures, such as the enforcement of anti-loitering laws or the clearing of homeless encampments from transit settings declined since 2016.

The most common service/outreach-related action reported by agencies was the provision of free fares to unhoused riders. Large transit agencies were more likely to take one or more of the services and outreach actions shown in Table 1. The plurality of respondents (46%) believed that their agencies maintain a balance between outreach and enforcement actions, but more respondents said that their agencies have more enforcement actions (24%) than those who said they have more outreach actions (16%).

During the pandemic, many agencies stopped collecting fares to reduce the risk of virus transmission at fareboxes, often located close to drivers. Some operators formally suspended transit fares for all riders; others paused fare inspection and enforcement checks (i.e., moved to an "honor system"). Agencies that adopted either strategy were more likely to report increased homelessness on their systems during the pandemic. However, differences in enforcement (the removal of fare checks), rather than changes in the listed fare price itself, likely explain the correlation. In other words, the broader issue of enforcement and policing of unhoused riders was more salient than the fare price on the books. As the pandemic subsided, many agencies restored fare collection and enforcement. Nevertheless, as we found from our interviews, some agencies hope to initiate or expand discounted-fare or fareless programs targeting unhoused riders.

### 3.5 Partnerships

Given that transit agencies have limited resources and that homelessness is a large societal problem, it is not surprising that most transit agencies (85%) enter into partnerships and collaborations with other entities to address it. Table 2 shows the types of partnerships reported, with large agencies statistically significantly more likely than small agencies to engage in partnerships ($p < 0.05$). Among these various partnerships, most survey respondents considered those with social service agencies as the most successful. We found that the pandemic led to an increase in collaborations with other entities seeking to address homelessness. Twenty-nine percent of agencies reported initiating new partnerships with social service agencies, shelters, city/county offices, and law enforcement agencies. This growth in partnerships compared to the findings of Boyle [5] indicates a shift toward a more holistic approach to addressing homelessness, but it may also be a reflection of agencies seeking to complement their inadequate resources in the face of increasing homelessness across U.S. cities.

**Table 2** Transit agency partnerships

| Partnerships | Agencies | |
|---|---|---|
| | # (out of 104) | Percentage |
| With local law enforcement agencies | 72 | 69.2 |
| With homeless shelters | 49 | 47.1 |
| With public social service agencies | 60 | 57.7 |
| With private or nonprofit social service organizations | 53 | 51.0 |
| With public health agencies | 39 | 37.5 |
| With other transit agencies | 16 | 15.4 |
| With other local governments | 33 | 31.7 |
| No partnerships | 15 | 14.4 |
| Don't know | 1 | 1.0 |

*Data source* Authors' survey

## 4 Strategies for Responding to Transit Homelessness: Interview Findings

We interviewed relevant staff from ten transit agencies and their partnering organizations, which have enacted response strategies that are particularly developed, unique, or frequently cited by staff at other agencies. The identified programs vary in scope, impact, resource burden, and organizational complexity. We categorized them into four major strategies: hub of services, mobile outreach (both smaller clinician/social worker programs and larger, comprehensive strategies), discounted fares, and transportation to shelters. A detailed discussion of these strategies can be found at Loukaitou-Sideris et al. [18], below we give a brief discussion of each.

### *4.1 Hub of Services*

This strategy concentrates a variety of outreach resources and services for unhoused riders in one or more central points in the city, at or near a major transit facility easily accessible via the transit network. The most successful, comprehensive example, the Hub of Hope in Philadelphia, Pennsylvania, is a partnership between the Southeastern Pennsylvania Transportation Authority (SEPTA), the City of Philadelphia, and Project HOME, a local nonprofit. Located at a downtown transit station, the Hub of Hope offers a variety of services to people experiencing homelessness, including case management, showers, laundry, snacks, primary medical care, and limited behavioral and dental health care. The Hub also provides transportation to shelters and outreach teams in surrounding areas through its many partnerships with service providers, government departments, law enforcement, and more. The Hub offers valuable lessons for other operators on its wide range of external partnerships, its emphasis on training and trauma-informed care, and its concentration of many important services for unhoused riders in one location.

### *4.2 Mobile Outreach: Smaller Clinician/Social Worker Programs*

In contrast to the Hub of Hope's model of centralized services, a number of transit agencies have adopted various mobile outreach strategies across their systems. The make-up, size, budget, and other details of these teams vary across the agencies studied, but each involves staff moving throughout the transit system to meet unhoused riders where they are and provide them services or connections/referrals to services. At the Sacramento Regional Transit District (SacRT), an intern from a local Master of Social Work program rides with transit police officers to meet with unhoused riders when there is a call for assistance. She speaks with them (including those identified on a list of “top ten” chronic offenders on transit), offers them services, and connects with their case manager, if possible. Similarly, at Denver Regional Transportation District (RTD), a full-time mental health clinician from a regional mental health center rides along with security staff on the transit system to de-escalate confrontations and link people with shelter services and counseling. Since the pandemic, the clinician has operated without accompanying police officers and has received more calls. In both cases, the new model of outreach teams is beginning to result in more referrals and improved outcomes.

### *4.3 Mobile Outreach: Comprehensive Outreach Programs*

Three large transit agencies in California, the Los Angeles County Metropolitan Transportation Authority (LA Metro), Bay Area Rapid Transit (BART), and San Francisco Municipal Transportation Agency (SFMTA) have launched comprehensive outreach programs, following the same general model as those in the previous section but of a larger scale.

As a key part of its homelessness response program, LA Metro deploys four mobile outreach teams; three are run by law enforcement agencies and one by the social service agency People Assisting the Homeless (PATH). These teams include trained staff tasked with referring unhoused people to services, working with back-office staff to place them into housing, and de-escalating situations on the system. In April 2020, LA Metro also initiated “Operation Shelter the Unsheltered,” in which police officers and PATH staff at key end-of-line stations ask unsheltered riders to disembark and offer to provide resources to those seeking shelter. Through its contract with PATH, LA Metro is able to provide temporary shelter in motels for its most vulnerable riders. Comparing the referral outcomes of LA Metro’s different outreach teams, we found that the civilian PATH partnership was more effective and also less costly in placing unsheltered individuals in housing than the agency’s partnerships with law enforcement teams [18].

The Bay Area’s transit regional homeless outreach program also deploys outreach teams, in downtown San Francisco (as a partnership between BART and SFMTA) and into other parts of the Bay Area. Each Homeless Outreach Team consists of two civilian outreach workers with crisis intervention training, who respond to dispatch calls, assist and connect unhoused transit riders to shelters and other services. These teams are part of BART’s broader efforts that also include “Pit Stop” restrooms, elevator attendants, and unarmed transit ambassadors.

### *4.4 Discounted Fares*

While the prior strategies aim at the housing and health needs of unhoused riders, the discounted fares strategy specifically focuses on their *mobility*. Some transit agencies provide reduced or free fares to enable people experiencing homelessness to travel on their systems. Three of the agencies whose staff we interviewed—King County Metro in Seattle, the Tri-County Metropolitan Transportation District (TriMet) in Portland, Oregon, and SFMTA in San Francisco—have such programs. King County Metro sells bus tickets at a 90% discount to local social service agencies addressing homelessness. TriMet provides free and reduced-cost transit tickets to over 90 organizations in its region to cover emergency transportation costs for people in crisis or with immediate need. Finally, SFMTA provides 2-year free transit passes to unhoused people who register with the City's Department of Homelessness and Supportive Housing, which in turn connects and provides those individuals with services and housing assistance. While discount fare programs do not diminish the number of people experiencing homelessness on transit systems, they nevertheless offer an important service to those unhoused individuals who participate.

## *4.5 Transportation to Shelters*

Some operators also seek to expand the access of unhoused individuals to destinations particularly relevant for them, namely shelters, which may not be well connected with transit. Programs that offer free transportation to and from homeless shelters are one of the most direct ways that transit operators can aid those experiencing homelessness.

A smaller operator, Metro Transit in Madison, established a program during the pandemic to provide free transportation between daytime and nighttime shelters. Meanwhile, the largest transit operator in the United States, New York City's MTA and the City's Department of Social Services have partnered with the Bowery Residents' Committee to engage with people experiencing homelessness at the end of lines, transporting them to and from shelters and connecting them to resources. The program greatly expanded when the subway ceased operating 24/7 in May 2020. In Los Angeles, LA Metro's outreach teams provide transport to motels for those experiencing homelessness, where they can spend the night. Since the onset of the pandemic, LA Metro teams stationed at the ends of major lines offer free bus transportation in the evenings to open shelter beds. And under Denver's Support Team Assisted Response (STAR) pilot program, a mental health clinician and a paramedic dispatched by 911 ride around on a repurposed van, respond to low-level behavioral health crises situations in the downtown area and in transit settings, and offer transportation to shelters and hospitals and connections to community organizations and resources.

## 5 Recommendations and Conclusion

The COVID-19 pandemic exacerbated the U.S. homelessness crisis, forcing the most vulnerable onto streets and transit settings. Even before the pandemic, most transit agencies faced challenges in responding to the needs of unhoused people on their systems, including a lack of dedicated resources and formalized policies, lack of government support, and negative reactions from housed riders. The pandemic changed the way that many transit agencies responded to visible homelessness on their systems, forcing them to adopt a variety of strategies, some more helpful to their unhoused riders (e.g., suspension of transit fares), others more punitive (e.g., closure of transit center buildings and enforcement of disembarking at the end of routes).

But even after the pandemic completely subsides, homelessness will remain, in the absence of a larger social welfare policy and affordable housing for the poor. In line with transit's social service role, we believe that operators should focus on providing their core transportation services to both housed and unhoused riders. How can transit agencies best do so? In what follows, we discuss a number of recommendations.

*Need for plans, policies, and evaluation metrics*: The survey showed that most agencies do not have formal policies or protocols on how to address homelessness on their systems. But as homelessness is a widely present and persistent challenge in transit settings, it makes sense for agencies to develop plans for responding to it, both during ordinary times and during crises like pandemics. A regard for the well-being and mobility needs of unhoused riders must be built into these long-range and emergency planning documents. Such plans should take into account the specificity of the transit mode (rail or bus), the size and needs of different local unhoused populations, and the available agency resources. Our study also found that transit agencies do not measure the effectiveness of their strategies. Key performance indicators are important and should include metrics like the number of unhoused riders referred to and placed into short-term shelter beds and long-term housing or other needed resources such as access to mental and physical health care.

*Need for outreach strategies*: We noticed a shift among many agencies toward pursuing more outreach strategies during the pandemic and hope that this trend will continue. A number of interviewees emphasized that law enforcement alone cannot address the root problem, while outreach and support—especially done separately from policing—may be more effective. Removing people experiencing homelessness from transit environments would frequently result in their reappearance in the same or another transit setting later, as they have no other places to go. On the other hand, seeking to connect them to shelter opportunities, social services, and medical or mental health resources presents a more effective way to respond to the issue and even possibly help some individuals get out of homelessness.

*Need for enhancing mobility for the unhoused*: Prior literature indicates that public transit is a very important travel mode for those experiencing homelessness. Providing free fares to people experiencing homelessness and connecting shelters to other important destinations through transit allows them to access these needs more easily. Since many unhoused people are already skirting around fare collection due to their inability to pay, agencies are not forfeiting much revenue by providing them free fares. Additionally, this would make it easier for bus drivers, who often find themselves having to resolve altercations over fares.

*Need for public education and staff training*: Operators often face complaints and pressure to simply sweep unsheltered individuals away from their system. Public information/education campaigns are important to educate housed riders about an agency's homeless outreach operations. Likewise, training bus drivers and other front-line personnel on how to best handle interactions with unhoused riders is critical.

*Need for partnerships*: During the pandemic, a number of transit agencies initiated partnerships with external entities to address the homelessness crisis. We hope this continues. As many transit agencies are not familiar with or well-equipped to handle homeless outreach themselves, joining forces with other municipal agencies, social service providers, and nonprofits can fill crucial knowledge and skill gaps and bring in additional financial and staff resources.

*Need for external funding*: The survey showed that the vast majority of agencies do not receive outside funding to address homelessness, and only a handful have dedicated staff or budgetary line items for this challenge. Transit operators and industry groups should lobby for grants and funds to respond to homelessness and hire and train the necessary personnel to do so. While it may seem unfair to transit agencies that they have to address a problem whose root causes they cannot solve, agencies can use that sense of unfairness as a powerful argument for greater funding and resources instead of a reason to ignore the problem.

In conclusion, homelessness represents a failure of our society to take care of and respond to the plight faced by its most unfortunate members. The pandemic exacerbated the crisis. One positive sign, however, is that some transit agencies rose to the challenge and initiated strategies and partnerships that will remain helpful in a post-pandemic world. Transit is a public service, and the transit industry should uphold its social purpose and contribute to the welfare and mobility of unhoused riders. It is clear, however, that the industry is dealing with the downstream effects of a structural problem. Ultimately, if we are serious in trying to help people experiencing homelessness, we need more housing and services for them.

*Note* This study was reviewed and approved by the University of California, Los Angeles Office of the Human Research Protection Program (IRB #20-001303, July 24 2020). Consent was given by all study subjects, and all data were anonymized.

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# Workers and the Post-COVID Transportation Gig Economy

**Amelia Regan and Nicola Christie**

**Abstract** The COVID-19 pandemic significantly reduced the demand for ride-hailing services but saw a sharp increase in e-commerce, grocery, and restaurant delivery services. As the economy recovers and demand increases, several issues are emerging. The tension between companies that wish to keep drivers as independent contractors, but which hope that large enough numbers of them return to the industry, and drivers who increasingly demand to be considered as employees will likely lead to more attractive labor contracts, and perhaps even unionization in the future. Prices for ride-hailing and delivery services are increasing rapidly, rendering the savings relative to the now mostly defunct taxi industry and traditional package delivery industries near zero. While that will lead to a reduction in demand, no one knows how much that reduction will be and how long it will last. This chapter addresses three overarching themes dominating analyses of these industries. The first is labor, the second safety, and the third environmental impacts.

## 1 Introduction

The COVID-19 global pandemic significantly reduced the demand for ride-hailing services but e-commerce, grocery, and restaurant delivery services have experienced a sharp increase. Ride-hailing drivers, aware of the plunging demand and wary of providing rides to strangers, reduced their engagement with ride-hailing companies such as Uber and Lyft in the United States, and increasingly added multiple delivery services to their portfolios. While the simultaneous use of multiple phone apps can cause many complications and safety concerns (see for example, [11, 12]), working

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for multiple companies is also easier than in the past due to aggregators such as Gridwise [20] and third-party apps such as [43].[1] Some drivers also shifted to driving for Amazon and Walmart, or perhaps working in their warehouses, as these companies (and many others) saw huge increases in e-commerce deliveries. New additions to the industry, whose emergence was hastened by the pandemic, are urban grocery delivery companies promising rapid (as fast as 10 or 20 min) deliveries. The so-called "dark stores" or "micro-fulfillment centers" are showing up in cities across the world, with New York City and London on the leading edge of this trend.

Some drivers in the United States took advantage of the federal unemployment benefits that were made available to self-employed workers, gig workers, and independent contractors under the federal CARES act that was signed into law in March, 2020 [47]. Those drivers do not appear to be returning to jobs with ride-hailing companies even as demand for rides begins to return.

This chapter summarizes the relevant literature (both academic and popular press) on transportation gig economy work pre-, during- and post-pandemic. The main goal is to identify the themes that will dominate the landscape of this industry in the next couple of years. The chapter addresses three overarching themes: labor, environmental impacts, and safety. In what follows, we discuss recent relevant studies and articles in the popular press in the context of these three themes. We also provide examples of under-reported benefits of the gig-economy industries and make some predictions about the industries going forward.

## 2 Overarching Themes

Before we review the related literature and popular press articles, we want to address some overarching themes. The first theme is labor. When Uber and then Lyft began operations in the United States, they claimed that they would provide value for customers by improving access and drastically reducing fares, and to drivers by providing flexibility and higher wages relative to the taxi companies. They have provided value for customers and, in some cases, increased mobility and access for those without private automobiles. They also appear to have broadened coverage for lower income travelers. To a certain extent, they have also provided flexibility for drivers. However, driver earnings were vastly exaggerated or perhaps cast in the best possible, rather than typical light, as most drivers earn under the minimum wage after fuel, insurance, and maintenance expenses are taken into account. After continuously losing money since their inception, the industry leaders have been steadily raising prices for passengers in 2021, without a corresponding increase in driver wages. We suspect this is because the success of the ride-hailing industry was predicated on the

[1] Gridwise is a free app for workers in the gig economy which helps them get more rideshare or delivery pings, and has features that allow them to track their mileage, compare earnings across platforms, etc. Sherpashare is also an app for ride-hailing drivers that offers them some financial management tools, allows them to track mileage, analyze their expenses, etc.

fact that they expected to be running huge fleets of autonomous vehicles (AV) by now. These companies never planned on a financially successful model with large numbers of drivers. The fact that both Uber and Lyft recently sold their autonomous vehicle development units (Uber to Arora for $10 billion in December 2020, and Lyft to a Toyota subsidiary company for $550 million in April 2021) suggests that, while development of AVs continues, large-scale deployment is *at least* 5–10 years in the future.

The second theme is safety. Research has shown that piece work and working for several apps at a time, which requires drivers to respond to requests while they drive, has led to significant safety issues for drivers. This holds both for ride-hailing and delivery drivers. Work in Amazon warehouses has been shown to be twice as dangerous as in similar companies, evidence that safety is not a prime concern for that company [18]. Another recent report provides evidence that delivery drivers working for Amazon partners have been instructed to turn off their safety monitoring software because they cannot meet their delivery quotas without speeding [24]. Further, the race to the bottom at Amazon also impacts the delivery operations at UPS, FedEx, and the US Postal Service because of their need to compete on price and delivery times. All three of these companies are hiring larger numbers of part-time workers, who do not receive the same benefits, nor the extensive training that full-time drivers receive.

The final theme is the negative environmental impacts of increased next- and same-day deliveries and of a shift from transit to ride-hailing. The impact on car ownership has proved to be minimal at best, and the increased reliance on ride-hailing operations has led to an increase in overall vehicle-miles-traveled (VMT) in nearly every market in the world. Finally, while it does not warrant discussion as an individual theme, no discussion of this industry would be complete without pointing out that for years in the United States and in many other markets, Uber and Lyft have engaged in persistent predatory pricing. Such pricing was only possible at first due to generous private funding for these companies, and then because of optimistic market valuations, which were based not on profitability, but on future company potential. Both companies have lost money hand over fist for years. For example, according to recent data on Statistica, Uber lost $8.5 billion in 2019 and $6.8 billion in 2020, while Lyft lost $2.6 billion and $1.76 billion in those years [44]. The fact that their losses went down in 2020, when they were providing fewer rides, is an indication of just how much they lose on typical rides. Delivery services (some of which are owned by Uber) also saw losses in 2019 and 2020, despite a huge uptick of demand in those years.

## 3 Overview of Recent Studies

Here, we discuss some of the primary works on ride-hailing services and e-commerce and restaurant and delivery operations. We separate these along the thematic lines discussed above.

### 3.1 Labor Issues

We first note that many studies conducted around the world find positive impacts on workers in the transportation gig economy. For example, a study of Chinese restaurant delivery workers, based on in-depth interviews with 50 workers and 800 responses to an online survey, found that workers experienced improved autonomy, belonging, convenience, enjoyment, equity, knowledge, and earnings [33]. On the other hand, studies in the UK have found that delivery drivers struggle with safety issues directly related to the algorithmic management nature of gig platforms [19, 37]. Other studies find that platform work creates a false sense of self-employment and that transportation gig economy companies such as Uber use technology against workers [10, 16, 49, 50].

In the United States, Uber and Lyft inflated driver wages from the start. In 2017, Uber paid a $20-million fine to settle US Federal Trade Commission charges that it had recruited drivers with false claims [48]. In addition, both companies misled drivers with their vehicle financing programs. On the one hand, those programs helped drivers who might not have been able to get vehicles to obtain financing, and also helped drivers to finance much nicer vehicles. But on the other hand, the programs left many workers beholden to jobs that were sold on flexibility but then forced them to work long hours, and with vehicles they could not easily afford to maintain. Gig economy driving jobs have benefits—both for consumers and for drivers—but the drivers who benefit the most are not full time (sometimes called "dependent" drivers); rather they are part-time ("supplemental" drivers), many of whom do not pay for their automobile expenses themselves [40].

Many states in the United States, and many countries, have worked hard to get gig economy drivers classified as employees rather than independent contractors. In some cases, these attempts have been successful, in others they have not. In November of 2020, India set new regulations on ride-hailing services specifying that the firms (Uber and Ola are dominant in the Indian market) can take no more than 20% of the drivers' fares and that surge prices are limited to 1.5 times of the regular fares. Work hours are also limited to 12 hours per day, and the companies must provide insurance [45]. In February 2021, the U.K. Supreme Court ruled that Uber drivers must be treated as workers and provided minimum wages and holiday pay [2]. California passed Assembly Bill Number 5 in September 2019 classifying many gig economy workers as employees [8]. The law was based on the Dynamex case. Dynamex is a last-mile parcel delivery company operating in North America. They perform last-mile delivery for many companies including Amazon and the U.S. Postal Service. Their drivers use and maintain their own vehicles. However, before the law was applied to ride-hailing and restaurant delivery companies, those companies banded together to write and then back a 2020 ballot initiative exempting their workers from the law [15]. They outspent the opposition by 10:1 in the fight to classify California drivers as independent contractors. Measure 22 passed in Fall 2020, with 59% of voters in favor. This was the single most expensive proposition in the state's history, costing more than 200 million dollars (LA Times 2020). Like many successful Proposition measures in California, it succeeded based largely on false and misleading advertisements. The measure was written by the corporations for the corporations, yet the advertising suggested that both drivers and consumers would benefit [51]. At the same time, findings in many studies indicate that most transportation gig workers are making far less than the minimum wage, that the impacts on prices of granting benefits to full-time workers would be modest, and that part-time drivers could continue to provide service during peak times [25, 26, 38]. Nevertheless, such findings were drowned out by the vast advertising campaign. By early 2021, all of these companies had increased their rates, betting that the fees which undercut any competitors in the first few years of operation had made consumers dependent enough on their services to keep using them. Time will tell how consumer demand will respond in the long run. And the saga in California is not over. In August 2021, a state Superior Court judge ruled that Proposition 22 was unconstitutional and unenforceable. The case will likely be finally decided by the California Supreme Court in 2022.

On the food delivery side of the gig economy market, the fact that Uber Eats, Grubhub, DoorDash, and other delivery companies inflate the costs of meals and often take 30–35% of the bill is leading to new emerging restaurant delivery services and also to new driver collectives which will cut out ride-hailing and delivery companies as middlemen and pay drivers more [35]. These companies represent a small share of overall services but should see an increased market share over the next few years. In some cases, cities are setting limits on the amount that delivery companies can charge for their services. In New York for example, the limit is set at 23%. Those limits will be tested in court in 2022 and perhaps beyond.

In the United States, unionization is an emerging issue that is gaining traction. The Teamsters, a union with a complicated history, but considerable success in related industries, announced that it would be targeting Amazon warehouse workers [35]. While other unionization drives in the United States have been unsuccessful, the Teamsters, who represent most hourly UPS employees and employees of several major trucking companies, seem better suited for this task than the other unions that have tried. They also have experience with nationwide (and North American-wide) unionization, and relatively deep pockets, which will be necessary to go head-to-head with Amazon. If they are successful, ride-hailing and delivery drivers would be the logical next target. Even if these unionization efforts fail, they will surely pressure companies to improve working conditions.

It is possible that this pressure (along with labor shortages) is already having an impact on gig economy companies. Amazon has recently increased tuition benefits for part-time warehouse employees and is offering significant signing bonuses for new employees. While these benefits do not directly impact the Amazon-uniformed independent contractors, who deliver Amazon packages in Amazon label vehicles, or the drivers who deliver at all hours of the day in their own unmarked vehicles, competition for labor is so high that these changes might trickle down into other markets.

## 3.2 Safety

Several recent studies have shown that ride-hailing and delivery drivers cause more crashes than typical drivers. An extensive study studied safety in U.S. cities where ride-hailing services had been introduced, finding an increase of approximately 3% in fatalities and fatal crashes, an increase in vehicle miles (km) traveled, an increase in hours of delay in traffic, and additional new car registrations. The authors' back-of-the-envelope calculations suggested that the annual cost in human lives in the United States due to ride-hailing services ranges from $5.33 billion to $13.24 billion [3]. Another study found that Uber was not associated with a decrease in alcohol-involved fatalities but it was associated with increased traffic fatalities in densely populated urban areas [4]. While other studies have been consistent with the ones just mentioned, some studies in the United States and the UK have found modest reductions in accidents as ride-hailing services entered markets [13, 29, 30].

The problem with gig workers in transportation is that the pressure to complete tasks and to work for several app companies at once leads to cognitive and physical strain. In turn, those strains, coupled with very tight schedules, lead to cutting corners, rushing, and crashes [11, 12]. Distracted driving is a primary cause of serious vehicle collisions. Krishen et al. [31] argue strongly that in transportation, safety is a culture and not a concept. We argue that gig economy transport operations do not have a dominant culture—much less the culture of safety that is found in leading trucking companies and established package delivery companies such as Schneider, JB Hunt, UPS, or FedEx. In fact, the pressure from Amazon to cut costs is creating ripple effects of poor safety conditions even in companies that have a decades-long history of strong safety cultures. Hudson's often cited "ladder of safety" culture starts with the first step coined "Pathological" (safety is the lowest priority), and then moves through "Reactive" (safety is important if there is an incident), "Proactive" (systems are in place to identify future safety issues), "Calculative" (systems are in place to manage incidents before they occur), and "Generative" (safety is the highest priority) [23]. As organizations move through these phases, there is increasing trust and increasing information sharing. However, the very nature of gig economy work and the attitudes of its major companies make gig work in transportation firmly planted in *pathological safety cultures*. Recent reports of Amazon flex drivers being managed and fired by bots are troubling. Of course, new technologies are important in supply chains, but gig workers are already alienated from the companies they work for, thus, adding a new level of distance helps to further erode safety.

## 3.3 The Environment

Hailed as environmentally friendly in the early days, even credible academic studies imagined that ride-sharing (as these companies were initially referred to) services would lead to a reduction in car ownership and vehicle miles (km) traveled [9, 14].

Ride-hailing companies were sold to the public on the basis of improved utilization of assets that would lead to a reduction in environmental impacts. The argument was that if a few automobiles were used much more, then fewer would need to be produced and sold. Further, if drivers could gain easy access to public transit (by using ride-hailing services for the first and last mile), then transit use would increase and car ownership would decrease. These predictions (and promises) were false. Several recent studies show that ride-hailing has led to significant increases in VMT in large U.S. cities, that those increases are largely due to transit users shifting to ride-hailing, and also due to deadhead (empty) miles driven by drivers between paid rides [39, 46]. In the meantime, car ownership has continued to increase in the United States and in China where ride-hailing services are widely available.

If fares continue to increase, and all indications are that they will, shared or pooled ride-hailing services might finally see an increase in use. To date, however, none of these services has been successful because most consumers are unwilling to book shared rides. This was true before the pandemic, and it became even more true during the pandemic. In fact, ride-hailing services killed off one of the longest running true shared-use transportation companies in the United States—Super Shuttle and their partner Execucar in 2019 (though they have since been reborn with different owners). At the same time, the increase in airport traffic due to ride-hailing services has been overwhelming in many locations [21].

That said, pooled ride sharing has promise, and a number of studies have examined the potential and characteristics of its demand [1, 22, 28, 41]. Most of those studies are done from the perspective of customers, but a recent study examines this issue from the view of drivers, finding that they are largely unhappy with the service and with its fee structures, which do not compensate them enough for the added trouble of serving multiple customers at once [34].

Studies have not demonstrated positive environmental impacts of grocery and restaurant delivery services; however, a recent emerging industry, namely extremely rapid grocery delivery, might finally have promise because its companies, some of which promise 10–20 min deliveries, tend to rely on active transport modes (bicycles and walking) to deliver within very narrow radii of urban grocery warehouses and grocery stores.

Just as ride-hailing services were expected to be dominated by autonomous vehicles by now, Amazon, UPS, FedEx, and other delivery companies have been counting on a faster rollout of sideway autonomous delivery robots, drones, and road delivery robots by now. Eventually, such autonomous systems may have positive environmental impacts [17].

## 4 Under Reported (And Perhaps Unrealized) Benefits

This chapter would be remiss without a discussion of some benefits of ride-hailing services that have perhaps gone under reported. In the United States, low-income neighborhoods that have been historically underserved by taxi services have been better served by ride-hailing services [5]. Further, race-based discrimination, common in taxi services, appears to be less prevalent in ride-hailing services in the United States [6]. Transit agencies and advocates have long argued that ride-hailing services could complement transit for first and last-mile travel and could also be used as cost-effective substitutes for many paratransit services [7, 28, 32].

Other benefits that might not be obvious to researchers in the United States is that in many cities in the world, travel by shared motorbike or automobile is much safer and more efficient than the alternatives such as walking in crowded urban areas, cycle-rickshaws, and now often electric cycles, which are common in cities in South Asia. Therefore, both workers (who now have access to a motorbike or automobile) and passengers are better off. In some instances, as in the examples of Grab and DiDi in Singapore, companies have provided accident insurance, critical-illness micro insurance, and financial aid to the families of drivers [42]. These benefits have made car ownership, which provides both benefits and status, possible for drivers who would not have achieved this otherwise. Studies in China have noted that delivery drivers can earn incomes that far exceed those in similar occupations such as waiting tables in restaurants [33]. In some countries travel for persons with disabilities has become much safer and widely available. In India for example, people with visual impairments have been much better served by relatively inexpensive ride-hailing services than they were with the alternative mostly chaotic forms of transportation [27].

## 5 The Future

As we discussed in this chapter, the COVID-19 pandemic has brought about significant impacts on the gig economy, negative for some companies, positive for others. But what will the future bring about for gig economy companies and their workers? In her recent in-depth book on the gig economy, Schor [40] points out that despite the promise of empowering workers, “at their worst, the companies have morphed into predatory employers.” She sees promise, however, in regulation, contracts for drivers and unionization. We see promise there too. A recent study by Pitlik [36] suggests that federalism in the United States impedes the realization of human rights for gig economy workers. Using Uber drivers as an example, she shows how discrepancies in regulations and decisions across states can result in human rights violations. It may well be that federal regulations will be needed to improve working conditions for transportation gig workers in the United States.

All three of the forces, regulation, improved contracts and unionization, could point the industry toward one in which both customers and drivers are treated with respect, in which the environmental impacts of these services are taken into account, and in which a safety culture is adopted across the board.

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# Impacts on the Economy

# LOST and Found: The Fall and Rise of Local Option Sales Taxes for Transportation in California Amidst the Pandemic

**Hannah King, Natalie Amberg, Jacob L. Wasserman, Brian D. Taylor, and Martin Wachs**

**Abstract** The COVID-19 pandemic dramatically affected the ability of localities to pay for their transportation systems. We explore the effects of the pandemic on local option sales taxes (LOSTs), an increasingly common revenue source for transportation in California and across the U.S. LOSTs have many advantages over alternative finance instruments, including that they can raise prodigious amounts of revenue. However, LOSTs rely on consumer spending, which lags during times of economic weakness. This is precisely what we observed in California counties during the initial months of the pandemic. LOST revenues did recover after the initial economic shock of COVID-19, albeit to a lower level than they would likely have otherwise. LOST revenue trends during the pandemic were affected by national and regional economic conditions and government policy as well. This public health crisis illustrates both the pitfalls and resilience of LOSTs during economic downturns and recoveries. The lessons from the pandemic's effects on LOSTs will be useful for policymakers and analysts in preparing for inevitable future crises and associated economic turbulence.

## 1 Introduction

Over the past five decades, financial responsibility for highways and public transit systems has gradually devolved from the federal government to states and lower levels of government. To fill the revenue vacuums left by this fiscal devolution, voters in

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many counties and localities across the United States have agreed to tax themselves to fund transportation. In California, 25 counties, home to a substantial majority of the state's population, currently finance major portions of their transportation systems and services—roads, streets, public transit, bikeways, and specialized services for elderly and disabled people—using revenue produced by voter-approved sales taxes [33, 35]. Local option sales taxes (LOSTs) are most common in California [22], the most populous U.S. state, and a quite diverse state that is often emblematic of transportation trends nationwide or at the forefront of them.

This emerging means of transportation finance was thrown into considerable uncertainty by the spread of COVID-19 and the pandemic-induced economic downturn of 2020. Accordingly, this chapter explores LOSTs in California amidst the COVID-19 pandemic. We begin by describing the prevalence of LOSTs for transportation in California and the types of transportation programs they support. We then investigate the effect of the pandemic and the resulting economic turbulence on sales tax revenues and, consequently, on transportation program budgets. We show that the pandemic and associated federal fiscal relief legislation affected counties' LOST revenue streams in variable ways, with noticeable differences in direction, degree, geography, and timing across counties. We conclude by examining the factors associated with this variance across counties and their implications for transportation finance and policy post-pandemic.

## 2 LOSTs: An Overview

Local option sales taxes have emerged over the past several decades in part as a response to a relative decline in federal transportation revenues. Federal funding for surface transportation (largely funded by national taxes on motor fuels) has been falling in inflation-adjusted terms per capita and per vehicle mile of travel. Most of this federal funding comes from taxes on motor fuels, supplemented by state fuel taxes, that are easy to administer and create a rough correspondence between amount paid and usage of the road network [21, 30].

This system of surface transportation financing worked well throughout much of the twentieth century, as vehicle ownership and driving both dramatically increased and tax rates were frequently adjusted upward to account for the effects of inflation. However, the ability of fuel taxes to fully pay for transportation projects began eroding over the last several decades as inflation, increasing vehicle fuel efficiency, increasing maintenance costs for an aging road system, and a waxing reluctance among elected officials to raise per gallon fuel tax levies combined to weaken fuel taxes as the centerpiece of transportation finance [19, 30, 37].

Relative declines in federal surface transportation funding have led states and local governments to seek alternative revenue sources. Transportation LOSTs—which are typically incremental increases to the sale of all goods and services subject to sales taxes and not just on fuel—are perhaps the most prominent of these local funding mechanisms. This is particularly true in light of the extreme reluctance of many local officials to raise property taxes since the "tax revolts" of the late 1970s and early 1980s [19, 37]. Currently, roughly 19% of California's transportation expenditures at the local level are funded using LOST revenues [10].[1]

LOSTs, both nationwide and in California, are typically approved by voters. They are most commonly levied by counties, though states can authorize other units of government to have them as well. As mentioned, LOSTs are levied on the price of all goods and services subject to sales taxes, which vary from state to state. Incremental rates typically vary from ¼ cent per dollar to 1 cent per dollar [17]. LOST ballot measures generally outline an estimate of forecasted revenues and specific projects to be funded by measure revenues and/or lay out funding criteria, such as percentages of revenues to be allocated toward projects for specific modes [18].[2] The project lists approved by voters are often longer and more costly than the generated LOST revenues can fund in the specified time horizon. Projects may be delayed or cancelled in response to revenue shortfalls. Unfunded projects often form the basis of new efforts to extend or renew LOSTs after their scheduled expiration. More rarely, revenues exceed forecasts, allowing priority projects to be delivered sooner than scheduled [4].

Often, a percentage of LOST revenues is dedicated to so-called "local return," namely to local governments within a county that may spend it on transportation projects (often local roads) of their choosing.[3] Thus, transportation LOSTs provide an alternative source of funding for transportation needs, with a different structure and method of enactment than fuel taxes. LOST funding is locally generated and therefore frees local governments from the constraints (and oversight) of federal and state funding. This allows cities and counties more discretion over which projects to prioritize [23]. Most LOST-funded projects are highway improvements and public transit, though the mix of projects varies substantially from place to place. LOSTs are usually authorized for a set period of time, often ranging from 10 to 20 years [12]. Measures are, however, often renewed, typically accompanied by a revision of project priorities and timelines. LOSTs with no expiration date, like Los Angeles County's 2016 Measure M, are occasionally approved by voters as well [23].

LOSTs inherently come with a degree of uncertainty tied to supply of and demand for taxable goods and services, thus linking transportation funding to much larger macroeconomic trends. For instance, the supply of taxable goods is influenced by

[1] This estimate includes expenditures from transportation planning agencies, city streets, county roads, transit operators, and special districts for transit and roads [10].

[2] In New York, Ohio, and Tennessee, local governments are allowed to use LOSTs as a source of general revenues (i.e., for non-transportation purposes). Other states that allow LOSTs are divided between those that specifically require an enumerated project list (e.g., Arizona, California, South Carolina, and Wyoming) and those that allow funds to be dedicated to broad project categories like "road improvements" (e.g., Florida, Iowa, Louisiana, New Mexico, Oklahoma, and Texas) [18].

[3] Spending rules are laid out in the LOST ballot proposition approved by voters. Local return funds may come with categorical spending requirements, but localities retain some level of autonomy regarding spending decisions. For example, Alameda County's Measure B allocates both local return funds and formula-based Americans with Disability Act funding to localities within the county [23].

the ability of supply chains to ensure that goods are available where and when they are demanded. During the COVID-19 pandemic, sales of many consumer goods were heavily affected, at least temporarily, by the disruptions to supply chains [20]. Likewise, consumers' level of disposable income influences demand, with lower-income and unemployed workers as well as those outside of the workforce less able and willing to spend. During economic downturns, such as during a pandemic, consumer demand declines as employment decreases and wages stagnate. Federal stimulus payments designed to counteract this—the Coronavirus Aid, Relief, and Economic Security (CARES) Act in March 2020 [15], the Coronavirus Response and Relief Supplemental Appropriations (CRRSA) Act in December 2020 [16], and the American Rescue Plan (ARP) Act in March 2021 [14]—also affected tax revenues. These laws included both direct payments (in each bill, respectively: $1,200, $600, and $1,400 per person earning $75,000 or less annually [28]) and support for public and private employers that helped sustain employment and wages [36].

The COVID-19 pandemic in California provided a vivid and timely example of how sales tax revenues are linked to the strength and structure of their regional economies. In the next section, we examine how the LOST revenues raised in each county relate to different characteristics of each county's economy. Our primary goal in this analysis is to identify factors that have an empirical relationship with LOST revenue generation during the pandemic. Our analysis in this chapter is largely descriptive; given the relatively small number of counties examined, we do not present a multivariate analysis nor make formal claims about causality or statistical significance. Rather, we illustrate commonalities and differences across California counties in relation to LOST trends, at a period when (at the time of this writing) every relevant variable has yet to be determined as the halting economic recovery proceeds.

Overall, we find that the strength of the local economy and the specific employment structure across industries in different counties are correlated with variations in transportation LOST revenues. Revenues in the initial stages of the pandemic in all counties fell below budgeted levels. LOST revenues did, however, hold up better as the pandemic wore on than many analysts predicted during the pandemic's early months. Revenues mostly increased after the pandemic's initial months, albeit with significant variation across counties. Perhaps counterintuitively, LOSTs generally fared worse in higher-income counties. Counties with heavy employment in certain sectors, particularly in information, professional services, and arts/recreation, also tended to lose more revenues.

## 3 The COVID-19 Pandemic and LOST Revenues

During the initial stages of the pandemic, uncertainty about both public health and the economy was at its highest, and many analysts produced dire near-term predictions of revenues falling far below previous forecasts [13]. Despite this initial fret and fluctuations within the pandemic, LOSTs proved unexpectedly resilient.

In March 2020, when California's shelter-in-place orders began, counties across the state braced themselves for drastic losses, layoffs, and budget cuts. The Los Angeles County Metropolitan Transportation Authority, for example, began prioritizing which services and projects could continue and which would not, in response to the dramatic declines in anticipated fare and tax revenue [24]. These worst-case revenue projections largely failed to manifest.

To determine how LOST revenues responded to the pandemic, we analyzed data from the California Department of Tax and Fee Administration (CDTFA) [5]. CDTFA collects sales taxes across the state, including LOSTs, and then returns the appropriate amount to each governmental recipient. The amounts generated by the sales tax are returned to counties a few months after they are collected.

Figure 1 shows that sales tax receipts began a steady decline as the state-level shelter-in-place order was announced on March 19, 2020. Receipts fell by $276 million between February and March. They continued to decline into May but rebounded in June and July, as businesses attempted to reopen, and more people began moving about and spending. Even so, the number of COVID-19 cases continued rising [11], and sales tax receipts fell. The number of new daily cases in California declined starting in July and reached a low point in September and October. After that, the number of cases grew dramatically again starting in November amidst a second major wave of winter infections. Sales tax receipts during this fall period began recovering when the number of new daily cases stagnated in September and October but quickly declined with the rise of infections afterward. Revenues also increased yet again after November with the advent of the holiday season. By the end of 2020, revenues had returned to levels seen during the previous year. LOST

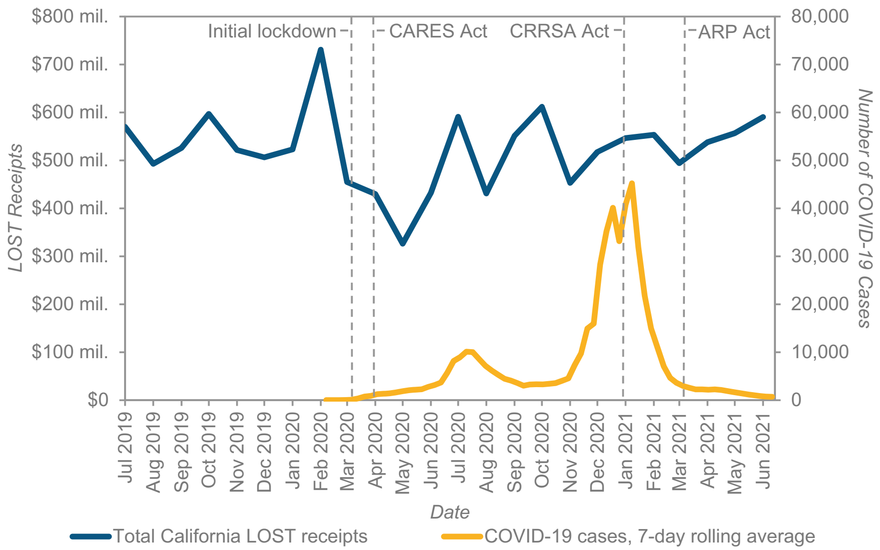


**Fig. 1** LOST receipts and COVID-19 cases in California. *Data sources* [9, 5]

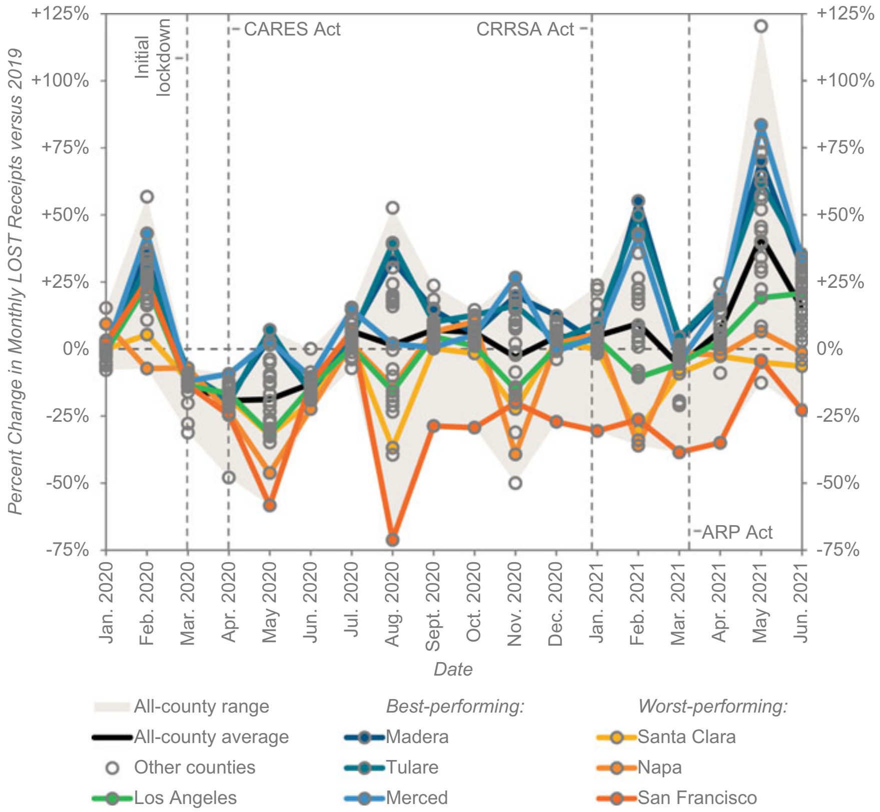


**Fig. 2** Changes in LOST receipts compared to the same month in 2019. *Data source* [5]

revenues thus recovered but did not exceed the high of early 2020 and were volatile throughout. At the state level, then, the primary effects of the COVID-19 pandemic on LOST receipts were to decrease them in the short run and make them more volatile and unpredictable in the medium run. COVID-19 also likely dampened any potential growth in LOST receipts that may otherwise have occurred.

Statewide trends in LOST receipts mask considerable variability across counties. Figure 2 presents the percent change in LOST receipts by month against the same month in 2019, capturing the large variation observed during 2020 and 2021.[4] The counties with the best- and worst-performing LOSTs are highlighted. Starting in March 2020, each county reported steady declines in LOST revenues. After California's mid-summer peak in COVID-19 cases, however, LOST revenues in agricultural counties like Tulare in California's San Joaquin Valley began to improve, with receipts actually 30%–40% *higher* than the same months the year before. While

[4] When a county has multiple LOSTs, Fig. 2 plots their average.

some counties across the state thus experienced growth in LOST revenues—agricultural Imperial County along the Mexican border, for instance, saw 53% *more* LOST revenue in August 2020 than August 2019—others, like the urban San Francisco County, reported revenues far lower than for the same months in 2019. Despite these differences, sales tax receipt trends across counties moved in similar ways at a few key points in the pandemic, such as in March 2020 when lockdowns began, and all counties reported LOST totals from 5% to 35% less than the previous year. Similarly, revenue growth compared with 2019 was approximately flat in all counties in December 2020, as cases began rising to record levels. Going into 2021, most counties reported increases in LOST receipts, with the highest all-county average since the onset of the pandemic occurring in May 2021.

## 4 Factors Affecting LOST Revenues During COVID-19

To explore these substantial differences across California counties, we examined the relationship between the change in LOST receipts and a number of policy, economic, and job market factors. We first examined the relationship between county-level lockdown restrictions and LOST receipts. After the initial lockdowns of March 2020, the state-imposed restrictions were based on a more systematic county-level system of tiers from late August 2020 to June 2021. Counties moved between tiers based on case rate thresholds and other public health metrics, with higher tiers having stricter restrictions on gathering and business operations [7, 11]. Though the initial enactment of the state-level lockdown order in March 2020 coincided with a dip in LOST receipts statewide (see Fig. 1), we do not find a consistent relationship between these subsequent county-level lockdown restrictions and county-level LOST receipts (or rate of change of LOST receipts). We observe much more volatility in COVID-19 cases than in LOST receipts, and contrary to our expectations, county-level LOST revenues and COVID-19 case rates (and the restrictions tied to them) largely moved separately. If anything, peak county-level case rates weakly coincide with slight *increases* in county-level LOST receipts, the latter possibly driven by holiday shopping. The lack of an obvious relationship between case rates and receipts is perhaps because the tier-based public-health-driven activity restriction system did not begin until five months into the pandemic. By September 2020 and after, the economic activities that underlie patterns in LOST receipts had had time to adjust to lockdown restrictions, as well as the pandemic itself. County-level restrictions imposed well into the pandemic may have not influenced LOST receipts much atop the existing public health restrictions in place across the state throughout the pandemic. In addition, the degree to which individuals and businesses abided by the restrictions and the strictness with which governments enforced them likely varied geographically as well. However, lacking data on compliance with these frequently-changing regulations, we observe little relationship between them and county LOST revenues.

Next, to better understand how national economic trends affected local revenues, we examined the relationship between unemployment and LOST revenues. We use unemployment as a proxy for the state of the economy. Though federal and state support for individuals during the pandemic has made the unemployment rate a less perfect metric for economic health, unemployment data have the virtue of being available across our entire study period and for all of our study counties. In theory, higher unemployment should lead to reduced incomes and, therefore, reduced spending on goods and services subject to sales taxes; so, we expected unemployment and LOST revenues to be inversely related.

Figure 3 plots the average unemployment rate for all counties with LOSTs and LOST revenues collected. For California as a whole, when unemployment rose, LOST receipts fell; when unemployment declined, LOST receipts increased. This relationship was particularly evident from January through July 2020, when the large spike in unemployment from the initial lockdown coincided with a drop in LOST revenues. During the second half of the year, however, the relationship between these two variables was somewhat more ambiguous.

Figure 3 also shows that unemployment was less volatile than sales tax revenues. While LOST revenues recovered after the initial drop, they did so unevenly, with revenues varying by hundreds of millions of dollars from month to month. By contrast, unemployment slowly and relatively consistently recovered over the succeeding seven months. Only in December 2020, amidst rapidly rising COVID-19 cases, did unemployment rise again.

However, the relationship between unemployment and sales tax receipts is not as straightforward at the county level. For example, counties that experienced a greater loss in sales tax revenue had lower pre-pandemic unemployment rates than those that gained or only slightly lost sales tax revenue. This pattern continued during the

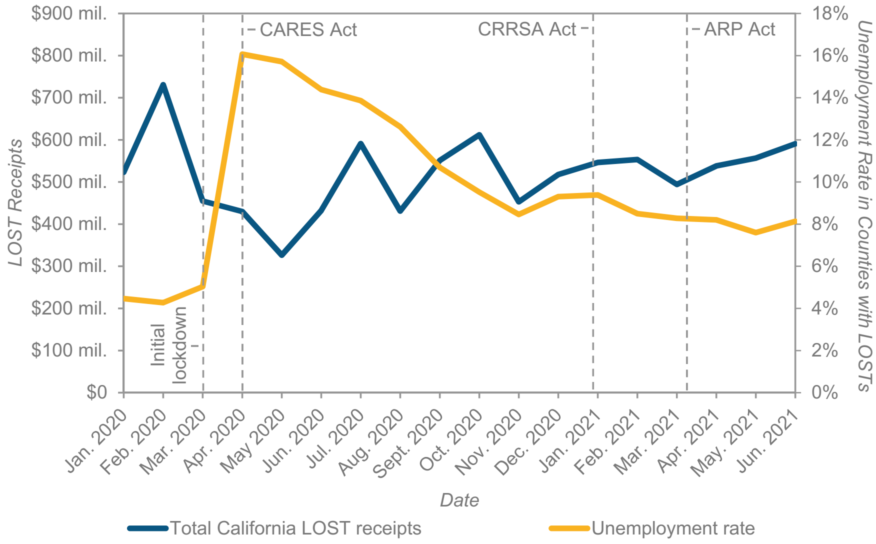


**Fig. 3** LOST receipts and unemployment in California. *Data sources* [8, 5]

pandemic: unemployment levels tended to be lower in counties with larger LOST revenue declines. At the same time, unemployment trends were broadly similar across most LOST counties: unemployment spiked sharply in March and April 2020 during the initial stages of lockdown orders in California and gradually declined thereafter, although by the end of 2020, the state-level unemployment rate (9%) still greatly exceeded levels seen a year before (around 5%).

Across all LOST counties, then, unemployment appears to be related to LOST revenue generation, particularly during the early months of the pandemic. On the whole, LOST receipts during the pandemic increased when unemployment fell, and vice versa. LOST revenues depend on consumer spending, so revenues drop when consumer demand does. That all counties followed this basic pattern shows that state- and national-level economic trends affected different counties in similar ways. This does not, however, explain variation in LOST revenue patterns across counties. To better understand county-level variation in LOST revenues, we examined additional, local socioeconomic factors.

One of those factors is income. Counties that maintained or increased LOST revenues during the pandemic had lower pre-pandemic median incomes than those that saw declines in tax receipts (See Fig. 4, top left). Although not all high-income counties had poorly performing LOSTs, all counties with the worst-performing LOSTs were high-income. Conversely, the counties with best-performing LOSTs were relatively lower-income. This pattern likely reflects the influence of income on consumer demand for taxable goods. Both absolute and relative spending on discretionary taxable goods and services tends to be higher for higher-income workers, who also make larger cuts to their spending during times of economic weakness. Lower-income individuals have more stable consumption patterns, as a smaller share of their spending is discretionary [3, 27, 31]. Therefore, counties with higher amounts of disposable income experienced more volatility in LOST revenues than lower-income counties.

Additional characteristics of counties' economies may also have contributed to patterns of LOST revenue collection during COVID-19. The pandemic affected various sectors of the economy differently, as government public health mandates, employer policies, consumer attitudes, and the toll of the disease itself unevenly affected the state's industries. For example, many office workers were able to maintain full-time employment by working from home rather than commuting into the office, while many service and retail workers, by contrast, faced lay-offs or furloughs because their place of business was forbidden from operating or allowed to operate only under reduced capacity. LOST revenue was likely depressed more in counties that rely heavily on industries that were heavily affected by COVID-19.

To explore the effect of industry composition on LOST revenue generation, we investigated whether counties with employment concentrated in particular economic sectors saw larger declines in LOST revenues. We compared employment across industry sectors to changes in LOST revenues in each county between 2019 and 2020. For most industries, we did not find an obvious relationship between industry-specific employment and LOST revenues changes. Two sectors where we did see such a relationship are the information sector (See Fig. 4, top right) (for example,

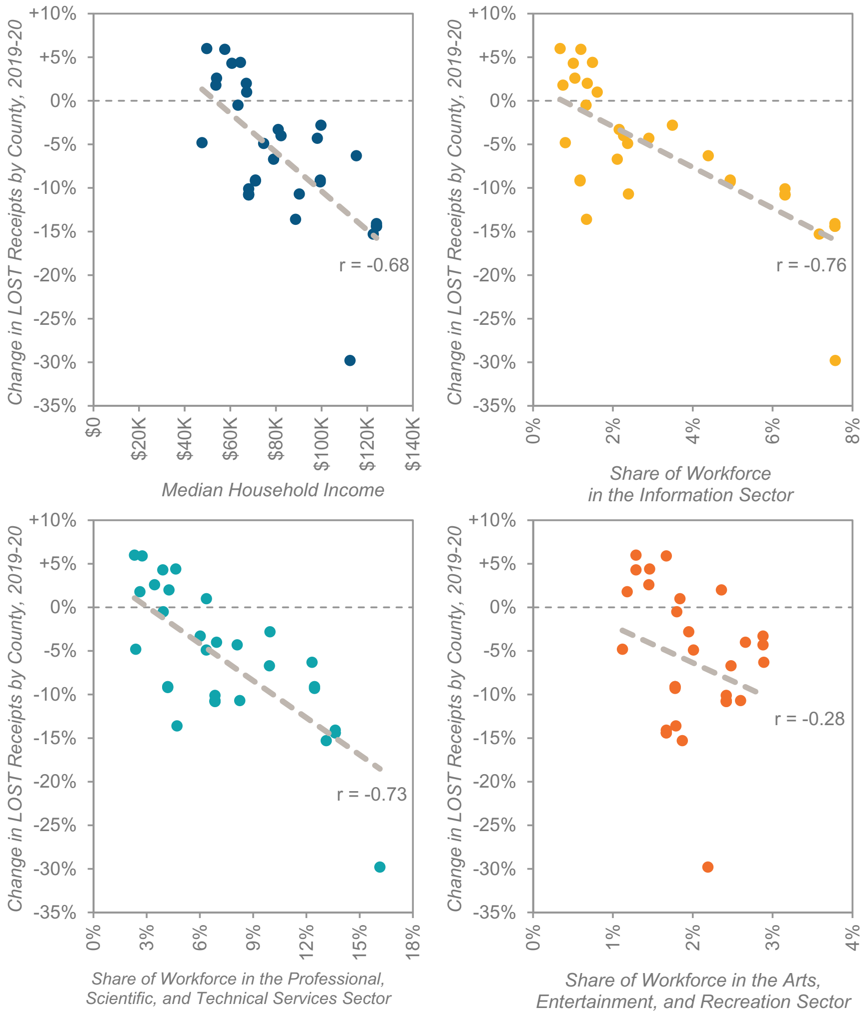


**Fig. 4** Changes in LOST receipts in relation to various characteristics of county economies. *Data sources* [8, 5, 34, 35]. *Note* As new measures in 2019, San Benito Measure G and San Mateo Measure W are excluded.

software companies) and professional, scientific, and technical services (See Fig. 4, bottom left) (for example, consulting and office work). Overall, counties with higher levels of employment in these industries tended to see larger LOST revenue declines during the COVID-19 pandemic. Employment in the professional, scientific, and technical services sector was up to four times higher in the counties with the largest revenue losses than in the best-performing LOST counties and up to eight times higher in the information sector. Workers in these sectors were much more likely to work from home during the pandemic and, we suspect, eschew discretionary out-of-home activities like dining out, discretionary shopping, travel, and entertainment, compared with workers in lower-income counties, who were more likely to work in other industrial sectors. These findings suggest that residents of these lower-income counties with relatively small shares of local employment in information technology and professional services tended to spend relatively less on out-of-home activities subject to sales taxes prior to the pandemic and thus had fewer taxable purchases to forego amidst the pandemic.

Similarly, we observe differences, albeit more modest ones, with respect to employment in arts, entertainment, and recreation (See Fig. 4, bottom right). During the pandemic, amusement parks, theaters, museums, concert venues, sporting arenas, and other types of destinations closed or were strictly limited in their operations. Counties that lost the most LOST revenues during the pandemic tended to have a higher percentage of employment concentrated in this sector.

## 5 Discussion

We find that transportation revenues in the 25 California counties with LOSTs collapsed at the start of the COVID-19 pandemic but recovered to a remarkable degree thereafter. Variation in LOST revenues across counties correlates with key differences in labor markets and consumer demand. For instance, LOST revenues in lower-income counties generally proved less vulnerable to the pandemic-induced economic downturn than revenues in higher-income jurisdictions whose residents have more disposable income, on average. Unemployment—a symptom of a weak economy and lagging consumer demand—was also associated with lower revenues. Similarly, counties with higher levels of employment in sectors whose operation was significantly curtailed under government public health restrictions experienced larger percentage declines in LOST revenues. Surprisingly, we find no substantive relationship between county-level LOST revenues and county-level lockdown restrictions. LOST revenues did fall after state-level lockdown restrictions were imposed close to the start of the pandemic, but later county-level restrictions did not noticeably coincide with patterns in LOST receipts.

The ability of LOSTs to generate revenue for transportation is therefore a function of both larger economic trends and local socioeconomic context. In some ways, this parallels the reasons jurisdictions adopt LOSTs in the first place: counties gravitated towards LOSTs amid a national trend toward the devolution of transportation finance and enacted them in response to local socioeconomic contexts. As our analysis illustrates, the resiliency of transportation LOSTs as a revenue instrument similarly relies on the interactions of national economic forces and local socioeconomic and policy contexts.

While LOST revenues declined due to the effects of COVID-19 on public health and economic activity, revenue decreases were not as large as some analysts first predicted. In part, this may be because many expected the economic impacts of the pandemic to resemble the Great Recession and its very slow, protracted recovery. However, these two economic downturns had fundamentally different causes. The Great Recession stemmed from weaknesses internal to the economic system (such as the rise of subprime loans and credit default swaps in housing finance markets), while the economic disruption of 2020 was spurred by a public health crisis that quickly, albeit temporarily, put an otherwise booming economy into an induced coma, with enormous effects on particular sectors, such travel and leisure. Moreover, as the number of COVID-19 cases and deaths decreased in large part as a response to rising vaccination rates, governments gradually relaxed public health restrictions limiting social and economic activities. As a result, the economic disruption caused by the COVID-19 pandemic started receding, allowing for a quick, though bumpy, recovery. By contrast, it took housing markets many years to recover from the effects of the mortgage finance collapse in the Great Recession. In addition, the three major federal COVID-19 relief bills provided funding to businesses, governments, and especially individuals and households to a far greater and faster extent than similar legislation in the Great Recession [26]. The Great Recession and what came after thus serves as a rather imperfect guide for the fiscal effects of COVID-19.

Federal relief and the relatively rapid economic bounce-back are good news for local government and transportation agency budgets in the wake of COVID-19. However, our findings highlight the need to better incorporate uncertainty into revenue projections. Sources of uncertainty include the strength of the economy and major public health events, among others [1]. Projections that do not account for uncertainty are less likely to consider rare, but plausible, futures—like a global public health crisis.

Incorporating uncertainty into financial planning may mean more flexible project priority lists to account for potential revenue shortfalls (or windfalls) in the ballot proposals placed before voters. For example, Fresno County's Measure C divided projects into higher-priority Tier 1 projects and lower-priority Tier 2 projects [23]. By approving prioritized project lists, voters, therefore, sign off on what should happen if revenues fall short of projections or project costs greatly exceed them. Issuing bonds from LOSTs can be another strategy to maintain steady revenue streams, if the measure includes bonding provisions. However, measures that do so still must account for the same uncertainties in sales tax revenues available for debt service on the bonds (which have first call on the revenues). Analysts might also consider a wider variety of revenue scenarios or explicitly implement scenario planning strategies or sensitivity analyses to account for multiple plausible futures.

Many transportation budgets overall fared better during the pandemic than LOSTs, due to emergency federal support. Despite losses in revenues from sources like fares and tolls, federal stimulus spending boosted many transportation budgets. For instance, public transit operators in California's counties with LOSTs received $9.5 billion in federal stimulus funds from the three federal COVID-19 relief bills [13–16]. These transit operators used federal stimulus funding to fill gaps in revenues from both dramatically lower ridership [32] and reduced LOST revenues.

Regardless of their performance during the pandemic, LOSTs are likely to continue to proliferate in the long run as a way to fund local transportation needs.

Voters tend to perceive LOSTs as a way to ensure locally generated tax revenues are expended locally, and LOSTs allow voters to export their tax burden, at least partially, onto non-resident visitors. LOSTs provide an alternative to motor fuel taxes, whose buying power will continue to decline over time as average vehicle mileage rises and as a greater share of the vehicle fleet is composed of electric and hydrogen fuel-cell cars and trucks. LOSTs also allow transportation system costs to be spread-out over all community members, some of whom benefit from transportation system improvements while paying no property taxes or taxes related to vehicle use. For example, carless renters may benefit from robust trucking delivery networks that ensure a continual supply of consumer goods.

Nevertheless, the pandemic has also laid bare and did not fundamentally change the disadvantages of LOSTs. As we have shown, LOST revenues are sensitive to the strength and structure of the economy. In addition, LOSTs are regressive with respect to income, in that lower-income people tend to dedicate a greater share of their income to purchases subject to sales taxes than higher-income people [2].[5] Likewise, LOSTs decouple transportation system use from transportation tax payments. As a result, heavy users of the transportation system may not pay enough in LOSTs to compensate for the costs they generate, and the reverse is often true for those who travel little. Unlike vehicle-miles-traveled fees and congestion pricing, LOSTs do not vary according to the different costs imposed by particular trips. And unlike motor fuel taxes, LOSTs do not implicitly tax travel-related pollution. All told, LOSTs may reliably provide revenues, but unlike road use charges (including motor fuel taxes), they do not send price signals to travelers about the social costs of travel that can encourage less socially costly and more sustainable travel.[6] LOSTs, in other words, are not a tool for managing transportation systems, merely one for funding them. This is not necessarily a fatal flaw—the primary purpose of revenue instruments is, after all, to generate revenues, and LOSTs are certainly successful at that, even amidst the worst global pandemic in more than a century. But a choice to rely on a mechanism like LOSTs is a choice to depend on an income-regressive tax instrument that offers little opportunity to optimize access or the welfare benefits of improving

[5] Any finance mechanism that does not account for the ability to pay when charging contributors is likely to be regressive with respect to income (except perhaps consumption taxes on luxury goods). For example, motor fuel taxes are also regressive with respect to income, although they may be less regressive than sales taxes [2]. In California, the regressivity of sales taxes is somewhat mitigated by the fact that food and transit fares (paid disproportionately by low-income travelers [29]) are exempt from sales taxes [2, 6].

[6] An ideal surface transportation funding mechanism might account for variation in the marginal social costs of travel by location, time of day, axle weight of vehicle, and vehicle emission profile. Ideally, more socially expensive trips should cost travelers more than less socially expensive trips, which should encourage more socially optimal travel overall.

system performance.[7] In this way, the choice of a revenue instrument can be quite costly.

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[7] Vehicle miles traveled fees and congestion pricing generate revenues that could be used to directly address the disproportionate harms to low-income residents and people of color (such as using congestion fees on a specific roadway to fund transit improvements along that roadway). Sales taxes lack this ability, as the place and time of their collection has almost no direct relationship to where and on what types of projects the revenues are spent [25].

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# E-Commerce and Mobility Trends During COVID-19

**Miguel Jaller and Sarah Dennis**

**Abstract** This chapter uses data from several sources, including health impact, mobility, and e-commerce transaction data to analyze shopping and mobility trends in the early months of the novel Coronavirus—COVID-19 pandemic. The analyses provide an overview of these trends in France, the UK, and the United States. The data, alongside a strategic review of other studies and sources, provide a picture of shopping and mobility during the pandemic. Shopping, and especially e-commerce, result in important, albeit difficult-to-predict transportation changes; thus, this chapter outlines a discussion of how the onset of the pandemic and the corresponding health restrictions might have impacted this relationship. We find that time spent at non-home locations decreased dramatically, while e-commerce transactions saw an increase. Immediately after public health restrictions were set in place, initial purchasing behaviors suggest some hoarding or stockpiling, followed by a clear increase in e-commerce transactions. Time spent at grocery locations decreased less than time spent at retail locations, which can be explained by the subsistence and maintenance nature of grocery shopping. Moreover, by June 2020, people in France and the United States were spending approximately the same amount of time in grocery locations as before the pandemic.

## 1 Introduction

The beginning of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus that causes the novel coronavirus disease 2019 (COVID-19) pandemic

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was surrounded by a great deal of uncertainty. This uncertainty manifested into swift and widespread restrictions, closures, and shifts in people's behavior—especially their shopping and mobility patterns. The outbreak began in December 2019 and led to the United States declaring a state of emergency in mid-March 2020. The following months saw confirmed cases climbing into the hundreds of millions with several million deaths reported worldwide.

COVID-19 is a respiratory illness, meaning transmission primarily occurs through coughing, sneezing, or other respiratory droplets of saliva or discharge [36]. Thus, limiting the spread of the disease requires respiratory etiquette and social/physical distancing measures [36]. The United States Center for Disease Control (CDC) [33] recommended maintaining six feet of separation from others (referred to as social distancing), not gathering in large groups, and avoiding crowded locations if possible. These requirements and recommendations, alongside the quickly increasing severity of the disease outbreak, resulted in drastic changes in social structures and operations. Stay-at-home (also Shelter-in-place, hereafter SAH) orders were put into place across the United States and around the world. Even more, restaurants, bars, and schools closed, economies and employment were disrupted, and communities restructured to accommodate social distancing practices.

This chapter uses data from several sources, including health impacts from John's Hopkins COVID-19 data [14], Google mobility data [11], and e-commerce (online shopping) transaction data from ContentSquare [4] to analyze aggregate mobility patterns and shopping behaviors seen across France, the United States, and the UK during the early months of COVID. Specifically, the chapter provides a snapshot of mobility and e-commerce behaviors in these three countries during the early months of the pandemic, from February 23, 2020 to July 19, 2020. The analyses, comparison of the three countries, and discussion of the potential impacts of SAH on these behaviors provide an understanding of the potential role of restrictions on accessibility and mobility. These are not only important for the next disruptive event but can also help inform demand management efforts, as it is hard to consider any other measure that can have such a profound effect on such behaviors.

## 2 E-Commerce

Today, more than 90% of the population in the United States uses the internet [3], allowing for the fast growth of e-commerce. In 2009, e-commerce contributed about 4% to total retail sales, growing to about 11.2% in 2019, and over 15% in the first quarter of 2021 (more than 20% growth in 2 years) [32]. In the last decade, e-commerce sales grew at a steady pace averaging around a 15% year-over-year increase, while the total retail sales in this time only grew at a rate of 4.4% [34]. Similarly in the UK, e-commerce sales made up 19.4% of all retail sales in 2019 and experienced a 46.1% year-over-year growth in 2020 [5]. The UK has the most robust e-commerce market in Europe according to its share of gross domestic product (GDP) and revenue [22]. France is also among the highest ranked e-commerce markets with the second highest revenue and the third highest GDP in Europe [22]. In France, between 2018 and 2019, the year-over-year growth rate was nearly 11.7% and is expected to have a compound annual growth rate of 10.4% through 2023 [17]. As a result, individual shopping behaviors have undergone considerable transformation, and the topic has received increased and continued interest from practitioners and researchers throughout the world.

For example, using regional Household Travel Survey (HTS) data from the Seattle region in the United States, Dias et al. [7] compared online and in-store grocery shopping behaviors. Their results suggested the underlying demand for shopping trips influences shopping channel and mode choice. Additionally, using the American Time Use Survey data to fit an econometric model, Jaller and Pahwa [13] identify participant characteristics that increase the likelihood of an individual shopping online. They identify several characteristics that contribute to a higher likelihood for online shopping compared to their counterparts, including females, shoppers in highly populated areas, shoppers in highly populated areas with higher education, and individuals living in highly populated areas with children. In the UK, approximately 87% of households had purchased something online in the previous year [5], and over 50% of shoppers were motivated to shop online primarily for the ability to compare prices and increase their number of choices [25]. In 2020 during the pandemic, compared to 2018 and 2019, a slightly higher proportion (49% compared to 45–46%) of participants indicated that they shop online because it is easier to search and buy [25]. In France, from a survey conducted in September 2019, the primary category of online shopping before the pandemic was fashion products (nearly 47%) followed by cultural products (nearly 37%), then electronics and appliances (35%) [8]. Other studies have analyzed the likelihood of online shopping using various data sources [1, 2, 9].

Overall, shopping is an important component of travel and transportation because it constitutes one of the activities that people need to fulfill and therefore can generate travel. Shopping can be for subsistence, maintenance, and discretionary items, for which there are different levels of potential travel flexibility and choice substitution. Shopping travel can manifest in single trips to the store and back, or as part of trip chaining behaviors in which store shopping constitutes a stop within a travel tour, such as commuting from work to home [16], which has important transportation demand management implications [26]. As a result, there are travel implications that are specific to a person's schedule, lifestyle, location, and the preferences towards different shopping channels. This variability is at the root of the complex problem of identifying the impacts of online shopping related to changes in travel and consumer behavior. The impacts of e-commerce on travel demand can be summarized in travel substitution, complementarity, modified travel, and induced travel. However, there is no consensus about the net effect of e-commerce on travel demand, though most of the literature has identified complementarity (i.e., online shopping encouraging more travel demand) [13, 37]. E-commerce does not only have these effects on personal travel, but to make the products available or delivered, requires logistics and distribution activities and decisions. For example, when a person orders goods online, they may obtain the item through delivery to the consumer's home by means of a delivery truck, van, passenger car, cargo bike, robot, or other, delivery to a pick-up location where the customer collects the items, which may involve travel on any mode; or no delivery, when the customer picks-up the item at a store, in what is known as "click-and-collect" or "in-store pick-up," or the new form made popular during the pandemic, "contactless curbside pick-up." As can be imagined, each of these scenarios has different transportation impacts, especially when considering that e-commerce retailers do not necessarily deliver all goods in one parcel or within one shipment. Therefore, the resulting travel demand is some combination of consumer, truck, van, or other delivery vehicle miles traveled (VMT), which can affect total VMT, localized VMT, environmental impacts, public health consequences, safety, and congestion.

## 3 COVID, E-Commerce, and Transportation

So far, during the COVID-19 pandemic, information and communication technologies (ICTs) have been used as substitutes for travel for different activities, primarily working and shopping. At the cusp of the COVID-related public health measures, VMT was reduced to 2008 levels in the United States. According to StreetLight county-level data, since the beginning of March 2020, every metro area in the country experienced a traffic reduction of at least 53%, with some areas in the Northeast corridor and coastal California experiencing travel reductions of at least 75% [31].

More importantly, empirical analyses found statistically significant relationships between the reductions in travel based on socio-economic and demographic data, the length of the SAH orders, and other variables. Specifically, employment shares in higher education industries, information, finance and insurance, real estate rental and leasing, and professional, scientific, and technical services, and high-risk and essential industries can help explain such reductions. That is, workers in high-information and management industries had a major negative impact on VMT. Following the results from Gitlab [10], these are the industries with a large acceptance of telecommuting and for which the transition to remote work may have been easier. Additionally, there has been a significant increase in e-commerce transactions. In the United States and the UK, e-commerce only represented about 11% and 20% of retail sales before the pandemic, respectively, therefore, there were almost 80–90% of sales that could be substituted to e-commerce. During the early days of the pandemic, several commodities experienced increases of more than a hundred percent.

There are additional transportation and economic impacts from e-commerce, such as those discussed by Mokhtarian [16]. These include changes in mode share, basket sizes (number of goods purchased), per capita spending, and demographics of those shopping through e-commerce channels. During COVID-19, it was also expected that travel (mobility) and shopping behaviors would change and exhibit these impacts. For instance, travel restrictions from SAH orders and the need to still access critical goods prompt the need to use alternate shopping channels (online) and substitute regular travel, precautionary/opportunistic buying, altered spending on some commodity types, changing frequency and basket size, and demographic effects (e.g., shopping patterns resulting from income and age distributions). Additionally, changes to household-bound tasks and their respective durations are likely to have occurred, resulting in drastic mobility shifts.

As discussed in this book, the COVID-19 pandemic and the associated public health measures changed transportation and travel in nearly every imaginable way. This is certainly the case for e-commerce transportation impacts as well.

## 4 Data

This section highlights some existing knowledge using COVID-19, mobility, and e-commerce data from the early months of the pandemic. The section introduces the primary data sources, and the following sections discuss findings based on the data and the existing knowledge and literature on this topic.

### *4.1 Johns Hopkins University COVID-19 Data*

We obtained data from the Johns Hopkins University Coronavirus Resource Center [14] which provides the daily count of confirmed cases, deaths, and recoveries worldwide (for January 23, 2020 through July 19, 2020). In addition, the fatality-to-case ratio was estimated for each country using the following method:

$$\frac{\text{Number of fatalities}}{\text{Number of confirmed cases}}.$$

The data are aggregated to different levels, including, global, country, regional (e.g., U.S. states), and sub-region (e.g., counties). This chapter uses the global and country-level (United States, UK, France) data.

### *4.2 Google COVID-19 Mobility Report*

Second, data were obtained from the Google COVID-19 Community Mobility Report [11]. This report was created based on Google GPS data and provides the percent change in time spent in several locations, including the ones relevant to this study: retail and recreation, and grocery and pharmacy, residential locations, and work locations. These locations are referred to in this chapter as retail, grocery, home, and work, respectively. This percent change is in reference to the base period, which, in this case, refers to the median amount of time spent in these locations from January 3, 2020 to February 6, 2020. The estimated percent change from the base period is estimated daily for the United States, the UK, and France from February 15, 2020 through July 19, 2020.

### *4.3 Content Square E-Commerce Impact Hub*

Lastly, Content Square [4] provides COVID-19 e-commerce impact data. For this study, the “Transactions Evolution” data were utilized, which provides temporally specific online transaction data. The data are in the form of an index, normalized around the base period (January 6, 2020 to February 16, 2020), which is set to an index of 100. As the pandemic progressed, the data available from ContentSquare, such as types, timelines, and geographies of each measure, were updated and changed. In this chapter, we utilize weekly measures from the United States, the UK, and France from February 23, 2020 to July 12, 2020.

## 5 Findings

### *5.1 Mobility: Home and Work*

We examined mobility changes in some of the most universally visited locations—home and work. Figure 1 shows the percent change in time spent at home and work, transactions, and fatality-to-case ratios for France, the UK, and the United States. The respective SAH or state of emergency (SOE) dates are indicated on each plot, marked with a vertical line and the date. For France and the UK, the SAH dates are March 17 and March 23, 2020, respectively. For the United States, the SOE date is March 13, 2020.

Looking first at the global stage (bottom right of Fig. 1), each curve follows a remarkably similar path. In the early months of the pandemic, as the fatality-to-case ratio increased, e-commerce transactions increased, nearly proportionally. This is likely also related to the fact that businesses around the world had to close their storefronts and/or limit their in-store capacity. Even more, as fatality-to-case ratios and confirmed cases increased, concerns began to mount, and people began avoiding and minimizing their time in public spaces. With that, and the abrupt shift that businesses made to the online platform, it is unsurprising that the global population shifted their shopping behaviors. With improved access and increased needs, the corresponding shift is certainly expected. However, these data tell us very little about whether people were shopping more (*complementarity*) or if they were shopping differently (*substitution*), or both. Because the data are limited, instead of following money (transaction totals or sales), our analyses followed population mobility. The following sections discuss more localized relationships between the COVID-19 fatality-to-case ratio

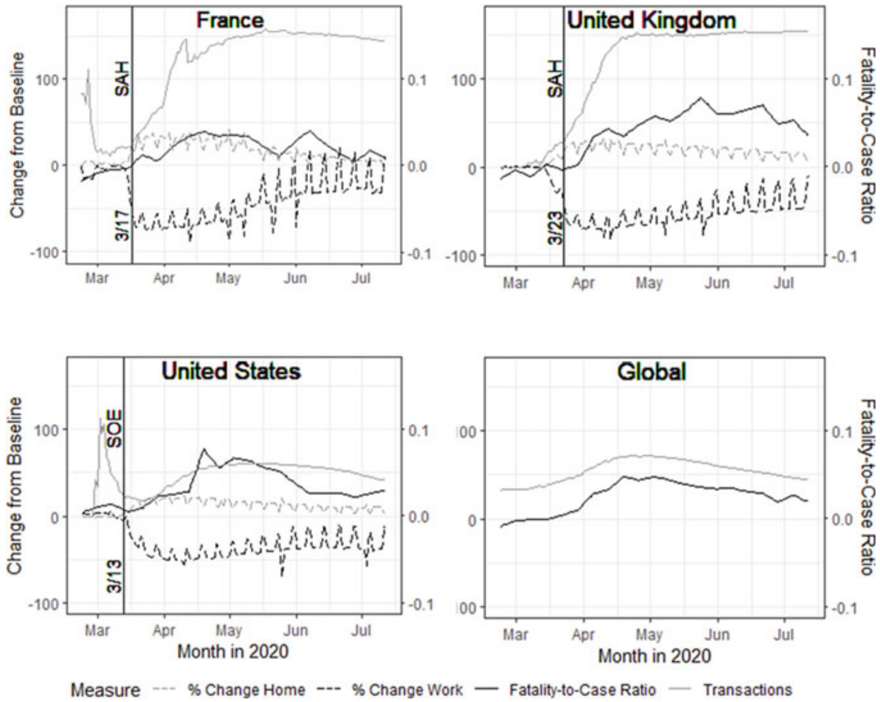


**Fig. 1** Percent change in time spent at home and work, compared to changing fatality-to-case ratios and e-commerce transactions. *Data sources* ContentSquare [4], Google LLC [11], JHU [14]

and transaction changes, as well as mobility data, first, for home and work, then for grocery and retail locations.

Across all three countries, the number of transactions saw notable increases following SOE/SAHs. It is also worth noting that in all three countries there is a distinct increase followed by a peak and at least some decline. In fact, immediately following the SOE/SAHs, the time spent at home and work locations, and e-commerce transactions diverge from the base case.

These results are as expected, especially given how many businesses were required to close their offices and stores. The transportation implications of such a change are dramatic. First, as weekday traffic is largely made up of drivers traveling between their work and home, without such travel needs, these trips are greatly reduced. This also comes with secondary outcomes, including reduced traffic congestion (and therefore faster travel times), people finding themselves with additional time that used to be spent on their commute, and fewer trips and tours (e.g., people are no longer stopping by the store on their way home from work). Even more, people being confined to their homes results in changes in demands for goods. This is true both for the quantity and type of goods. The full impacts vary across the three countries, with France and the UK exhibiting time spent at work being reduced by 70–75%, whereas the reduction in time spent at work only reached about 50% in the United States, providing an indication of the degree of SAH and other mitigating measures.

Manheim and Denkenberger [15] suggest that social distancing and isolation measures are difficult due to the need for people to access essential goods, including food, cleaning supplies, toilet paper, and others. However, with social distancing measures in place and SAH orders in effect, businesses, individuals, and communities adjusted their shopping habits and behaviors. Many food and other retailers reworked their business strategies and logistics networks to meet higher-than-predicted demands and unanticipated social requirements such as social distancing [12, 18–20, 38]. This includes companies reprioritizing the speedy shipment of essential goods and deprioritizing the shipment of non-essential goods. Retail stores closed their storefronts, grocery stores offered high-risk-only hours and filled an increased number of online pickup orders, while bars and restaurants offered or adopted free contactless delivery services.

Stackline (a retail intelligence and software company) shows increased purchases of health and food-related goods (e.g., weights, bread machines, non-perishable foods), and a decrease in the online purchases of items such as swimwear and travel goods in March 2020 compared to March 2019 in the United States [29]. Table 1 shows the general e-commerce purchase changes identified:

Additionally, items related to crafting (e.g., crafting kits, art paint), beauty (e.g., hair dye, nail care, skin care) and working from home (e.g., desks, chairs, computer monitors, computer mice, keyboards) also increased. Meanwhile, items such as motorcycle and car parts (e.g., tires, wheels, shocks) decreased alongside wine racks, bar and wine tools, glassware, and drinkware, hand tools, phones, and many others [29]. These results, especially those categories that experienced increased demand, highlight the fact that people were adjusting their lives to spend more time at home. With more time spent at home, and less time spent driving, commuting, or otherwise outside of the home, people spent money on entertainment and hobbies, self-care, and their at-home working environments. From the grocery category, there seem to be three main categories of food within this section: non-perishables (soup, grains

**Table 1** Retail types and COVID-19-related changes in the United States

| Retail type | Direction | This retail type includes, for example |
|---|---|---|
| Travel | Decreased | Luggage, cameras, snorkeling equipment, camping equipment |
| Grocery | Increased | Bread machines, soup, grains and rice, pasta, vegetables, jerky and meats, chips, crackers, snack foods, pet foods, baking mixes, and ingredients |
| Health | Increased | Gloves, women's health goods, health monitors, herbal supplements, smoking cessation |
| Sports Equipment | Increased | Weight training, yoga equipment, fitness equipment |
| Fashion | Decreased | Apparel for men, women, and children, shoes, watches and accessories, jewelry |

*Source* Stackline [29]

and rice, pasta, chips, crackers, snacks, pet food—suggesting stockpiling behaviors), foods that might experience a supply shortage (vegetables, meats), and groceries for hobby/entertainment (bread machines, baking mixes, and ingredients).

With public health guidelines in place that restrict travel and group gatherings, it is unsurprising that travel, fashion goods, and group entertainment goods (wine racks, bar and wine tools, glassware and drinkware) saw decreases in transactions. The other decreased categories, vehicle parts, hand tools, and phones, are likely representing the impacts of uncertain financial situations, and therefore hesitancy to spend large sums of money at once. It is worth noting that the categories that increased are largely composed of (utilitarian) goods that are comparatively low-cost compared to those that decreased.

## 5.2 *Mobility: Grocery and Retail*

This section compares the previous findings with the time spent in retail and grocery locations. The data in Fig. 2 show the difference between the European countries

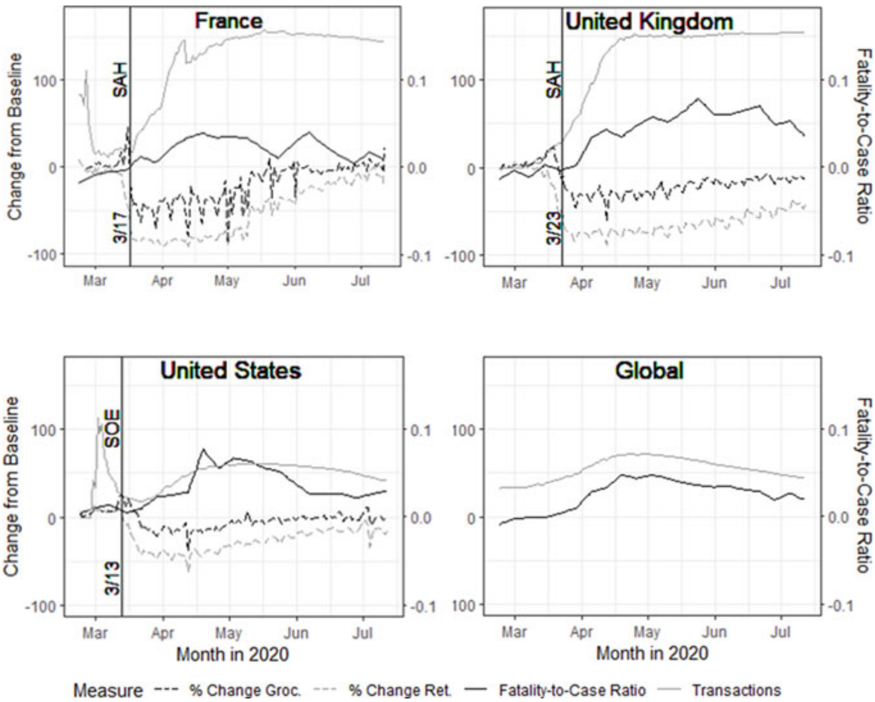


**Fig. 2** Percent change in time spent at grocery and retail locations, compared to changing fatality-to-case ratios and e-commerce transactions. *Data sources* ContentSquare [4], Google LLC [11], JHU [14]

of France and the UK on the one hand, and the United States on the other hand, with respect to changes in mobility. We can see that the reduction in time spent at groceries and retail locations in the United States was only half to that experienced in France and the UK. With retail time decreasing between 80 and 90% in France and the UK, and only to about 50% in the United States. The results also show the relative importance between grocery shopping and retail shopping, though the results are certainly biased because retail experienced stricter closures, whereas groceries were deemed essential locations and were allowed to remain open, for the most part.

Additionally, the outstanding trend is that for each country there is a spike in the amount of time spent in grocery locations almost perfectly coinciding with the emergency response measures being implemented. It is expected that consumers exhibited hoarding behaviors during COVID-19 [23]. Specifically, Dablanc [6] reports consumer hoarding or stockpiling in France. Hoarding/stockpiling depletes in-store inventories, further highlighting the need for e-commerce, which allows consumers to access essential goods with little to no exposure [23]. Figure 2 seems to support this finding for each of the countries in this study—the spike in time spent at grocery locations (likely when people began stockpiling or hoarding goods) is followed immediately by an increase in e-commerce transactions. This could have been to get access to goods that were sold-out and unavailable locally (consumers were *supplementing* their in-person shopping), or to avoid in-person interaction (*substituting* in-person shopping), or both. Each of these possibilities results in unique transportation outcomes, the effects of which depend on quantities of goods, shipment modes and types (e.g., two-day shipping or other), and the sector of goods, among other things.

Even more, each of these spikes is followed by a dramatic drop in the percentage of time spent in both grocery and retail locations. Also, worth noting is that immediately after the major drop in mid-March 2020, there is a slight positive trend for all countries for both groceries and retail. This might suggest that people responded very strongly at first, then eased-up on their avoidance of these spaces. In fact, in France and the United States, the data suggest that by June, people were spending the same percentage of time in grocery locations as prior to the regional onset of COVID. This seems to suggest that although there were distinct and dramatic population-wide reactions to the pandemic, changed behaviors may have only been temporary. Figure 2 also complements the findings from Table 1, as it shows a more dramatic reduction in retail shopping (e-commerce transactions and time spent at retail locations) than time spent at grocery locations. This is true across France, the UK, and the United States, and through time. Even more, within this time, retail gets eventually closer to the pre-COVID baseline, although it never meets it.

Finally, the data show that for each country, the time spent at grocery and retail locations and transaction changes diverge, starting immediately when the public health restrictions were set in place, even when the fatality-to-case ratio was higher before (see France and United States). Dablanc [6] found that in the greater Paris region, e-commerce shopping increased, but did not fully replace lost in-store shopping. She also finds that online food orders increased, consumption of non-food goods dropped by approximately a third, and in general, households consumed less overall during SAH orders [6].

Just as interesting, although not a perfect trend, these measures converge again by the end of the study period. In France, the change in transactions nearly reaches zero (the pre-COVID baseline); in the United States, it is near the baseline, although still maintaining increased e-commerce transactions (even though time spent at grocery locations was back at the baseline); and in the U.K. the e-commerce transactions remain well above the baseline. In each country, e-commerce transactions return more slowly to the baseline than time spent at grocery and retail locations. It is currently unclear whether e-commerce transactions will return to the baseline, especially because the pandemic introduced new e-commerce shoppers to new systems and services. It is entirely possible that people who were not using e-commerce services before the onset of the pandemic have now learned and adjusted, matching the services offered with their safety/comfort level. It is also possible that e-commerce businesses improved their services in a way that is attractive to consumers, even in a post-pandemic world. Although it seems that at the country level, people largely returned to spending just as much time in grocery locations as they were before the pandemic, time will tell if e-commerce transactions return to their respective baseline (which was already experiencing rapid growth). In the United States, for example, e-commerce sales experienced rapid growth in the second quarter (most of the period analyzed in this chapter), the share of e-commerce sales to retail sales declined in the third quarter, but increased in the fourth quarter (as expected following the seasonal trends). While it is expected that there would be a net increase in e-commerce because of the pandemic, first quarter data from 2021 seem to indicate that the e-commerce sales may revert to the growth trend from the last decade (with a slight increase), and the pandemic-generated growth may not be sustained.

As mentioned, in most SAH-enforced locations, retail and recreation places were usually closed, whereas grocery stores and pharmacies remained open. This is one of the only periods in recent history where full substitution can be observed for a number of trips through ICTs. Despite some of these findings, there is already evidence that relaxing some of the SAH measures, and the reopening of the economy, have resulted in increases in physical travel activity, with traffic volumes and congestion reaching pre-pandemic levels [24, 35]. This natural experiment can serve as a reference of the maximum reduction in travel that could be achieved through travel demand strategies. Never before (in normal times) has a travel measure been able to achieve such reductions, travel substitution, and behavioral change.

## 6 Conclusion

The COVID-19 pandemic brought many important changes to transportation, mobility, and e-commerce. This chapter discussed sector-specific mobility changes related to e-commerce transactions. In the early months of the pandemic, time spent at non-home locations decreased dramatically, while e-commerce transactions saw a corresponding increase. Immediately after public health restrictions were set in place, travel and shopping behaviors suggested some precautionary and opportunistic buying (through hoarding or stockpiling), followed by a clear increase in e-commerce transactions. It is unclear at this point, if the increase in e-commerce transactions is the result of substitution or complementary shopping. It is also unclear whether e-commerce will remain elevated from the pre-pandemic baseline, even in a post-pandemic world. Current trends suggest that there would be a return to the norm for time spent at grocery and retail locations, and possibly e-commerce transactions. For the period analyzed in this study, e-commerce transactions tend to converge back to the pre-pandemic time, but do not fully return yet.

E-commerce purchases represent trends that were being largely speculated in the media. This includes the fact that people were making more e-commerce purchases related to hobbies and crafts, health and wellness, and work-from-home equipment. On the other side, people purchased fewer travel goods, swimwear and fashion, and entertainment or vehicle parts. It is estimated that these findings are the result of the following influences: tight or uncertain financial futures, people wanting to stay entertained while at home, and people maximizing the use of time they were no longer spending on other (out-of-home) activities on things such as self-care and fitness.

In terms of shopping and mobility, time spent at both grocery and retail locations decreased, with retail decreasing more than grocery. This is likely the result of groceries and pharmacies being deemed essential (and allowed to remain open), while many retail locations closed their storefronts. It may also be related to financial hardships and reduced demand for some retail goods. Importantly, time spent at grocery locations returned and stabilized at the baseline relatively quickly (within about two months), especially in the United States and France. Meanwhile, time spent at retail locations does not return to the baseline within the study period, although in France it is close.

Importantly, the results presented in this chapter show an increase in e-commerce transactions and a decrease in mobility. As previously stated, shopping-related mobility has largely returned to the baseline, and e-commerce transactions remain above the pre-pandemic baseline during this study period. If this relationship holds, or if e-commerce does not return to the pre-pandemic norm, there are many potential transportation impacts that are important to understand. The direction of transportation impacts depends largely on the disaggregate behaviors, specifically, the mode of delivery or pickup of the parcel. During the pandemic many businesses began offering online orders for pick up (such as grocery stores), while others have opted for expanded delivery services (groceries from retailers and gig services). This led to consumers using new services and/or using old services more often. Given the combination of possibilities for how consumers can obtain the goods they purchased online, and the uncertainty related to if or how these behaviors may persist, it is difficult to predict how the pandemic will impact transportation for years to come.

Nevertheless, it is important to highlight some findings and reflections: First, although there may have been fears from news about the pandemic and pandemic-related fatalities, the rapid increase in e-commerce transactions became only evident, as a result of substitution of travel, once the SOE or SAH orders were put in place, which led to the closing of stores, restaurants, and other locations. Second, even under sustained fatality-to-case ratios (e.g., in France and UK), mobility started to increase again to pre-pandemic levels. Third, while it is not clear why the time spent at home didn't increase as much (about 30%), even with the time at work and shopping locations significantly decreasing, it would be important to study if people used the additional time in other activities, and whether those activities led to induced travel demand or not. Lastly, the extreme and unprecedented conditions brought by the pandemic and the measures that ensued forced many people into drastic behavioral changes, and this represents a unique opportunity to study impacts on travel demand (e.g., how much travel could be reduced, effects of e-commerce and shopping substitution). However, it is also clear that without clear policies or strategies, people will tend to travel as much and spend as much time in activities post-pandemic as they did pre-pandemic, thus affecting any long-lasting system mobility benefits experienced during the early months of the pandemic.

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# COVID-19 and Food Shopping: Results from California and Comparisons with China and South Korea

**Jean-Daniel Saphores, Lu Xu, and Bumsub Park**

**Abstract** Following the first stay-at-home order in March 2020, many Californians responded with panic buying: they stocked up on masks, and hoarded toilet paper, hand sanitizer, canned food, bread, and pasta. Restaurants had to stop on-site dining services, and some even closed permanently. Californians adapted to the evolving restrictions imposed by the pandemic by switching to alternative channels for their groceries and experimenting with meal deliveries from participating restaurants. The purpose of this chapter is to analyze the impacts of the COVID-19 pandemic on how Californians shopped for groceries and prepared meals before and during the pandemic based on a random survey of 1,026 Californians conducted at the end of May 2021. To better contextualize observed changes in California, we also investigated grocery and prepared meals purchases in China and South Korea, two countries at the forefront of online grocery shopping and meal deliveries that provide a window into possible alternative futures for e-grocery and meal deliveries in California. We conclude by reflecting on how our increasing dependence on online grocery shopping and meal deliveries may impact travel.

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# 1 Introduction

Among its many impacts, the COVID-19 pandemic has led to a sharp increase in online shopping for groceries and prepared meals. In this chapter, we examine the impacts of the pandemic on household grocery and prepared meals purchases in California based on a random survey of 1,026 Californians conducted for us in May 2021 by IPSOS (the third largest global market research company). We consider two questions. First, how did the pandemic affect the purchase of groceries in brick-and-mortar stores, online with delivery, or online with store pick-up? Second, how did the pandemic impact meal purchases, either consumed in restaurants (dining-in), at home after take-out, or at home after delivery? These two questions are connected since prepared meals represented approximately 55% of food expenses in the United States before the pandemic, with the remaining 45% going to food purchased in grocery stores [32].

To put our results in perspective, we investigated changes in the purchases of groceries and prepared meals in South Korea, one of the world leaders in e-grocery (online grocery retail) and prepared meals deliveries to households, and in China, which has made considerable investments in logistics for food deliveries over the past few years. These two countries provide a window into alternative futures for e-grocery and meal deliveries in California.

Understanding changes in residential deliveries from e-grocery and meal deliveries is important to logistics managers, transportation engineers, urban planners, and policymakers at a time when California is trying to reduce road congestion and air pollutant emissions from transportation, and meet its climate change targets.

# 2 Literature Review and Background

This section presents a snapshot of a quickly growing literature dealing with the impacts of the COVID-19 pandemic on food purchases, eating, and meal deliveries. The reviewed studies provide valuable information during a time of rapid change; however, they rely on data not collected via random sampling, and extending their findings to a broader (target) population should be avoided. We also present pre-pandemic trends in the United States, China, and South Korea.

## *2.1 Food Shopping, Diets, and COVID-19*

The COVID-19 pandemic has significantly increased our dependence on e-commerce for satisfying our basic needs. For example, Instacart, a popular grocery delivery service in the United States, reported a 500% year-over-year growth in April 2020

[30]. Large increases in e-grocery were also reported in other parts of the world (e.g., see [3, 8, 37]).

We found very few studies that focused on e-grocery. Exceptions for the United States are Unnikrishnan and Figliozzi [36, 37], who surveyed online residents of the Portland–Vancouver–Hillsboro metropolitan area to understand their e-commerce and home delivery service preferences. Their results indicate that higher income, tech-savvy, and health-concerned households were more likely to buy more groceries and meals online during the COVID-19 lockdown.

Other studies explore how restrictions put in place to fight the pandemic affected food shopping and eating habits. These restrictions combined with a loss of employment and/or the disease of friends and relatives have generated high levels of depression, anxiety, and stress [39], which in turn caused some people to consume more comfort foods, increasing the risk of diseases such as diabetes, which themselves are risk factors for COVID-19 [17]. On the other hand, researchers who surveyed people from 38 countries between April and June 2020 [10] found instead increases in planning, selecting, and preparing healthy foods, which was positively related to time availability and stay-at-home restrictions.

### *2.2 Restaurant Deliveries*

Some researchers have examined people who ordered food online, their loyalty to food delivery platforms, and their use of food delivery apps. These studies originate from a broad range of countries, including India [25], Vietnam [22], Indonesia [31], China [42], and Thailand [27]. They do not, however, analyze how meal deliveries changed during the pandemic and why.

### *2.3 Pre-pandemic Trends*

Pre-pandemic, the simple acts of purchasing food and meals were already changing with the growth of online shopping, either with home delivery or with store pick-up (click-and-pick). However, the popularity of e-grocery and meal deliveries varied widely between and within countries because of a broad range of factors [8]. To illustrate this diversity, we contrast pre-pandemic trends in the United States, China, and South Korea.

In the United States, despite the rapid development of online shopping, e-grocery made up less than 4% of grocery sales in 2019 [5]. The first reason is that safely delivering meals or fresh foods to customers requires relatively expensive investments, while grocers and restaurant owners typically have thin margins. Second, although they save customers shopping trips, home deliveries can be inconvenient by forcing customers to wait at home for deliveries.

Despite potential obstacles, spurred by startups like Instacart, many traditional grocers were experimenting with online deliveries before the pandemic (e.g., Walmart started offering online shopping in 2007 [38]). Food deliveries were also taking off with the emergence of the gig economy. Revenues from food deliveries reached $22 billion in 2019 with 95 million users [7].

In China, e-grocery was more developed pre-pandemic than in the United States. In 2019, over 80% of Chinese households had tried e-grocery, 40% were shopping online for groceries at least weekly, and e-grocery's share of the grocery retail market was 10% [23]. Advances in e-grocery were made possible by large investments from several large Chinese companies. For example, Alibaba Group, a Chinese multinational technology company launched a new online and offline retail store called Hema in 2015. An offline Hema store combines a supermarket with restaurants and fulfills online orders. As of the summer of 2021, over 230 Hema shops operate in 21 major Chinese cities [16].

To provide quick deliveries of perishable goods, some companies without physical stores set up fulfillment centers[1] near residential compounds. One example is MissFresh, which had 1,500 fulfillment centers in 20 major cities before the pandemic [11]. Thanks to an abundant workforce from rural areas, millions of delivery riders were hired for last-mile deliveries, enabling deliveries throughout the day [41]. For example, automation and relatively cheap labor enable Hema in major cities to offer delivery within 30 min for customers residing within three kilometers of a Hema store [16].

Another key difference is that in China people commonly make digital payments using digital wallets linked to their bank account in mobile apps from WeChat pay or Alipay and do not need a credit or debit card. As a result, mobile payments totaled $790 billion in 2016 compared to $74 billion in the United States [24]. Lastly, an innovation, community group buying, was emerging in China before the pandemic, with a group of shoppers placing joint orders large enough to get discounts.

In South Korea, just before the COVID-19 pandemic, in 2019, online food sales represented 24% of the total food retail market ($23.2 billion out of $96.9 billion). While the entire food retail market was growing at 3.3% annually, the growth rate of online food sales was exceeding 40% per year (Food Information Statistics System 2020). One reason for this trend is demographic change. With a steady increase in the number of dual-income and nuclear families, the consumption from super retail centers (such as Costco in the United States), which offer low prices for in-person, large volume purchases, has been decreasing. Conversely, the consumption of easy/ready-to-cook food and the demand for quick fresh food deliveries have been increasing. As a result, online food sales in 2019 exceeded food sales from super retail centers, and the gap widened further during the pandemic [1].

Key players in online food sales in Korea include Kurly Inc., Coupang, Emart, Naver, and Baemin. Kurly Inc. is a startup that introduced an overnight grocery delivery service in 2015. Coupang (NYSE: CPNG) and SSG.com (owned by Emart (KRX: 139480)) soon followed, and the online food market, which was only $8.7 M

[1] A fulfillment center is a warehouse that picks, packs, and ships orders to customers.

in 2015 grew 80 times by 2019 [21]. Coupang, the first South Korean online shopping firm with its own nationwide distribution network, provides overnight deliveries of fresh foods. Emart, the largest offline retail company in South Korea, has also invested massively in online food services. Naver (KRX: 035420) is an IT platform company that provides an online food shopping platform. As of 2019, it had the largest online revenue with \$18.2 billion [29]. Finally, Baemin is the most popular meal delivery company with a 78% market share.

## 3 Empirical Study

### *3.1 Survey*

In late May 2021, we asked IPSOS to conduct a survey of Californians using KnowledgePanel, the oldest and largest (~60,000 members) probability-based online U.S. panel. Thanks to its size, the subset of Californians in KnowledgePanel is representative of the California population. To overcome limitations from phone-based sampling (since many Americans no longer have a landline), members of KnowledgePanel were recruited using address-based sampling (the Delivery Sequence File of the U.S. Postal Service). Special efforts were made to include harder-to-reach populations, such as African Americans, Latinos, Veterans, Americans with disabilities, LGBTQI and non-binary people, rural residents, and non-internet and cellphone-only households. IPSOS provides new panel members without internet access with a tablet and a mobile data plan.

Conducting a survey with KnowledgePanel offers several advantages. First, it allows overcoming the self-selection bias since respondents are chosen based on their characteristics, which are recorded when they enroll and updated annually. Second, participant fatigue is minimized, with panelists taking on average two to three KnowledgePanel surveys per month. Third, surveying a panel helps address mode bias by asking questions only online. In addition, using KnowledgePanel helps address non-response bias, thanks to high (~70%) survey response rates.

Our survey was first written in English and tested by graduate students. The survey's first part inquires about commuting and telework before and during the pandemic. Its second part inquires about how Californians shopped for groceries and prepared meals before and during the pandemic, and what they intend to do after.

A pilot study was fielded by IPSOS to 25 respondents to test our questionnaire and their feedback was incorporated into the final survey instrument. To include respondents who were Spanish speakers, we translated the survey into Spanish and pre-tested it with native speakers. Both versions of the survey were administered starting on May 22, 2021. By the end of May 2021, 1026 respondents had provided valid answers.

### 3.2 Data Analysis

First, we scaled the selected responses of the California population about grocery shopping and food deliveries using the weights calculated by IPSOS. This enabled us to discuss results in terms of the California population. Because of its panel recruitment process, the raw distribution of KnowledgePanel members mirrors the distribution of U.S. adults. For selecting general population samples, IPSOS' approach ensures that a random sample from KnowledgePanel behaves like a sample drawn with an equal probability of selection.

After our sample had been collected and processed, design weights were adjusted in three steps to account for differential non-response using selected socio-economic distributions for Californians 18 and over from the 2019 American Community Survey.[2] In Step 1, design weights were computed to reflect the selection probabilities of California members of KnowledgePanel. In Step 2, these design weights were raked to the distributions of the following variables: gender by age, race-ethnicity, education, household income, and language proficiency. Finally, in Step 3, calculated weights were examined to identify outliers (none were found), then scaled to aggregate to our total sample size (N = 1,026).

Second, we conducted chi-square tests of independence in two-way contingency tables comparing answers (1) during versus before the pandemic; and (2) after versus before the pandemic.[3] All tests were statistically significant at 1%. So in our discussion below, we omit specific test results and focus instead on the practical significance of observed differences.

### 3.3 Findings

We organize our findings into two sub-sections that deal with the following two questions (our baseline is our respondents' behavior just before the pandemic):

1. How Californians shopped for groceries (in-person at brick-and-mortar stores, online with home delivery, or online with store pick-up) during the pandemic, and how they intend to shop after the pandemic?
2. How Californians purchased and consumed prepared meals (eat on-site, take-out, or order online with delivery) during the pandemic, and how they intend to purchase prepared meals after?

Shopping for Groceries

[2] The American Community Survey (ACS) is a survey conducted annually by the Census Bureau. It collects socio-demographic, economic, and housing information, which is used to inform how more than $675 billion in federal and state funds are spent every year (https://www.census.gov/programs-surveys/acs/about.html).

[3] These tests were conducted using the final sample weights described above with the "Svy" command in Stata, a general-purpose statistical software package developed by StataCorp for data manipulation, visualization, and analysis. It is widely used by researchers in many fields.

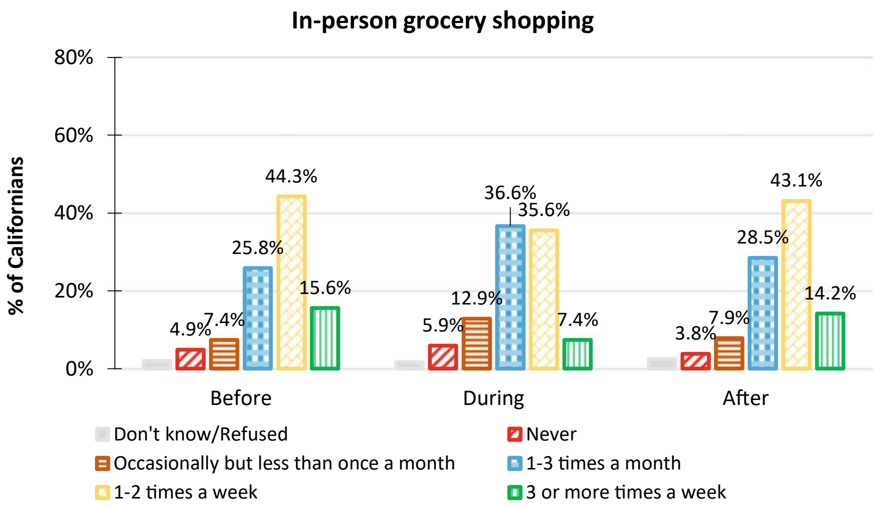


**Fig. 1** Changes in in-person grocery shopping in California. *Data source* Authors' survey

In Fig. 1, we can see, as expected, a decrease in grocery shopping during the pandemic: the percentage of Californians who visited groceries one to three times per week dropped from 44.3% to 35.6%, while the percentage of those who went three times or more per week was cut in half (from 15.6% to 7.4%). Conversely, the percentage of Californians who rarely or never went grocery shopping in-person increased (from 7.4% to 12.9% and from 4.9% to 5.9% respectively). At the same time, our middle category (one to two times a week) increased from 25.8% to 36.6%, so Californians simply went grocery shopping in-person less frequently, but most continued to patronize brick-and-mortar grocery stores.

After the pandemic is over, our respondents expect to return to in-person shopping, although not quite to the same level as before the pandemic: the percentages of Californians who expect to shop for groceries in stores three or more times a week, or one to three times a week are 14.2% and 43.1% respectively, down from 15.6% and 44.3% pre-pandemic.

During the pandemic, many traditional grocers invested in e-grocery [33]. Figure 2 shows that the pandemic pushed almost 9% of Californians, who had never shopped for groceries online, to try e-grocery with home deliveries: during the pandemic 59.6% stated they had never used e-grocery, down from 68.5% before. Moreover, those who had tried it before started using it more.

Gains are even more substantial for click-and-pick (customers order online and drive to supermarkets or dedicated warehouses to pick up their orders). However, 78.2% of Californians had never used it before, hence the percentage fell to 64.9% during the pandemic (Fig. 3). Our survey findings also suggest that post-pandemic, many Californians will still go to brick-and-mortar grocery stores for most of their needs (likely for fresh products) and complement their grocery needs with online shopping. Most of the e-grocery gains that appear are here to stay, although the

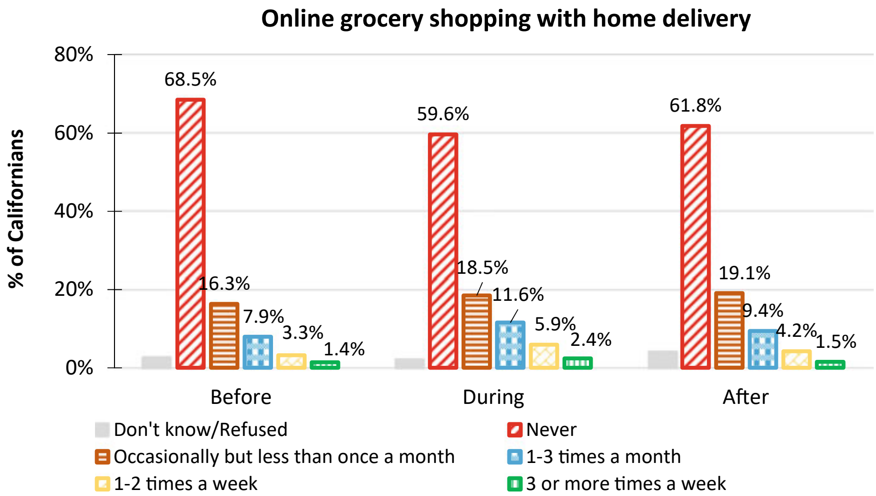


**Fig. 2** Changes in online grocery shopping with home delivery in California. *Data source* Authors' survey

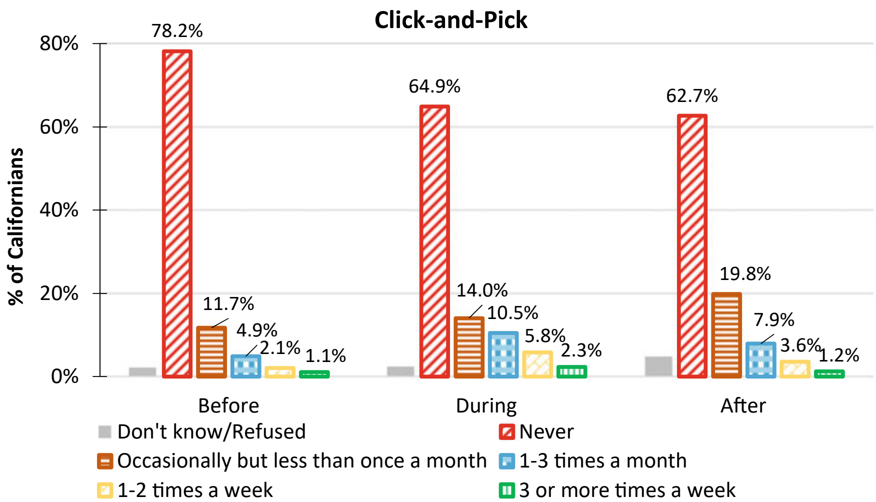


**Fig. 3** Changes in click-and-pick for grocery in California. *Data source* Authors' survey

frequency of online shopping for groceries may dip slightly, immediately post-pandemic, for both home delivery and click-and-pick. However, Californians intend to use click-and-pick more frequently post-pandemic than pre-pandemic.

Implications for travel are not clear at this point. While an increase in online grocery shopping with home delivery should lead to a decrease in household vehicle-miles traveled (VMT), the magnitude of that decrease will depend on the relative popularity of click-and-pick (which saves time but does not decrease travel) and home deliveries. It will also depend on the density of the demand for home deliveries (overall VMT for deliveries will decrease as the demand for groceries in a neighborhood increases, enabling one delivery vehicle to fulfill more orders per trip), and the mode used for these deliveries.

Meal Purchases

Social distancing restrictions put in place during the pandemic caused many restaurants to close temporarily, causing many Californians to stop eating out (see Fig. 4: 40.9% never ate in restaurants during the pandemic versus 12.9% before) or went very rarely to restaurants between March 2020 and March 2021 (32.5% during versus 22.7% before). Likewise, the percentage of Californians who used to dine-in regularly before the pandemic dropped sharply.

Our results provide reasons for optimism; however, Californians appear to be ready to go back to dining-in after the pandemic is over. The percentage of those who stated they would never dine-in after the pandemic is down to 6.8% (from 12.9% before the pandemic) and percentages for all other frequencies are up compared to the pre-pandemic period, except for "three or more times a week" (3.5% after versus 5.9% before). As highlighted in a recent Los Angeles Times article [9], the announced tsunami of restaurant bankruptcies has not materialized as of the summer of 2021, partly because of government support. So, it is too early to assess the long-term damage of the pandemic to the restaurant industry in California.

Take-out (Fig. 5) did not change much between before and during the pandemic. We just note that slightly more Californians did not order take-out food during the pandemic compared to before (possibly to avoid any contacts or because their favorite restaurant was closed). Moreover, at the other end of the frequency scale, slightly

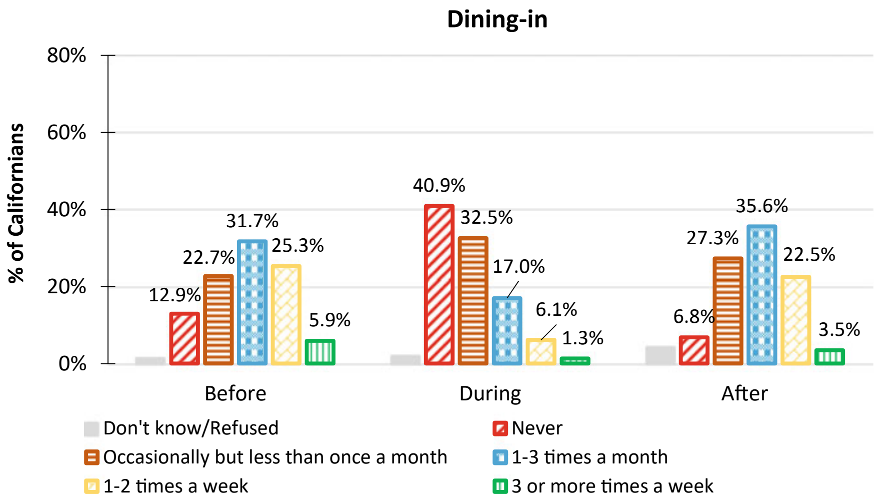


**Fig. 4** Changes in dining-in habits in California. *Data source* Authors' survey

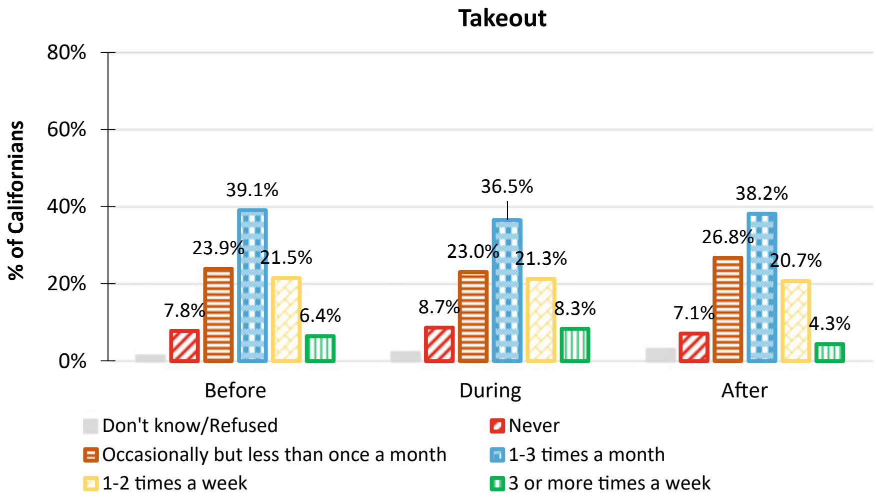


**Fig. 5** Changes in take-out food orders in California. *Data source* Authors' survey

more Californians ordered take-out three or more times a week (8.3% during versus 6.4% before). Conversely, meal deliveries resulting from online orders benefited most from the pandemic. As shown in Fig. 6, the percentage of Californians who never used that approach dropped from 63.0% before to 54.5% during the pandemic.

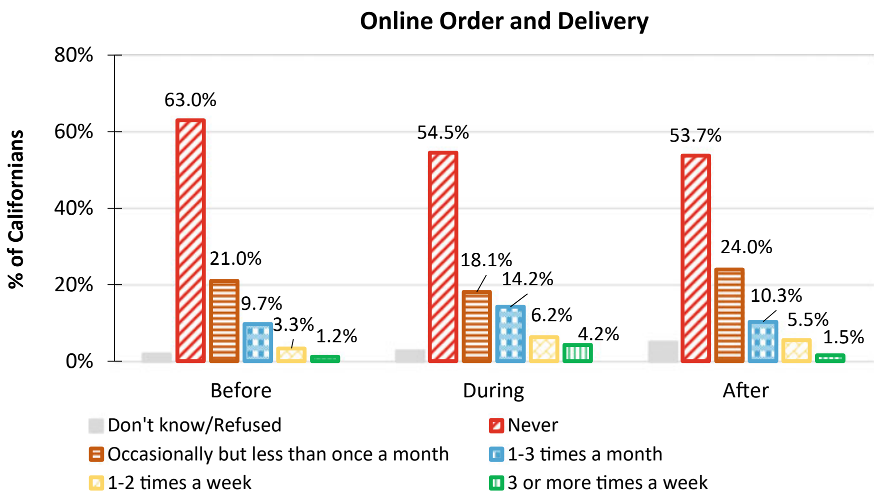


**Fig. 6** Changes in online meal orders with delivery in California. *Data source* Authors' survey

### 3.4 Discussion and Conclusions

In this chapter, we presented results from a May 2021 survey of Californians on how the pandemic changed the way they shopped for groceries and prepared meals, and how the situation may differ post-pandemic. We found that during the pandemic, Californians consolidated their trips to grocery stores, as the percentage of those who used to shop in-person for groceries three times per week or more dropped from 44.3% to 35.6%, while the share of those who went more frequently was cut in half. Conversely, almost 9% of Californians ordered groceries online (with delivery) for the first time, and those who were familiar with e-grocery used it more frequently. Click-and-pick was an even bigger winner with over 14% of Californians using it for the first time.

Conversely, traditional restaurants were deeply affected by the pandemic, with the percentage of Californians who never or rarely (less than once a month) had meals at such restaurants more than doubling to 73.4%, up from 35.6% in early 2020. The frequency of take-out orders did not change much overall during the pandemic, while deliveries of online orders surged. Indeed, 8.5% of Californians who had not used that option tried it during the pandemic, and those who were familiar with it used it more frequently.

Our results suggest that most of the gains in meal deliveries from online orders are here to stay. Industry reports show that delivering prepared meals (and groceries) brought in a lot more revenues during the pandemic [34]. Indeed, DoorDash Inc.'s recent filing for an initial public offering and earnings reports from Uber Technologies Inc., Grubhub Inc., and Postmates show that these four companies earned a combined $5.5 billion between April and September 2020, which is more than twice as much as during the same period in 2019.

The future may be bumpy for meal deliveries, however, as none of the delivery app companies are currently profitable. Moreover, many restaurant owners feel that the pandemic forced them to accept unpalatable deals with these companies, and delivery drivers may just be biding their time until the economy improves [34].

The pain experienced by restaurants resulted in gains for grocers. Indeed, traditional U.S. grocers did well in 2020 [33]. For example, Kroger (the largest supermarket chain by revenue in the United States and the second-largest general retailer behind Walmart) saw its total sales increase by 14.2%, excluding fuel sales and dispositions (asset sales) during the fiscal year 2020 [33]. A key reason for this success is the change in the split between food-away-from-home and food-at-home expenditures, as people were staying away from or simply could not go to restaurants. Before the pandemic, the ratio was 55–45% in favor of food-away-from-home, but the pandemic reversed that split [32].

Overall, the pandemic provided a window of opportunity for traditional grocers to invest in online grocery shopping, and many took advantage of it. While e-grocery was a niche business before the pandemic, it is now part of the core business of traditional grocers, and survey results indicate that most of their gains are likely to survive the end of the pandemic, especially for click-and-pick.

These are significant and important changes, but e-grocery and the delivery of meals ordered online changed even more in China and South Korea. We turn to this topic next.

## 4 Impact of the Pandemic on e-Grocery and Meal Deliveries in China and South Korea

In China, the pandemic did not last as long as in the United States or South Korea. The pandemic started in Wuhan at the end of 2019. From January 23, 2020 to April 8, 2020, Wuhan was in strict lockdown, while other areas experienced some restrictions depending on the local situation [35]. By mid-April 2020, the worst appeared to be over. Many firms restarted their activities, and the GDP grew by 3.2% in the second quarter of 2020 [28]. During the first 3–4 months of 2020, however, the pandemic had a big impact on people's lives and affected their shopping behavior.

As a result, the share of e-grocery, which was approximately 10% of the grocery market in 2019, could more than double to between 18 and 28% by 2022 [23]. While e-grocery first became popular in major Chinese cities, its adoption is now accelerating in smaller cities. Fueling this growth are continuous investments and innovation from e-grocery retailers like JD supermarket/JD.com (China's largest online retailer and overall retailer), and community group buying leaders like Xingsheng Selected Company (a fresh produce chain that operates small neighborhood stores).

Strict pandemic lockdown measures also stimulated innovation. Since visitors were not allowed to enter residential compounds, and face-to-face interaction with delivery drivers (once a near-daily feature) ceased, delivery companies rolled out a "contactless delivery" system, dropping off packages at designated locations. Additionally, live streaming e-commerce, which previously focused on fashion and cosmetics, expanded into food, with services like Taobao Live or JD Live helping local farmers sell their products [15]. Famously, the influencer Li Jiaqi collaborated with Guangquan Zhu, a renowned host, to sell over $6 million worth of local products from Wuhan in a 130-min live broadcast [6]. So, while it was already popular before the pandemic with approximately 30% of the population participating in 2019, live streaming reached 39% of the Chinese population (560 million people) in 2020 [14].

In South Korea, the first wave of the pandemic started in late January 2020 and peaked on March 1, 2020. The spread of the virus remained under control until the summer of 2020, thanks to efficient nationwide social distancing measures, but local community infections soared in metropolitan areas in August of 2020. Then a third wave took off toward the end of 2020, especially in larger cities, and the number of new cases has plateaued since, as the country started (as of June 2021) vaccinating its population. This longer exposure period, compared to China, has given time for deep changes in e-grocery and meal deliveries.

Indeed, the pandemic saw e-grocery sales further increase their lead over traditional grocery sales (online caught up with offline in 2019) [1]. For example, in 2020, after the start of the pandemic, online purchases of processed foods and beverages increased by 46% and those of raw food by 69%, compared to 2019. In contrast, offline retail food sales stagnated or declined. One driver of change was overnight deliveries, a service that brings customers fresh food early morning for orders placed by midnight of the previous day. Kurly Inc., a leading overnight delivery startup, recorded sales of $838 million in 2020, 130% more than in 2019. This market is expected to grow further as new competitors from retail, shipping, and IT enter this sector.

Driven by long-term demographic changes, home-meal replacements (i.e., pre-packaged food and instant meals), which are sold through multiple channels, also saw explosive growth, as the quality of these meals improved [19]. Another South Korean sector that saw major changes during the pandemic is the food delivery market, with a 78% increase in sales in 2020 over 2019. This reflects a behavioral change in food purchasing as many South Koreans have been reluctant to eat out to minimize social contacts. In a recent survey, 43.6% of respondents increased their spending on meal delivery/take-out, while a whopping 62% decreased their dine-in (restaurant) expenses [20].

## 5 What Does the Future Hold for California?

The COVID-19 pandemic has accelerated the digitalization of shopping that was propagating unevenly at different scales. To better understand the ripple effects, it is useful to adopt a framework proposed by transition studies [12, 13]. In this framework (also see [8]), the adoption of a technological innovation is best explained by how it is applied, by-laws and regulations, the policy context, the availability of capital, and of course, the tastes and beliefs of its recipients (here consumers), rather than by the technology itself. It thus requires a holistic perspective [12] with a particular focus on the interrelationship between economic change and the diffusion of that innovation [2].

In that context, the COVID-19 pandemic created a window of opportunity for change (the increasing reliance on e-grocery and prepared meals) driven by public intervention (social distancing and stay-at-home orders). Differences in local tastes (linked for example to the changing structure of households in the case of South Korea), the regulatory context (e.g., zoning for local warehouses in residential areas in China), the density of conventional grocery stores, innovation (e.g., overnight delivery of fresh goods in South Korea or 30-min deliveries from MissFresh in China), and economic conditions, therefore, explain the observed differences in the penetration of e-grocery and meal deliveries discussed above.

If they could be implemented cheaply and in an environmentally friendly way, e-grocery and the delivery of meals ordered online have much to offer to complement traditional food shopping. They should be particularly of interest in California, with its large immigrant population and abundant workforce, but further expansion may require local zoning changes to allow convenience stores with lockers or small refrigerated depots in residential areas (like in China) from where orders could be fulfilled, possibly on electric two-wheelers for now, and later using small robots.

If not for convenience, e-grocery should be encouraged on equity grounds to provide better access to fresh and nutritious foods to disadvantaged groups. Indeed, it is well-known that because of urban population dynamics and redlining, African Americans in many areas have less access to supermarkets [4, 26] than other groups. As a result, poor people in predominantly black neighborhoods or rural areas tend to shop at dollar stores [40] and rely more on fast food outlets [18], which has detrimental long-term health effects such as obesity and cardiovascular disease.

At this point with the publicly available data, researchers cannot say much about the impact on travel of how Californians would shop for groceries and prepared meals post-pandemic. For logistics firms providing delivery services, this calls for detailed data about the trajectories of delivery vehicles (i.e., GPS data). At the household level, researchers need to jointly collect travel and online activity data to better understand the substitution effects between online shopping and in-store travel. Urban planners and policymakers should consider changing local zoning laws to allow for the presence of small fulfillment centers in residential areas, incentivize the purchase of electric delivery vehicles to reduce air pollution, emissions of greenhouse gases, and noise in residential areas, and work with electric utilities to install the necessary electric charging infrastructure. Finally, we should continue to study the evolution of e-grocery and meal deliveries abroad (e.g., in China, South Korea, or Europe) to further inform how best to implement a sustainable and equitable transportation system.

***Note***: The survey used to collect the data analyzed in this chapter was found to be exempt under University of California, Irvine HRP Policies and Procedures (https://research.uci.edu/human-research-protections/policies/). The survey was conducted by IPSOS, which randomly sampled the California members of KnowledgePanel. Only anonymized data were received by the research team.

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# Understanding and Modeling the Impacts of COVID-19 on Freight Trucking Activity

**Yiqiao Li, Andre Tok, Guoliang Feng, and Stephen G. Ritchie**

**Abstract** Restrictions on travel and in-person commercial activities in many countries (e.g., the United States, China, European countries, etc.) due to the global outbreak and rapid spread of the coronavirus disease 2019 (COVID-19) have severely impacted the global supply chain and subsequently affected freight transportation and logistics. This chapter summarizes the findings from the analysis of truck axle and weight data from existing highway detector infrastructure to investigate the impacts of COVID-19 on freight trucking activity. Three aspects of COVID-19 truck impacts were explored: drayage, long and short-haul movements, and payload characteristics. This analysis revealed disparate impacts of this pandemic on freight trucking activity because of local and foreign policies, supply chain bottlenecks, and the dynamic changes in consumer behavior. Due to the ongoing effects of COVID-19, it is not yet possible to distinguish between transient and long-term impacts on freight trucking activity. Nonetheless, a future expansion of the study area and the incorporation of other complementary data sources may provide further insights into the pandemic's impacts on freight movement.

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## 1 Introduction

Restrictions on travel and in-person commercial activities in many countries (e.g., the United States, China, European countries, etc.) due to the global outbreak and rapid spread of the coronavirus disease 2019 (COVID-19) have severely impacted the global supply chain [12] and subsequently affected freight transportation and logistics. In early 2020, Ernst & Young LLP (EY US) conducted a survey of 200 senior-level supply chain executives across various sectors, such as consumer products, industrial products, retail companies, etc. in the United States [9]. According to the survey results, 72% of the companies experienced negative effects from the COVID-19 pandemic [9]. One particularly impacted industry was the automotive sector, all the automotive companies that participated in the survey reported a negative effect. This was caused by three main factors: the disruption of Chinese exports of auto parts, the interruption of automobile manufacturers in Europe, and the closure of assembly plants in the United States [17]. Similarly, nearly 97% of industrial product companies also experienced negative effects from the pandemic. On the other hand, 11% of companies reported positive impacts from the COVID-19 pandemic, such as industries that produce essential customer products. The demand was partly driven by the panic-buying of emergency-related products such as toilet paper, canned foods, etc. [5, 15]. In freight transportation and logistics, the ocean shipping and railroad volumes declined by 25% and 20% in the United States, respectively, reflecting the impacts on international and long-distance domestic freight transportation. In contrast, the last-mile truck delivery spiked significantly to more than ten times year on year. In addition to the high demand for essential goods, the surge of e-commerce due to the social distancing restrictions (see Chap. 7), limited personal travel, and the increased time spent at home also increased the demand for consumer products that fueled the growth of last-mile truck movements.

The San Pedro Bay Port Complex comprising the ports of Los Angeles and Long Beach has been ranked as the busiest in North America for over two decades. It serves as the main U.S. gateway for international trade and was severely affected by the global supply chain disruptions caused by the COVID-19 pandemic. This chapter is focused on investigating the effect of the pandemic on some specific truck activities in the State of California. First, we utilized container statistics published on the webpage of the Port of Los Angeles [14] and the Port of Long Beach [13] to analyze the year-over-year changes in the container counts between 2019 and 2020 and to assess the impact of the global supply chain disruptions effects on the export and import container counts at the Port of Los Angeles. Subsequently, we observed the volume changes of trucks by their operation characteristics near the Port of Los Angeles using the Weigh-In-Motion (WIM) data. This chapter summarizes the findings from the analysis of truck axle and weight data from existing highway detector infrastructure to investigate the impacts of COVID-19 on the freight trucking industry. Three aspects of COVID-19 truck impacts were explored: drayage, long and short-haul movements, as well as payload characteristics.

# 2 Data and Site Description

## 2.1 Type of Sensor Infrastructure

The data for this study was obtained from Weigh-in-Motion (WIM) traffic detector sites located along major freeway and highway corridors in Southern California. WIM sites are equipped with sensors that measure axle spacings and weights of trucks as they traverse the mainline at highway speeds. These direct measurements can be used to distinguish trucks by axle-based classification categories such as the Federal Highway Administration (FHWA) scheme (Table 1) and truck weights, respectively [8].

This study focuses on FHWA Class 9 trucks, which are defined as five-axle tractors pulling a semi-trailer and are the predominant axle configuration associated with trucks that haul domestic and international freight in the United States. Further insights into truck characteristics can be obtained through a more in-depth analysis of WIM data, such as trailer configuration and payload by Hyun et al. [11]. This study applies and extends the work by Hyun et al., which investigated the association of truck axle spacings with certain trailer configurations that are of particular interest in freight activity analysis. For example, tractors hauling 40-foot intermodal containers associated with the port drayage movements have axle spacings that are quite distinct from their line-haul counterparts. These inferences are used in this

**Table 1** FHWA vehicle classification

| Class | Vehicle type | Description |
|---|---|---|
| 1 | Motorcycles | Two axles, two or three tires |
| 2 | Passenger cars | Two axles can have one or two-axle trailers |
| 3 | Pickups, panels, vans | Two axles and 4 tire single units can have 1 or 2 axle trailers |
| 4 | Buses | Two or three axles, full length |
| 5 | Single unit two-axle trucks | Two axles, six tires (dual rear tires), single unit |
| 6 | Single unit three-axle trucks | Three axles, single unit |
| 7 | Single unit with four or more axles | Four or more axles, single unit |
| 8 | Single trailer three or four-axle trucks | Three or four axles, single trailer |
| 9 | Single trailer five-axle trucks | Five axles, single trailer |
| 10 | Single trailer six or more axle trucks | Six or more axles, single trailer |
| 11 | Multi-trailer five or fewer axle trucks | Five or fewer axles, multiple trailers |
| 12 | Multi-trailer six-axle trucks | Six axles, multiple trailers |
| 13 | Multi-trailer seven or more axle trucks | Seven or more axles, multiple trailers |

*Data source* FHWA Traffic Monitoring Guide [8]

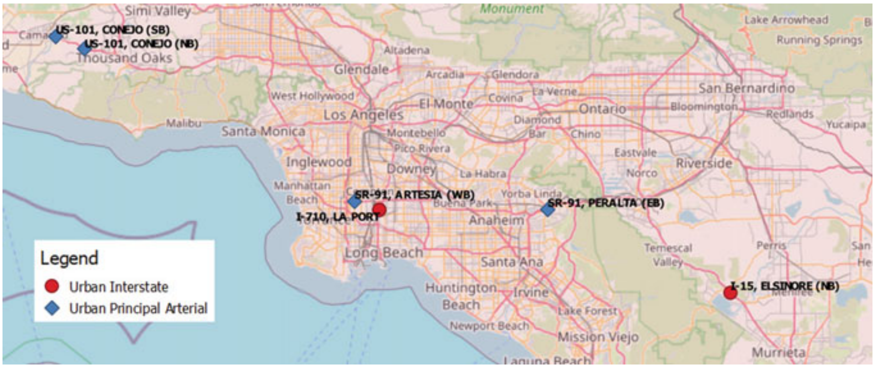


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**Fig. 1** The geographic distribution of the study sites. *Data source* OpenStreetMap, California Department of Transportation (Caltrans) WIM Locations

study to analyze the disparate impacts of COVID-19 on drayage movements, long and short-haul movements, and payload characteristics.

## *2.2 Data Description*

We obtained data from six WIM sites along four major freight corridors across Ventura, Los Angeles, and Riverside counties in Southern California. The geographical distribution of the WIM sites with their corresponding facilities' functional classes is presented in Fig. 1.

The selected detection sites capture significant movements of drayage trucks (e.g., WIM sites along I-710 near Los Angeles port) and long- and short-haul trailers and domestic containers (e.g., WIM sites along US-101). Each WIM record includes axle spacings and weight data of each vehicle that traversed the detection site. In this study, the axle spacings data is used to infer the volumes of drayage trucks versus trailers and domestic containers and short- versus long-haul trailer and domestic container movements, while the weight data is used in the payload analysis. We would like to acknowledge that the aforementioned predicted truck body configurations through WIM records only provide rough estimates for our COVID-19 freight impact analysis.

## *2.3 COVID-19 Timeline in California*

With the outbreak of COVID-19, California's governor declared a state of emergency on March 4, 2020, and implemented a state-wide stay-at-home order on March 19,

**Table 2** COVID-19 timeline in California

| | Description | Time |
|---|---|---|
| Phase 1 | Pre-COVID | Before March 1, 2020 |
| Phase 2 | First lockdown | From March 1, 2020 to May 31, 2020 |
| Phase 3 | Reopen | From June 1, 2020 to October 31, 2020 |
| Phase 4 | Second lockdown | From November 1, 2020 to December 31, 2020 |

*Data source* Phase definitions based on Wikipedia "COVID-19 Pandemic in California"

2020. However, plans for reopening were released on April 28. Subsequently, the state entered an "early-stage two" reopening. This phase allowed the reopening of some low-risk businesses. On May 28, 2020 most of the counties in California started to enter stage 3 of reopening, and places such as salons, museums, and zoos began to reopen. After five months, the United States surpassed 11 million confirmed COVID-19 cases, and the Governor announced a limited stay-at-home order to arrest the rapid spread of the virus. This lockdown order was similar to the first lockdown order with small modifications, applying only to purple-tier counties (those with the highest concentrations of the disease) between 10 pm and 5 am daily. Thus, in order to investigate the pandemic's impacts on freight movements alongside the policy changes, this analysis segmented the calendar year into four phases aligned with the essential lockdown events (Table 2). The monthly average truck volumes obtained from 2016, 2017, and 2019 were used as the baseline to compare with the corresponding truck volumes in the year 2020 (the year of the COVID-19 outbreak).

## *2.4 Data Pre-processing*

Prior to the truck activity analysis, we pre-processed and aggregated raw WIM data according to the following steps: First, we validated the raw WIM data by comparing the front-axle weight and inter-axle spacing with the reference values from the literature [10] to ensure adequate data quality. Second, we identified time periods containing data gaps at each location, based on the significance of the headway between consecutive vehicles, and subsequently excluded them from the dataset. Finally, we estimated and aggregated into monthly intervals daily truck volumes for each detection site. In this chapter, we took the average of the years 2016, 2017, and 2019 monthly truck volumes available to us to establish the baseline seasonality effect and used the average of the three pre-pandemic monthly volumes as the baseline to analyze the pandemic's impacts on truck movements in 2020. The average weekday volumes of each phase were used in the analysis.

## 3 Truck Characterization for Highway Freight Activities Impacts by COVID-19

In order to investigate the pandemic's impacts on various truck activities, we categorized trucks by their physical and operational characteristics into three schemes: (1) drayage versus trailers and domestic containers, (2) long- versus short-haul trailers and domestic containers, and (3) empty versus full-load trailers and domestic containers. We define full-load trailers and domestic containers tractor-trailers as those having gross vehicle weights approaching the legal weight limit. The characterized trucks used in this chapter were primarily inferred from the axle configurations and gross vehicle weight (GVW) information obtained from WIM data according to their distinct statistical distribution. It should be noted that several other tractor-trailer configurations such as platforms may share similar axle spacing configurations with trailers and domestic containers tractor-trailers. This should not detract from the analysis, as the targeted truck configurations in this study—40 ft intermodal containers and trailers and domestic containers—are dominant in their axle configuration. Hence, the WIM volume estimates of trucks by these configurations remain a useful metric for analysis.

### *3.1 Drayage Truck Activity*

Drayage trucks represent heavy trucks that transport intermodal containers between the seaports or intermodal railyards and many other freight facilities. The standard sizes of the containers used for transport freight are 20 feet, 40 feet, and 45 feet in length [2], where 40 ft containers are most commonly used and observed along highway freight corridors due to their cost-effectiveness [4]. Hence, we inferred 40 ft intermodal container truck volumes from among five-axle tractor-trailers and focused on observing volume changes of 40 ft containers at three typical drayage truck corridors near the San Pedro Bay Port Complex to study the impacts of pandemic travel restrictions on drayage truck movements.

Container Counts at the San Pedro Bay Ports

Drayage trucks transport a significant share of intermodal containers to and from the San Pedro Bay Port Complex. Thus, understanding the changes in container counts is one of the essential steps prior to the drayage truck activity analysis. In this section, we reviewed container count data reported by the Port of Los Angeles [14] and the Port of Long Beach [13] to assess the impact on supply chain disruption by the pandemic. Figure 2a presents the year-over-year percentage changes of the total import and export container counts from 2019 to 2020. Both import and export container numbers decreased at the beginning of 2020 compared to the previous year, with a decline in the magnitude of reduction toward the middle of the year. The intermodal container counts showed a subsequent year-over-year increase starting from August 2020. This

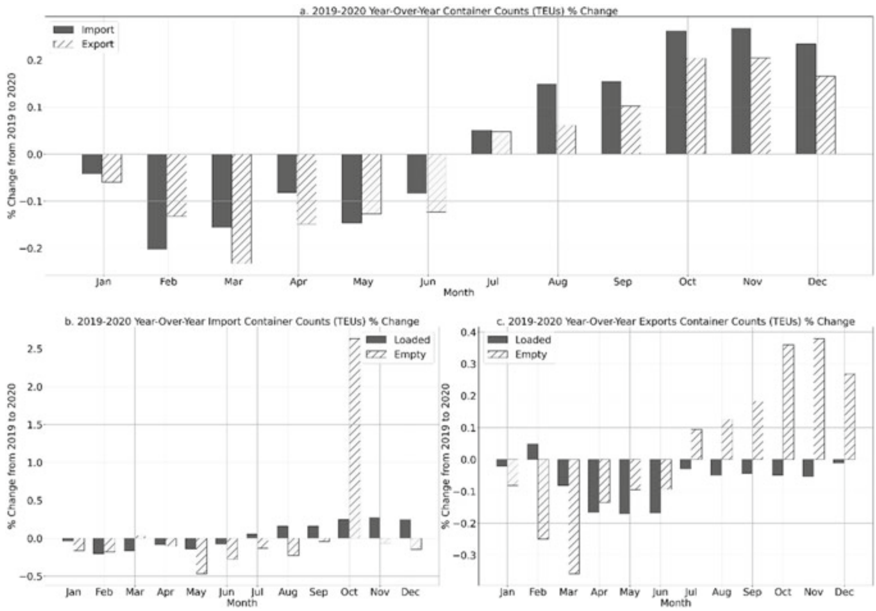


**Fig. 2** Container statistics from 2019 to 2020. *Data sources* Monthly container counts data were obtained from the ports of Long Beach [13] and Los Angeles [14]

trend could be potentially caused by the supply chain disruption at the beginning of the year, with subsequent signs of recovery of some of the essential nodes in the supply chain from some Asian countries. However, drayage operations were significantly affected by operational bottlenecks such as limited container yard storage and driver shortages. Next, we break down the overall import and export container counts into loaded imports, empty imports, loaded exports, and empty exports to understand the demand and supply changes in the international trade (Fig. 2b, c).

Figure 2 presents the year-over-year percentage changes of import and export container counts and highlights the increase in freight demand in the United States, which has significant downstream impacts on portside truck traffic. We explored how the increased portside demand impacted truck activities by their operational characteristics near the port area. Interestingly, the year-over-year percentage changes of import empty container counts spiked in October. According to the October data in 2019, there was a significant reduction in the counts of import empty containers at the Port of Long Beach. Therefore, the spike of import empty container counts is unlikely caused by the pandemic and is out of the scope of our study.

Drayage Truck Identification

In a previous study, Hyun et al. [11] found that 40 ft intermodal container trucks present distinct physical characteristics in terms of vehicle length, axle spacing, and overhang distributions compared to other trailer body configurations within Class 9

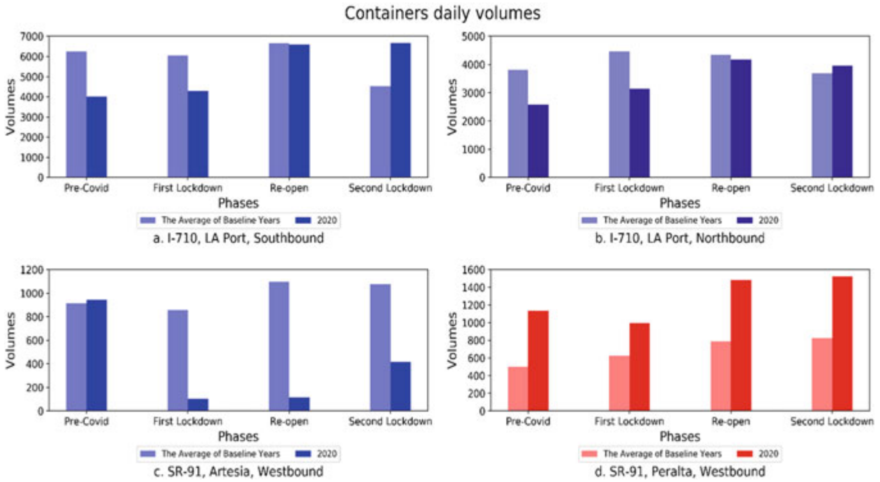


**Fig. 3** Volume changes on drayage movements. *Data source* WIM data records were obtained from the California Department of Transportation (Caltrans)

trucks. This analysis adopted the approach by Hyun et al. and recalibrated the decision boundary of their model with the newly collected WIM measurements to identify 40 ft container trucks from Class 9 vehicles. The identified 40 ft intermodal container trucks were used for the analysis of COVID-19 impacts on drayage movements.

Pandemic Impacts on Drayage Movements

We investigated three WIM sites—I-710 at LA port, SR-91 at Artesia, and SR-91 at Peralta—where higher 40 ft intermodal container truck volumes were observed, as an example for our drayage movement analysis. Figure 3 presents the volume changes of 40 ft intermodal container trucks across these three WIM sites between the average of baseline years and the year 2020.

The WIM site is located along the I-710 freeway, north of the I-405 freeway interchange, and captures a significant proportion of the outbound and inbound container truck volumes from and to the port of Los Angeles and Long Beach. As Fig. 3 shows, 40 ft container volumes saw a 30% reduction at the beginning of 2020, compared with the average of baseline years for both export and import containers. The volume reduction occurred prior to the implementation of the stay-at-home order in California and was likely caused by the supply chain disruption of the U.S.'s major trading partner countries such as China, which went into a lockdown three months ahead of California [6]. Drayage truck volumes gradually recovered after California's reopening. Interestingly, drayage truck volumes surpassed the average of baseline years, especially in terms of export (Southbound) volumes during California's second lockdown, when China was reopening its economy. According to the goods export data from the U.S. Census Bureau, the monthly export values in the United States increased by approximately 10% from the reopening to the second lockdown phase [16].

As Fig. 1 shows, both Artesia and Peralta are located along the State Route 91 freeway. The Arteria site is located between the I-710 and I-605 freeways, while the Peralta site is situated further east near the border between Orange and Riverside counties. Hence, despite their locations along the same freeway, data from these sites show dissimilar volume changes before and after the onset of the pandemic (Fig. 3). The Artesia WIM site is located near several third-party logistics companies, which serve small businesses, while the Peralta site serves as one of the gateways from the San Pedro Bay Port Complex to major warehouses in the California Inland Empire. This may reinforce the disparate effects observed during the COVID-19 pandemic, with significant negative impacts on small businesses and benefits for large e-commerce firms.

## 4 Long- and Short-Haul Trailers and Domestic Containers

Trailers and domestic containers refer to the enclosed box-shaped semi-trailers which are designed to carry palletized, boxed, or loose freight. This section describes the investigation of COVID-19 impacts on long and short-haul trailers and domestic container activities and reports on how the pandemic affects their movements. In this section, we first identify trailers and domestic container trucks from other five-axle tractor-trailers through the recalibration of the model by Hyun et al. [11] using the WIM dataset obtained in this study. Second, we develop a long- and short-haul truck identification algorithm to distinguish long- and short-haul trailers and domestic containers based on their distinct axle spacing between the steering and leading drive axles, as tractors equipped with sleeper units have a longer axle spacing. Finally, we report our observations in volume changes of long- and short-haul trucks between the baseline years and the year 2020.

### *4.1 Long-Haul Trailers and Domestic Containers Identification*

Long-haul trucks are primarily responsible for inter-regional highway freight movements. They serve as critical connectors between locations over 250 miles apart, including population centers, ports, border crossing, and many transportation hubs [7]. The California Vehicle Inventory and Use Pilot Survey conducted in 2014 revealed that tractors with sleeper cabs are predominantly associated with long-haul trips to facilitate overnight rest stops commonly associated with long-haul movements. The sleeper unit attached to the rear of a tractor cab results in an extended axle spacing between the first and second axle (AS1). In this section, we utilize this physical attribute typically associated with long-haul trucks to estimate long-haul truck volumes from the collected WIM data. First, we investigate the AS1 distribution of trailers and domestic containers. Then, we group the Class 9 trailers and domestic containers into long- and short-haul trucks according to their AS1 distribution using the Gaussian Mixture Model (GMM). Finally, we aggregate the identified long- and short-haul trailers and domestic containers at the monthly level for further analysis.

### 4.2 COVID-19 Impacts on Long- and Short-Haul Trailers and Domestic Containers Movements

In this section, we focus our analysis on three urban principal interstate corridors as shown in Fig. 4. Overall, short-haul truck volumes in 2020 increased over the baseline years and showed an increasing trend across all four phases. Short-haul trailers and domestic container trucks are commonly used to transport freight between warehouses and local retail centers.

At the beginning of the pandemic, the panic shopping behavior led to high demand for groceries and daily consumables. This may have influenced the increased activity of short-haul trailers and domestic containers in their attempt to re-stock emergency supplies at retail centers from regional warehouses. On the other hand, an expected corresponding significant increase in long-haul trailers and domestic containers was not observed. In hindsight, these observed disparities may have revealed the impending depletion of inventory at major distribution centers, as the demand for consumer products overwhelmed existing inventory that could not be readily replenished, as evidenced by the reduction in long-haul trucking activity. Such phenomenon has also been corroborated in survey results summarized by the American Transportation Research Institute (ATRI) and Owner-Operator Independent Drivers Association [3]. ATRI reported that the truck trip lengths decreased during the pandemic, according to their survey results. In particular, the longest two trip categories in their survey decreased by 13.4% [3].

## 5 Payload Analysis

Truck payloads refer to the maximum cargo weight that a truck can carry. It is an essential truck attribute that is considered in commodity-based freight forecasting models for freight planning applications. In this section, we extract the payload characteristics from trailers and domestic containers to understand how the proportions of full and empty load trucks changed throughout the pandemic.

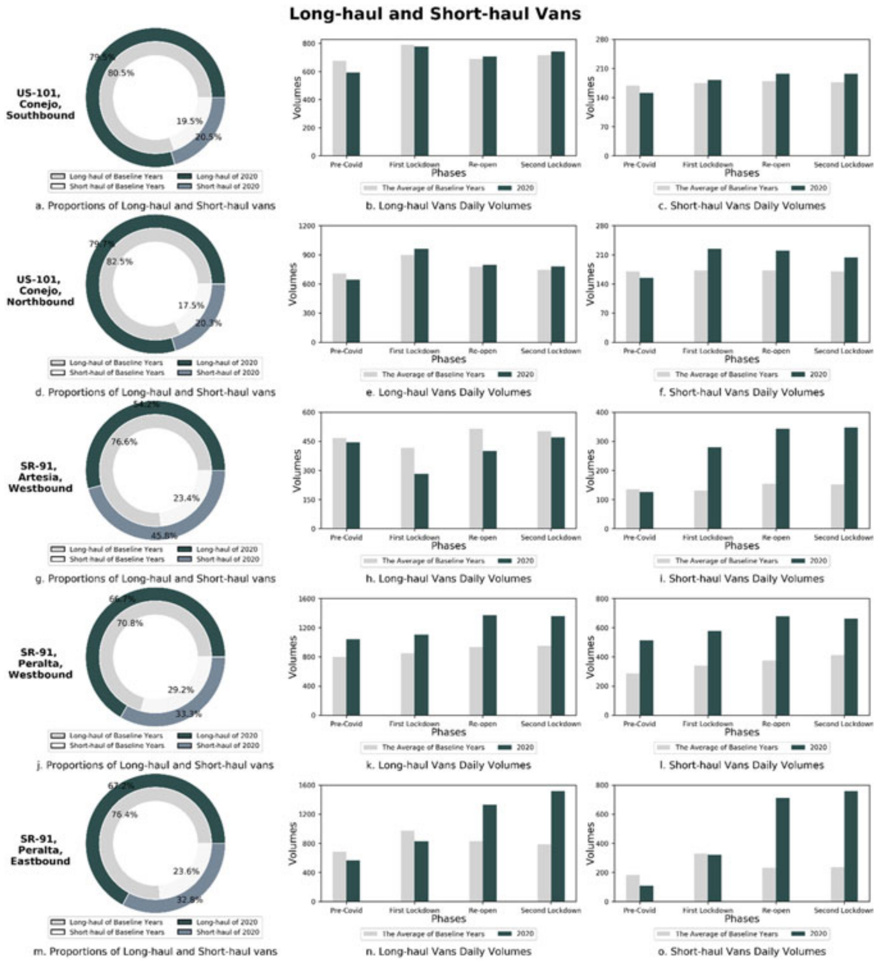


**Fig. 4** Long- and short-haul truck volume changes. *Data source* WIM data records were obtained from the California Department of Transportation (Caltrans)

### *5.1 Payload Characterization*

We developed a payload characterization model to identify empty and full-load trailers and domestic containers using WIM data. We utilized the gross vehicle weight (GVW) obtained from the WIM system and adopted GMM to estimate the decision boundary of determining empty and full-load trailers and domestic containers through the GVW distribution. The estimated empty and full-load trailers and domestic containers were aggregated at a monthly level. The average weekday volumes of each phase were used to analyze the pandemic's impacts. We excluded from our analysis partially loaded truck volumes since they are mixed with the proportion of empty trucks and the trucks which are loaded approaching the weight limit.

## 5.2 Trailers and Domestic Containers Payload COVID-19 Impacts Analysis

We used data from two WIM sites—US-101 at Conejo and I-15 at Elsinore—in this analysis. The US-101 WIM site captures truck activity between the Los Angeles metropolitan area (LA Metro) and the California Central Coast, while the I-15 location monitors truck movements between the San Diego and Imperial County Regions and the LA Metro. As Fig. 5 shows, the volumes of empty trailers and domestic containers in 2020 were slightly lower than the baseline years, whereas the full-load truck volumes significantly increased. The pie chart presented on the left of Fig. 5 shows the change in the proportion of full-load and empty trucks between the baseline year and 2020, where the inner ring represents the baseline years and the outer ring represents 2020. While empty-load volumes remained comparable to previous years, an increase in full-load volumes was observed at both locations after the onset of the pandemic. In fact, the proportion of full-load trucks increased by around 12% in both directions at Conejo and 3% northbound at Elsinore. This increase in full-load

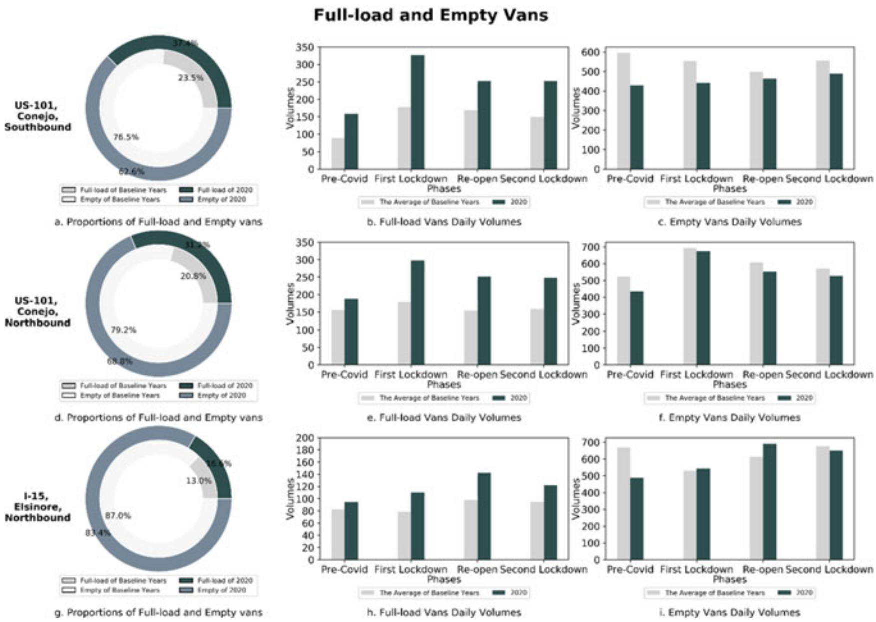


**Fig. 5** Payload characteristics. *Data source* WIM data records were obtained from the California Department of Transportation (Caltrans)

volumes may be indicative of a change in the types of commodities hauled along these corridors, where trucks may have hauled more commodities associated with heavier payloads through these corridors, especially at Conejo. Coincidentally, the Federal Highway Administration had extended the maximum gross vehicle weight (GVW) of each truck to 88,000 lbs. for transporting emergency supplies during the COVID-19 pandemic in certain states to address driver shortages [1]. However, the sustainability of this payload shift needs further investigation.

## 6 Discussions and Takeaways

In 2020, many countries implemented stay-at-home restrictions to curb the rapid spread of coronavirus. Pandemic-related absences from work severely affected the global supply chain and created significant bottlenecks in the logistics network. At the initial phase of the pandemic, China shut down many factories in response to the crisis. However, as a critical node of the global supply chain and essential trade partner, China's lockdown had a consequential effect on the U.S. economy and impacted its highway freight movements. The reduction of freight supply and demand from China at the beginning of 2020 and the immense freight demand surge in the U.S. resulted in year-on-year container counts decreases and subsequent increases, which significantly affected the portside truck traffic. In addition, the COVID-19-related travel restriction changed personal travel behavior and the demand for essential goods, due to panic purchasing, and subsequently reshaped the truck travel distance and the weight distribution. This chapter focused on investigating the truck volume changes at specific locations along major freight corridors near the Port of Los Angeles to observe truck count changes between the baseline years and the year 2020. We mainly focused on truck activity changes in three different aspects: drayage, long- and short-haul movement, and payload characteristics.

### *6.1 Drayage Movements*

According to the volume changes along I-710, the drayage truck volume reduction started before the observed outbreak of COVID-19 in California and aligned with the timeline of global supply chain disruption. Not surprisingly, the drayage movement appeared closely linked to the global supply chain at the port area. Drayage truck data collected from urban principal arterials shows that the drayage volume changes are dissimilar for different truck routes. The drayage movements on the truck routes connected to third-party warehouses serving small businesses were reduced, while the drayage movements serving large e-commerce warehouses showed significant increases. The drayage truck movements were reshaped during the year 2020 for major drayage corridors.

### 6.2 Long- and Short-Haul Movements

The WIM data collected from urban principal arterials showed a slight reduction in long-haul truck volumes. On the contrary, the short-haul movements increased significantly over baseline years. Similar results have also been found in the survey data reported by ATRI [3]. The observation of increased short-haul movements could be explained in part by the transportation of consumer goods from local warehouses to retail centers to meet increased consumer demands, while the reduction in long-haul truck movements could reflect the industries' inability to replenish inventory at the major distribution centers.

### 6.3 Payload Characteristics

The WIM data collected from the urban inter-state truck corridor presents the change in payload characteristics from the baseline year to the year 2020. The volume of empty trucks saw a slight reduction, while full-load trucks saw a significant volume increase. The increase of trucks with full payloads may be indicative of a change in the types of commodities hauled due to the pandemic's impact. A more in-depth analysis of changes in commodities would involve more complex tools such as the commodity-based California Statewide Freight Forecasting Model.

The analysis performed in this chapter is meant to provide an overview of the multifaceted impacts of COVID-19 on the freight trucking industry. While fairly abbreviated, this analysis clearly demonstrates the disparate impacts this pandemic has had on trucking activity as a consequence of local and foreign policies, supply chain bottlenecks, and the dynamic changes in consumer behavior. Due to the ongoing effects of the pandemic, it is not yet possible to distinguish between transient and long-term impacts on freight trucking activity. Nonetheless, a future expansion of the study area and the incorporation of other complementary data sources may provide further insights into the COVID-19 impacts on freight movement.

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# Impacts on Environment and Safety

# Traffic, Air Quality, and Environmental Justice in the South Coast Air Basin During California's COVID-19 Shutdown

**Shams Tanvir, Dwaraknath Ravichandran, Cesunica Ivey, Matthew Barth, and Kanok Boriboonsomsin**

**Abstract** Historically, Southern California suffers from the worst traffic congestion and air quality levels in the country. During the COVID-19 pandemic in 2020, we observed a major reduction in economic and social activities within the region, leading to changes in roadway traffic and air pollution levels in a variety of ways. Within six weeks of the pandemic-induced lockdowns, freeway traffic volume dropped as low as 50%; however, it has since gradually increased back to pre-pandemic levels. The changes in freeway traffic volume have not been uniform across the Southern California region, and neighborhoods with different socio-economic profiles were affected differently. These disparities have brought up environmental justice concerns, particularly for disadvantaged communities that live adjacent to major roadways and warehouse centers. We monitored the changes in vehicle and human activities across communities in Southern California and explored correlations that are useful for developing various mitigation measures at both the local and regional levels. In this study, we go beyond regional analysis and examine the effects of the pandemic on traffic at a transportation corridor and local levels to examine possible equity issues. Results show that, in general, the level of traffic dropped less in

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disadvantaged neighborhoods during the pandemic. Further, traffic flow rebounded in these neighborhoods faster than in other communities.

## 1 Introduction

The COVID-19 pandemic and the consequent lockdown and social distancing requirements have had a monumental shift in the way people travel [25]. The transportation sector has been impacted in several ways—commute trips have been replaced by telework or remote work [21], public transit ridership has plummeted [24], e-commerce activities have replaced shopping trips [20], and local and international tourism activities have been halted [22]. All these changes have resulted in a temporary reduction in the number of vehicles on the road and a consequent reduction in vehicle-miles traveled (VMT). By the end of March 2020, traffic volumes in most major urban areas in the United States dropped by as much as 50% [17]. However, traffic volumes rebounded rapidly with the easing of travel restrictions. A research team based at the University of Maryland measured the level of mobility-related activity at different stages of the pandemic using mobile device location data [26]. They found that mobility levels rebounded significantly in the last week of April 2020 due to fewer people staying home, more non-work trips, more out-of-state and out-of-country trips, and longer travel distances. By June 2021, commute trips and transit trips had not yet returned to pre-pandemic levels. In combination, the pandemic has reshuffled trip frequencies by trip purposes, trip distances, and mode choices of travelers. However, different population groups reacted differently to the travel restrictions and social distance requirements [8]. These differences varied by income and education levels [5]. Higher-income communities experienced larger mobility reductions compared to those of lower-income communities. This heterogeneity in mobility reduction across space necessitates a disaggregate and localized approach to analyzing transportation impacts, especially in large and complex metropolitan areas such as the Greater Los Angeles area.

On-road transportation is one of the major sources of pollutants responsible for poor air quality. In the early stages of the pandemic, cities in the United States and abroad experienced a reduction in the concentrations of nitrogen dioxide ($NO_2$) and particulate matter ($PM_{2.5}$). During February–April 2020, satellite observation revealed that $NO_2$ concentration dropped by 40% in Chinese cities, while cities in Western Europe and the United States experienced a 20–38% drop in $NO_2$ compared to the same period in 2019 [3]. Pan et al. [15] compared the surface air quality monitoring data between March 20 and May 5, 2020 to the same months in 2015 through 2019 in California and found a 27.3% reduction in $PM_{2.5}$ concentration and an 8.1% reduction in ozone concentration. These regional air quality improvements are in line with the level of regional reduction in mobility activity, particularly for transportation-related pollutants. However, the impact of heterogeneous reductions in mobility levels in different communities due to the pandemic on localized air quality has not yet been examined. In addition to changes in localized air quality, different communities experienced different levels of exposure to air pollutants depending on time spent at home versus outdoors. In combination, these patterns may have exacerbated the air quality conditions in communities that are disproportionately burdened by pollution.

In this chapter, we explore how mobility activity has changed in different communities in the South Coast Air Basin. We then compare air quality observations in 2020 to air quality observations in 2017–2019. Next, we investigate the relative change in mobility activity in communities of different socio-economic and public health backgrounds. Finally, we examine the relationships between changes in mobility activity and reductions in pollutant concentration at a local level.

## 2 Data and Methods

In this section, we discuss the data sources used to analyze trends and effects of the COVID-19 lockdowns in the Southern California Region. We use three types of data: (1) mobility data to capture how human and vehicle activity change, (2) air quality data to capture changes in traffic-related pollutant concentrations over time, and (3) environmental justice data to understand the socio-economic and public health characteristics of different communities. In this chapter, we limit the scope of analysis to Los Angeles, Ventura, Orange, San Bernardino, and Riverside counties. Using the data collected, we compare trends, discover possible correlations, and speculate on the reasons for these correlations.

### *2.1 Mobility Data*

Vehicle Activity Data

We collected vehicle activity data from the Caltrans Performance Measurement System (PeMS) [4], including the total vehicle flow and average speeds at different stations on freeways and major highways. The statewide database was filtered to retain data from Caltrans districts 7, 8, and 12, which encompass Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties, and which fall within the South Coast Air Basin defined by South Coast Air Quality Management District. Over 5,000 stations were available in these areas to record traffic activity. Total vehicle flow is defined by the number of vehicles registered at a location during a defined time interval, and speed is the average speed registered by passing vehicles during the same time interval. We assessed vehicle activity within the PM peak period for typical weekdays, between 3 and 7 pm Tuesday, Wednesday, and Thursday from January 1, 2020 to June 30, 2021, excluding holidays. The filtering was done to look at consistent data during the peak afternoon traffic patterns, which are unaffected by possible abnormalities such as holidays, seasons, etc. We set January 2020–February

2020 as the pre-pandemic baseline period for comparison. This baseline period was unaffected by pandemic-related trip reduction. Additionally, this period captured the expected trend of yearly traffic growth for the Southern California region.

The initial review of the PeMS database revealed that many of the traffic stations recorded values of zero flow and speed at certain times, reflecting non-operational stations. To avoid data being skewed from these non-operational stations, a minimum threshold on directly observed data was set for a station to be included in the analysis. We omitted stations with less than 80% of data observed, resulting in a final sample of 2,981 stations.

To create baseline traffic and speed levels, traffic flow and speed data were averaged weekly during the specified period for each station. These averages ($\Delta VA_{it}$) were used to calculate weekly changes in traffic flow and speed using the formula:

$$\Delta VA_{it} = \frac{baseline_i - current_{it}}{baseline_i} \times 100$$

where the $baseline_i$ refers to the baseline value of traffic flow or speed in station $i$, and $current_{it}$ refers to the value of traffic or speed observed in week $t$ in the same station.

Human Activity Data

Data from Community Mobility Reports prepared by Google [1] was used to analyze human activity trends in certain industries and markets during the COVID-19 lockdowns. Daily human activity data were analyzed between January 1, 2020 and September 30, 2020 for Imperial, Orange, San Bernardino, Los Angeles, Riverside, and Ventura counties. Activity types included groceries and pharmacies, parks, residential, retail and recreation, transit stations, and workplaces.

The activity levels show how visits and the length of stay at different places change compared to a baseline. The baseline is the median value, for the corresponding day of the week, during the 5-week period of January 3, 2020 to February 6, 2020. The activity levels are derived from proprietary location-based information accessible to Google. We calculated the daily percentage change in human activity ($\Delta HA_{iat}$) using the following formula:

$$\Delta HA_{iat} = \frac{baseline\,activity_{ia} - current\ activity_{iat}}{baseline\ activity_{ia}} \times 100$$

where the $baseline\ activity_{ia}$ refers to the baseline activity level for type $a$ in county $i$, and $current\ activity_{iat}$ refers to the activity level of type $a$ observed on day $t$ in the same county.

### *2.2 Air Quality Data*

For the air pollution analysis, we obtained ground-level concentration data from the California Air Resources Board (CARB) Air Quality and Meteorological System Database for a total of four near-road sites and 16 non-near-road sites in the South Coast Air Basin, which includes portions or all of Los Angeles, Riverside, San Bernardino, and Orange counties. All negative or missing data were excluded from the averaging.

We computed diurnal profiles for 2020 and 2017–2019 averaged pollutant concentrations at selected locations for March and April. We used weekly 3–7 pm differences (2020—avg (2017–2019)) for weekly traffic comparisons. We should note that we selected a different baseline period of air quality data from the baseline period for the activities described above because air quality measurements are highly seasonal.

### *2.3 Environmental Justice Data*

We used the California Communities Environmental Health Screening Tool (CalEnviroScreen) to gather the socio-economic and public health data of different communities [18]. CalEnviroScreen (CES) 3.0 score is a composite score that combines multiple environmental factors at the census tract level. CES 3.0 can be used to identify environmentally disadvantaged communities that are affected by and vulnerable to different sources of pollution. In this chapter, we look at the CES 3.0 score, diesel particulate matter (PM) percentile, and pollution burden. The CES 3.0 score is the CalEnviroScreen score generated from the pollution score multiplied by the population characteristic score. A higher CES 3.0 score indicates a more disadvantaged community. The pollution burden is the average of percentiles from the pollution burden indicators. The diesel PM percentile represents the emissions detected from on-road and non-road sources.

## 3 Results and Discussion

### *3.1 Vehicle Activity Trends*

A spatial analysis of traffic activity was conducted for the South Coast Air Basin. Figure 1 shows the overall trend of VMT for all vehicles combined and for trucks separately. Peak traffic reductions were observed in the first week of April. However, by the third week of June 2020, traffic levels had rebounded back with about a 7% reduction observed from the pre-pandemic baseline. Truck VMT rebounded more quickly than the overall VMT.

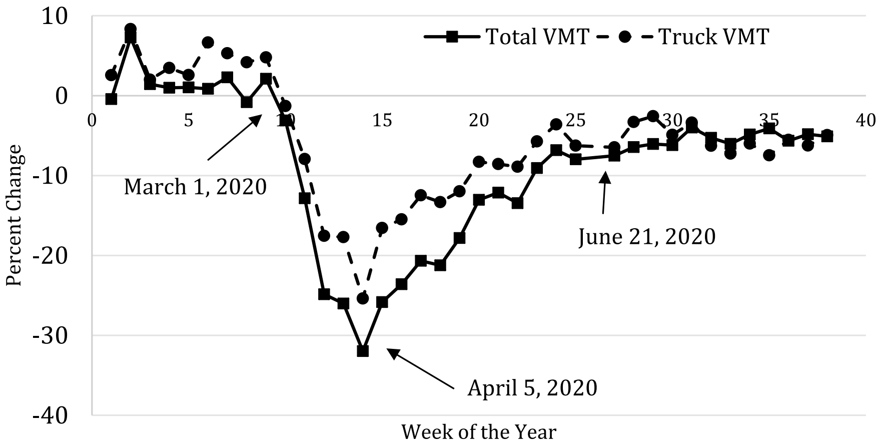



**Fig. 1** Percentage change of weekly VMT in Caltrans district 7 during the PM peak period (3 pm–7 pm) in 2020 compared to January 1, 2020–February 29, 2020 baseline. *Data source* Caltrans Performance Management System (PeMS) (https://pems.dot.ca.gov/)

To monitor both the spatial and temporal trend of vehicle activity, we created a series of maps at the census tract level similar to those in Fig. 2. The $\Delta VA_{it}$ values for both total flow and average speed recorded at PeMS stations in the same census tract were averaged, and those values were assigned to the respective census tract.

Figure 2 depicts the spatial disparity in the reduction of vehicle mobility. Lighter tones were assigned to census tracts experiencing above pre-COVID-19 levels of traffic activity, and darker tones were assigned to tracts with reductions in traffic activity. These maps were generated at weekly intervals to track the dynamic nature of the changes in traffic data caused by the COVID-19 lockdowns. Most of the census tracts in the South Coast Air basin showed a greater than 25% drop in total flow. Traffic flow started to recover gradually by the end of April 2020. However, as of June 2021, the total flow had not recovered to pre-pandemic levels. In April 2020, the average speed increased by more than 10% in most census tracts. During this time of high vehicle activity drop, census tracts that experienced heavy congestion in the pre-COVID period experienced more than a 50% average speed increase in the PM peak period.

## 3.2 *Human Activity Trends*

County-level human activity data from Google shows the effects of the COVID-19 lockdowns on certain industries and activities in the Southern California region. Figure 3 shows the percentage change in daily residential and workplace activities in Orange county. Orange county residential activity increased by 30% in the first week of April 2020, whereas workplace activity was reduced by more than 50% during

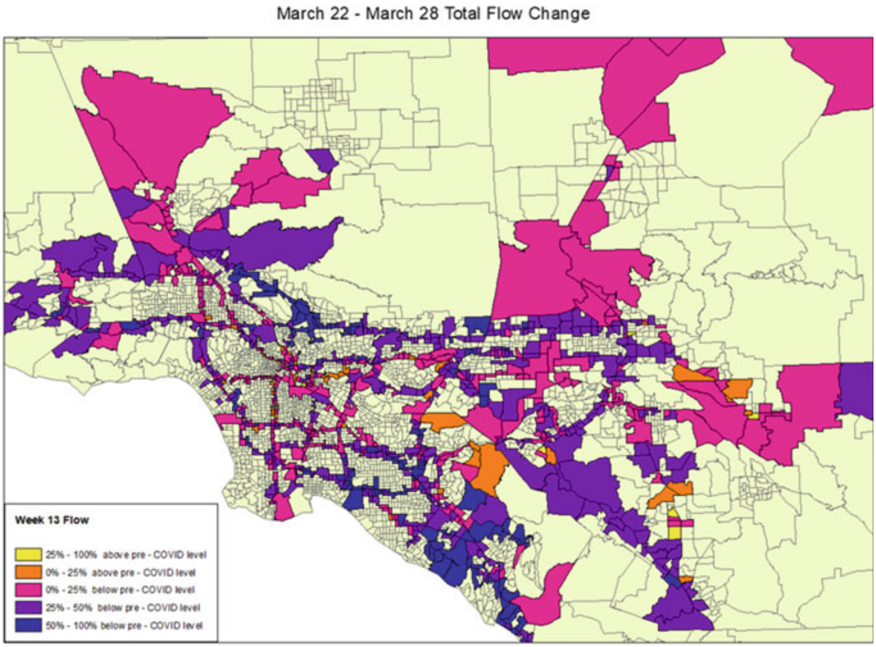
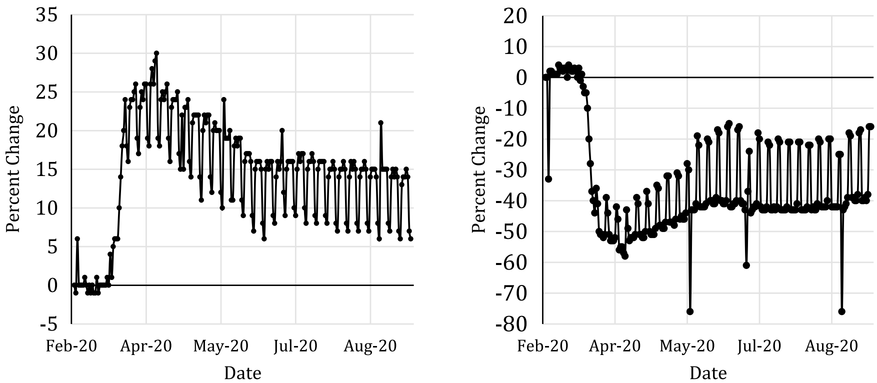



**Fig. 2** Change in total traffic flow in different census tracts of the South Coast Air Basin during week 13 (March 22, 2020–March 28, 2020) compared to January–February 2020 baseline. *Data source* Caltrans Performance Measurement System (PeMS) (https://pems.dot.ca.gov/)




(a) Change in residential activity

(b) Change in workplace activity

**Fig. 3** Daily percentage change in human activity during the pandemic in Orange county compared to January 3, 2020–February 6, 2020 baseline. *Data source* Community Mobility Report (https://www.google.com/covid19/mobility) the same period. However, residential activity increases were smaller in the Inland Empire region (Riverside and San Bernardino counties), averaging less than 20% during the peak of the pandemic lockdown period (March 20–April 20, 2020). In contrast, workplace activity showed similar trends in the Inland Empire compared to Orange and Los Angeles counties. This result points to the fact that a significant part of the Inland Empire population could not afford to stay in their homes, or had jobs that precluded teleworking, even during the height of the pandemic [6]. A large portion of the coastal area jobs is performed by Inland Empire residents, many of whom were considered "essential workers" during the pandemic [14, 19]. A portion of the existing vehicle activities in the coastal areas may be attributable to commuters traveling from other regions, including the Inland Southern California region. This phenomenon is evidenced by the higher residential activity in the coastal areas than in the inland regions and the historical trend of long commuters coming from the inland region for jobs in the coastal cities.

### *3.3 Air Quality Trend*

Coastal Southern California experienced a wet March 2020 (4.11 inches of precipitation at Los Angeles International Airport (LAX)), as reported by the California Nevada River Forecast Center. This led to frequent washout events in the Basin and obscured the impact of emissions reductions on ozone levels. A warmer, drier April 2020 (2.68 inches of precipitation at LAX) provided a window to more clearly observe the nonlinear impacts of emissions reductions on ozone levels in the Basin. It was observed that reductions in on-road emissions led to higher ozone production in the western Basin, which was further exacerbated by increasing temperatures [9, 16].

To understand the impacts of traffic reductions at near-road and non-near-road locations, we highlighted air quality trends at four sites within the South Coast Air Basin. Anaheim and Ontario are near-road sites that monitor air quality along major highways, I-5 and CA-60, respectively. Azusa and San Bernardino are non-near-road sites and represent urban locations. Azusa is approximately one mile from a major highway (I-210). San Bernardino is located near a large railyard, and the air quality observations at this site are influenced by heavy-duty vehicle traffic that services this railyard.

Reductions in traffic volumes during the March and April 2020 lockdowns led to observed reductions in near-road traffic-related air pollutants, most notably carbon monoxide (CO). Diurnal profiles for the Anaheim near-road site suggest that the monthly averaged CO concentrations were below the typical range of variability compared to the 2017–2019 average, and differences were similar to those found between companion near-road and non-near-road locations [11] (Fig. 4). CO concentrations were lower than the 2017–2019 average but within the range of variability at the Ontario near-road location. These results confirm the vehicle activity observation that there was a greater reduction of commuters on the I-5 freeway (Anaheim)

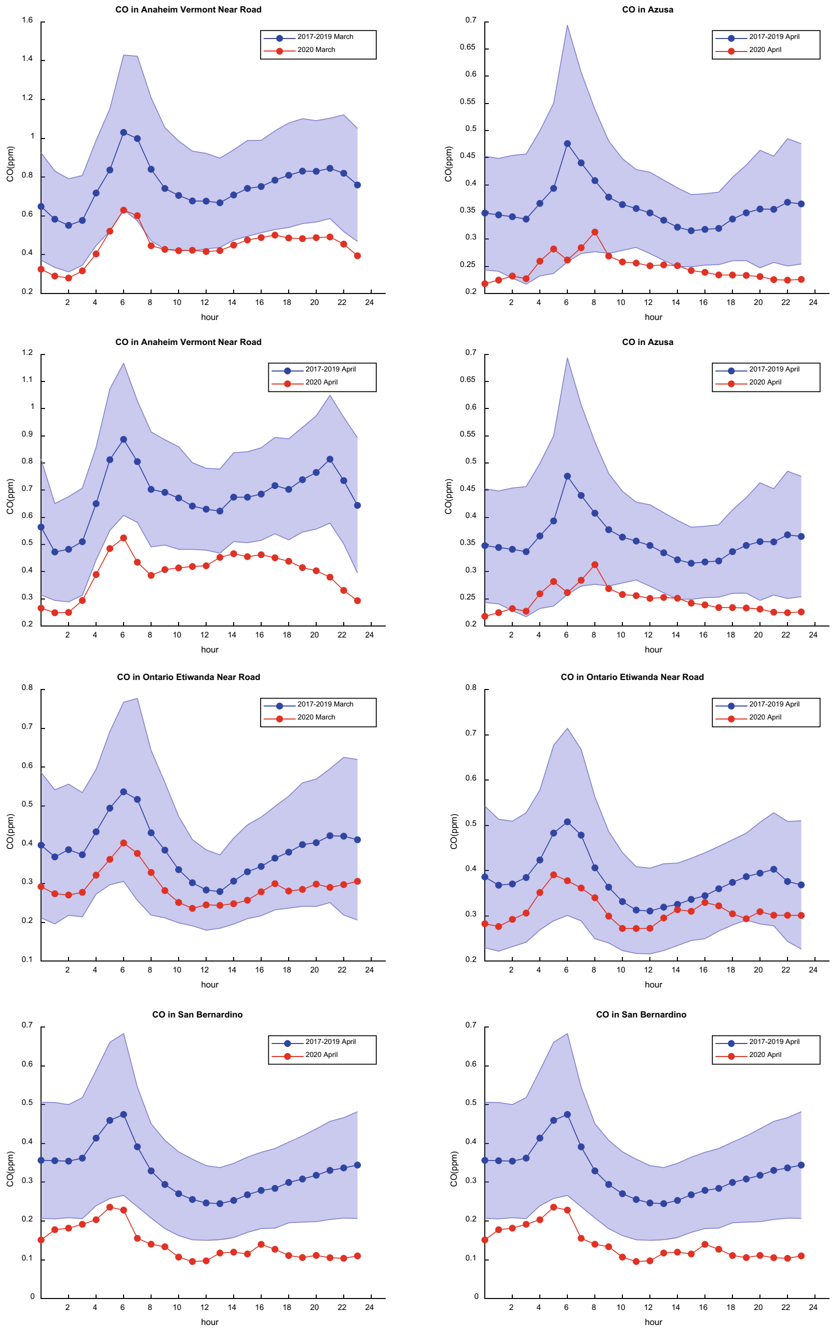



**Fig. 4** Monthly averaged diurnal profiles of 2017–2019 (circles) and 2020 (diamonds) CO concentrations (ppm) at Anaheim (near-road), Azusa, Ontario, and San Bernardino for March (left) and April (right). *Data source* California Air Resources Board (CARB) Air Quality and Meteorological Information System Database (AQMIS). *Note* The shaded area is the standard deviation of 2017–2019

compared to CA-60 (Ontario), which services a region of the Basin with more essential workers. San Bernardino CO was also below the 2017–2019 range of variability. Evening CO at Azusa was outside the 2017–2019 range of variability in April; however, in March concentrations were lower and within the range of variability. Reductions in NOx concentrations were lower than the 2017–2019 average but within the range of variability for March and April at all locations, with the exception of Anaheim near-road evening concentrations in April, 6:00–8:00 pm at Ontario, and 5:00–8:00 pm at Azusa (Fig. 5).

### 3.4 Community-Level Traffic Activity Shift

The CES 3.0 score for each census tract within the South Coast Air Basin is an indicator of community-level socio-economic and environmental exposure conditions. A higher CES 3.0 score indicates a more disadvantaged and vulnerable community. A logarithmic fit was developed according to Eq. 1 below:

$$\Delta \text{Traffic Flow}_{\text{it}} = \beta_{0\text{t}} + \beta_{1\text{t}} * \log(\text{CES3.0}_{\text{i}}) + \varepsilon \tag{1}$$

where $\Delta\, Traffic\ Flow_{it}$ is the percentage change in weekly PM peak traffic flow in week $t$ in census tract $i$ compared to baseline traffic flow in census tract $i$. $CES3.0_i$ is the CES 3.0 score, $\beta_{0t}$ is the intercept term, and $\beta_{1t}$ is the slope term of the fit. $\varepsilon$ is the error term. The level-log specification means that $\beta_1$ can be interpreted as the change in traffic flow resulting from a 1% increase in the CES 3.0 score.

Figure 6 shows how traffic flow changed ($Y$-axis) with the census tract level CES 3.0 score ($X$-axis). The fitted relationships were developed for each week $t$ during the pandemic. The difference in traffic flow drop between the most disadvantaged and the least disadvantaged community was 30% according to the fitted line in Fig. 6. Week 12 was chosen to show the maximum level of disparity found during the analysis period.

Figure 7 shows the temporal progression of the fitted parameters. The intercept, $\beta_0$, represents the traffic drop level for the least disadvantaged communities (CES 3.0 = 0). The slope, $\beta_1$, represents the rate of change in traffic levels in the more disadvantaged communities. The value of the slope was highest in week 12 (March 15, 2020–March 21, 2020) as shown in Fig. 7b. Figure 7a indicates the shift in overall traffic drop in the South Coast Air Basin with time. Traffic levels started dropping significantly in the first week of March and started recovering after the second week of April 2020. However, the recovery process has stalled since the last week of June 2020. The disproportionate effect of reduced vehicle activity in disadvantaged communities, shown in Fig. 7b, peaked during the highest level of traffic reduction. Nevertheless, the slope value representing the rate of change in traffic drop in more disadvantaged areas stayed around the same level (between 5 and 10) during the entire pandemic period with an occasional peak happening in the

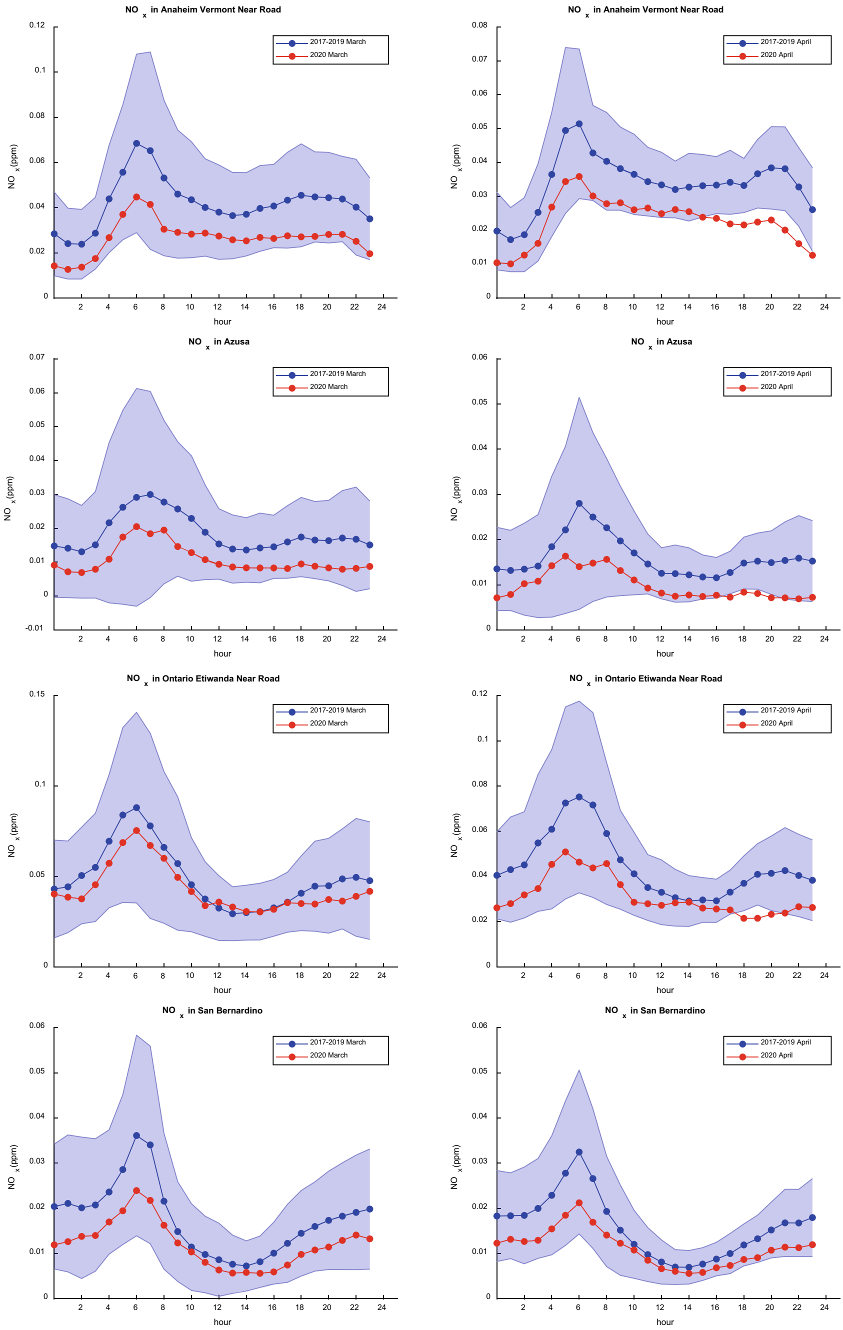



**Fig. 5** Monthly averaged diurnal profiles of 2017–2019 (circles) and 2020 (diamonds) NOx concentrations (ppm) at Anaheim (near-road), Azusa, Ontario, and San Bernardino for March (left) and April (right). *Data source* California Air Resources Board (CARB) Air Quality and Meteorological Information System Database (AQMIS). *Note* The shaded area is the standard deviation of the 2017–2019 measurements

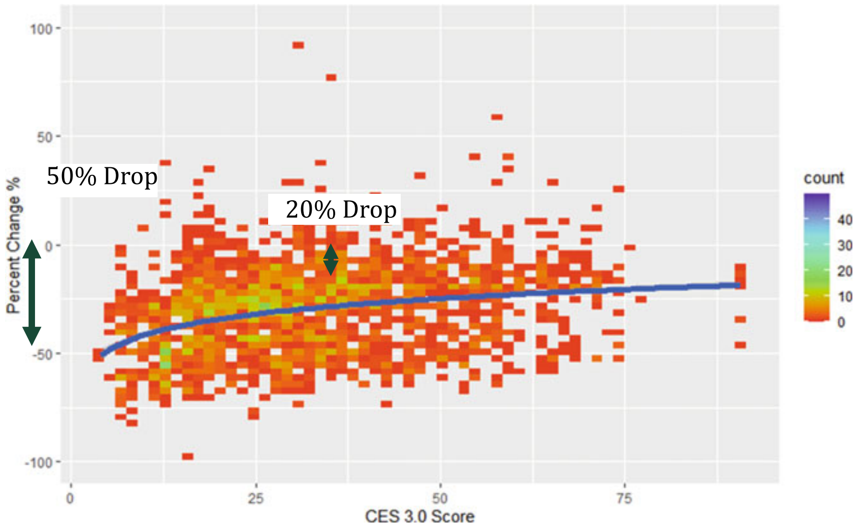



**Fig. 6** Variation of traffic flow reduction at census tracts of different CalEnviroScreen 3.0 scores during the 12th week of 2020 (March 15, 2020–March 21, 2020). *Data sources* Caltrans Performance Measurement System (PeMS); CalEnviroScreen (CES) 3.0. (https://pems.dot.ca.gov); (https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30). *Note* The solid line represents a logarithmic fit. Higher CES 3.0 scores represent more disadvantaged communities

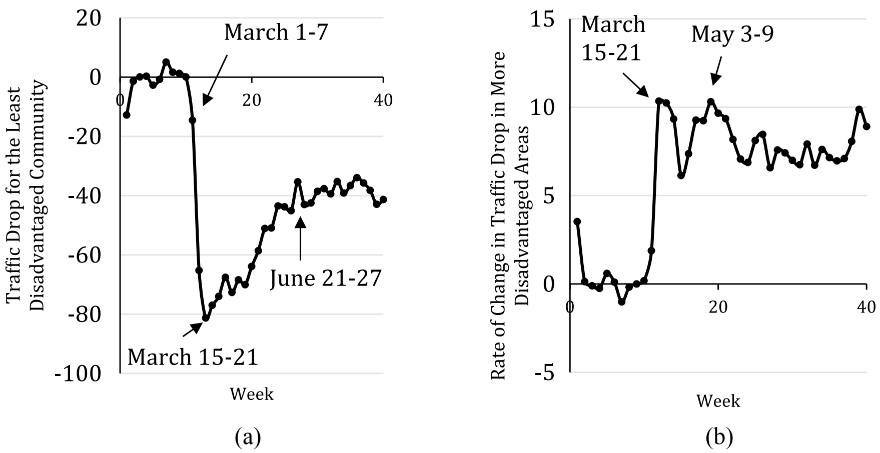


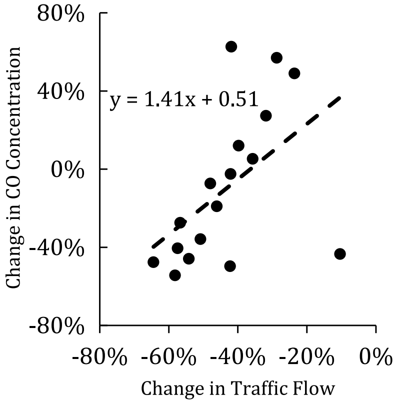

**Fig. 7** Temporal progression of logarithmic fit parameters. *Data sources* Authors; Caltrans Performance Measurement System (PeMS)

first week of May. This trend verifies the sustained nature of the lack of ability to conduct remote work in the disadvantaged communities throughout the pandemic [6]. Whenever additional social distancing measures were imposed, such as lockdowns, highly educated workers residing in more socio-economically advantaged communities could stay at home and work remotely. Kochhar and Passel [10] showed that individuals with a bachelor's degree or higher were almost three times as likely to telecommute during the pandemic than individuals with only a high school diploma. They also found that only 40% of workers in the United States work in jobs that can be teleworked. Census tracts with higher CES 3.0 scores representing relatively disadvantaged communities included a lesser college-educated population than the low CES 3.0 communities. Consequently, the disadvantaged communities had fewer opportunities to telework and experienced relatively higher levels of vehicle activity.

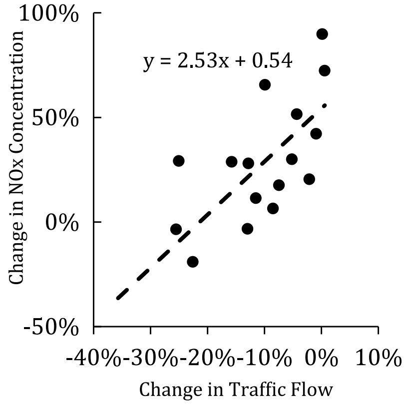
### *3.5 Mobility Activity Effects on Air Quality*

One of the main goals of this study was to observe the shifts in traffic activity and explore the corresponding air quality improvements. We observed changes in air quality caused by the changes in traffic activity. Carbon monoxide (CO) and oxides of nitrogen ($NO_X$) were selected specifically as traffic-related pollutants. Particulate matter (PM) was not selected because the measured $PM_{2.5}$ and $PM_{10}$ values are not as responsive to mobility activity as CO or $NO_X$. Song et al. [23] suggested that the ground measurement of $PM_{2.5}$ does not have enough spatial variability to capture localized variations in mobility activity. Air quality monitoring sites were identified that were located on a census tract with available PeMS stations.

Figure 8a represents the relationship between percentage changes in CO concentrations compared to the pre-COVID baseline with the corresponding percentage changes in traffic flow for a near-road air quality measurement site. This site is located close to I-5 in Anaheim, CA near the Loara Elementary School (its distance from the I-5 is 375 m). The scatterplot in Fig. 8a includes 14 weekly observations between March 2020 and July 2020. A linear trendline is also added over the points to demarcate the overall correlation between total traffic flow and air quality. The change in traffic level for the air quality monitoring site was calculated by averaging the change in traffic flows recorded at the PeMS stations within the census tract containing the air quality site. For this particular site, the corresponding census tract had a CES 3.0 score of 28.23 representing a relatively advantaged community. The corresponding traffic volume drop during the mid-March to mid-April period was more than 50%. At the same time, the CO concentration was reduced by 40% on average. As the traffic level started rebounding in May 2020, CO concentrations were very similar to the pollutant concentrations measured during the same time in the 2017–2019 period. However, CO concentration in the Anaheim site increased by about 40% by the end of June 2020. It is possible that the meteorological conditions in the summer months of 2020 were significantly different than during 2017–2019. Additionally, the location was relatively far from the freeway, further than a typical




(a)




(b)

**Fig. 8** **(a)** Changes in weekly carbon monoxide (CO) concentration for the Anaheim near-road site with changes in weekly traffic flow in the corresponding census tract. **(b)** changes in weekly oxides of nitrogen ($NO_X$) concentration for the Ontario near-road site. *Data sources* Caltrans Performance Measurement System (PeMS); CARB Air Quality and Meteorological Information System Database (AQMIS). *Note* Both sites were analyzed for 14 weeks between March 2020 and July 2020

near-road air quality site and, therefore, the reduction in highway traffic may not be representative of the vehicle activities closest to the site.

Figure 8b shows a similar trend for $NO_X$ at the near-highway air quality measurement site in Ontario, CA. The site is only 33 m (108 ft) away from the centerline of interstate I-10 and is located within very close proximity to a warehouse district in the Inland Empire. The trendline shows an overall reduction in the $NO_X$ concentration with a reduction in the total flow in the vicinity of the air quality site. However, the overall $NO_X$ concentration was higher in most weeks compared to similar weeks in 2017–2019. The $NO_X$ level was recorded at 0.016 ppm on March 30; however, it gradually increased to 0.042 ppm on April 27, an increase of greater than 150%. This localized observation of increased $NO_X$ concentration is missed in the regional study conducted by [12]. They found a 32% reduction in weekday NO concentration at the Southern California sites from March 1 to April 30, 2020. The increase of the $NO_X$ level starting in late April 2020 may be due to increased trucking activities near the site. The Ontario warehouse district is one of the major hubs serving the Port of Los Angeles and the Port of Long Beach. In addition, the area houses major regional distribution hubs of popular e-commerce companies. Despite a marked reduction in passenger transportation, certain types of freight activity have been mostly unaffected and in some cases were positively correlated with the number of COVID-19 confirmed cases [2, 7]. Therefore, increased e-commerce activities during the pandemic may have caused increased concentrations of $NO_X$ in the warehouse districts.

Identifying a generalized relation between changes in traffic flows and changes in air quality is an elusive goal. The air quality impacts of traffic reduction are highly localized—depending on the pollutant being considered and the local meteorology. There are several other environmental facts that affect air quality measurements, such as the positioning of the air quality sensor, land uses (e.g., residential, industrial), and the distance of the air quality monitoring station from the nearest highway.

## 4 Conclusions

The COVID-19 pandemic has generated an unprecedented set of changes in travel behavior and transportation system operations in the United States and abroad. This chapter focused on the shift of traffic patterns and localized air quality in the Southern California Air Basin. The basin houses more than 17 million people, nearly half of the population of California. Spatial heterogeneities exist in communities living in the area in terms of socio-economic and environmental exposure conditions. Our focus was to analyze the reduction of traffic levels and improvements in the air quality at the neighborhood level.

First, we found that vehicle activity shifts, as observed from the highway traffic flow levels in the area, were locally variable. Most areas in the Inland Empire experienced a rebound in traffic levels faster than the relatively more advantaged communities in the Orange and Los Angeles counties. The human activity trends according to Google-reported data also support a similar disparity in residential activities. However, Google data were inconclusive as to whether workplace activities were different at the county level. County-level aggregation of human activity data is too coarse to decide whether there was community-level variability in in-person access to workplaces. Detailed origin–destination surveys would be an important supplement to identify the users of the vehicles operated during the shutdown.

Second, near-road air quality monitors recorded up to a 50% reduction in CO and a 40% reduction in $NO_x$ from March 20, 2020 to April 20, 2020. However, the near-road air quality improvements in the inland regions were not outside the usual variation of the baseline (2017–2019) measurements. This phenomenon could potentially be attributed to a higher concentration of "essential workers" and commuters in the inland region [14, 19].

Third, the more disadvantaged a community was according to the CalEnviroScreen 3.0 score, the lesser was the extent of its traffic reduction. This chapter developed an approach to quantitatively capture this disparity. Using a level-logarithmic regression of traffic-level shift from a pre-pandemic baseline on the CES 3.0 score, our approach dissects the two potential forces causing traffic volume shift: (1) the overall drop in regional travel due to overarching restrictions, and (2) the disproportionate shifts in different localized regions with varying socio-economic conditions. The results suggest that the more acute restrictions caused sharper contrasts between traffic levels in advantaged and disadvantaged communities.

Finally, we found a general trend of decreasing traffic-related pollutant concentrations with reductions in traffic volume in the vicinity of the monitoring site. This trend was strongest along the highways because the traffic activity was measured using the PeMS station data that were available only on Caltrans-managed highways. Air quality stations farther away from the highways were influenced by local transportation activities such as grocery deliveries and short-distance trips. Although we did not measure local vehicle activities, the measured CO and $NO_X$ values provide some indication of vehicle activities in the non-near-road sites. Overall, the results suggest that any disproportionate change in vehicle activity will translate to corresponding disproportionate exposure to traffic-related pollutants.

## 5 Policy Implications

The results in this chapter have profound implications for setting policies regarding travel demand management (TDM) and e-commerce infrastructure planning. Telecommuting has been promulgated as one of the TDM measures to reduce work trips and improve air quality. However, disadvantaged communities have less access to "remote work" because of the nature of these jobs and the level of technological sophistication they require. Targeted incentives could be provided to businesses in underprivileged communities to establish telecommuting programs for employees.

The proliferation of e-commerce business in recent years has initiated the establishment of storage and distribution centers across the county. Over one billion square feet of additional industrial real estate will be needed by 2025 to accommodate the accelerated growth and adoption rates of e-commerce due to the COVID-19 pandemic [13]. The Inland Empire example pointed to higher traffic-related pollutant concentrations near the warehouse districts. California Air Resources Board established the Community Air Protection Program (CAPP) to reduce the exposure to air pollutants in California. So far, six communities within the South Coast Air Basin have been part of CAPP. All six communities have the potential to be disproportionately impacted by increased freight activities from pandemic-induced e-commerce growth. More consumption of online shopping items increases warehouse activities. However, most consumers of these e-commerce items are not residents of the warehouse districts. Air pollution control districts and local municipalities need to ensure that the expansion of warehouse activities does not create a disproportionate impact on the air quality in disadvantaged communities. In cases of unavoidable new developments of warehouses or increased warehousing activities, strategies that help reduce the emissions or reduce exposure should be considered. Electrifying the heavy-duty, currently diesel-operated, vehicles used in transporting warehouse-related goods will help ameliorate the air quality of the surrounding communities.

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# Climate and Fiscal Impacts from Reduced Fuel Use During COVID-19 Mitigation

**Fraser Shilling**

**Abstract** In U.S. states, as in most of the world, mitigation of the spread of COVID-19 was implemented by cities, counties, and governors' offices through "shelter-in-place" (SIP) and "stay-at-home" orders and related actions (e.g., closure of non-essential businesses). There were several important impacts of government SIP orders on traffic volumes, which in turn had impacts on fuel use and greenhouse gas (GHG) emissions. In this chapter, I estimate GHG emissions and fuel tax revenue at the state and nation scales before, during, and after the SIP guidance. I find that due to approximately 50% reductions in estimated vehicle-miles traveled, U.S. GHG emissions that cause climate change were reduced by 4% in total and by 13% from transportation in the eight weeks after the SIP orders went into effect. This reduction put the United States on track to meet its annual goals for GHG reduction under the Paris Climate Accord. I also calculated that the rapid decline in travel resulted in savings of $5 billion/week to U.S. drivers and a loss of $0.7 billion/week in tax revenue to the states. These consequences should feature in future transportation and climate planning as important variables that may stochastically appear, and which are beyond the influence of transportation agencies.

## 1 Introduction

Transportation is one of the primary contributors to global greenhouse gas emissions (GHG) that cause climate change [7, 12]. Transportation is also composed of many modes, including walking, cycling and ground-based, water, and air vehicle systems, all of which have partially interchangeable GHG footprints due to mode shifts [13]. Because of its importance in contributing to climate change, transportation in general and mode shifts, in particular, are important in planning for ways to mitigate climate change through travel reduction, mode-shifting, and electrification [1, 7]. In addition, it is possible to assign carbon footprints for mobility based on activity, which is tied

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to income, and develop pricing for individual mobility choices to encourage reduced carbon emissions [15].

Estimating GHG emissions from vehicles includes life-cycle and instantaneous emission measurements and models, and is based on assumptions about fleet composition, fuel-use efficiency, fuel composition, electrification, and travel distances [8]. The primary attention in efforts seeking to reduce GHG emissions is often given to changing the energy source of vehicles (e.g., through electrification), or vehicle fuel efficiency for fossil fuel use. However, shifting travel to non-mechanized modes, paying attention to individual actions to achieve de-carbonization, and reducing mechanized travel distances could result in substantial GHG emission reductions, especially if combined with vehicle-based mitigation strategies [15].

In addition to the externalized costs to the environment, and by extension society, of individual and collective decisions to drive private vehicles, drivers also incur additional costs to maintain and fuel their vehicles, depending on the distance traveled [5]. These costs may encourage reduced driving, and thus reduced emissions, in lower-income populations [9]. Vehicle sharing has emerged both organically as an individual strategy to save money on vehicle ownership and commercially through ride-hailing and other services [3]. The actual benefits of changes in private vehicle operation in terms of GHG emissions and climate change will be measured as a combination of total miles traveled and total fuel consumed.

In California and other U.S. states, mitigation of the spread of COVID-19 was initially implemented by cities, counties, and governors' offices through "stay-at-home" and "shelter-in-place" (SIP) orders and related actions (e.g., closure of non-essential businesses). This resulted in a very rapid decrease in personal travel, especially notable in public transit (see also Chap. 17 in this volume) and air travel. In a series of reports during the spring and summer 2020, the Road Ecology Center (https://roadecology.ucdavis.edu) pointed to the potential unintended impact of reduced traffic—reduced traffic crashes and thus injuries and fatalities for people involved in the incidents (see also Chap. 11 in this volume), reduced collisions with wildlife, reduced GHG emissions, and reduced fuel use. These unexpected benefits of COVID-19 mitigation actions were highlighted during contemporaneous press articles as "silver linings," a sort-of relief valve for the persistent stress of the pandemic. The Road Ecology Center and later publications (e.g., for rail, Tardivo et al. [14] point to this period of travel adjustment as a good time to learn new ways to plan transportation. Over a year since the first SIP orders, most modes of travel that were reduced have increased, some (such as single-occupancy vehicles) to levels similar to before the pandemic. But the lessons from the pandemic-induced travel reduction were not lost and are being captured in books like the one you are reading.

This chapter investigates several short-term and continuing impacts of government SIP orders on rates of travel, as measured by vehicle-miles traveled, estimated fuel use, estimated fuel-cost savings to drivers, and estimated lost revenue to states from reduced fuel tax. I define four periods of U.S. road-vehicle travel during the pandemic: Phase 0: immediately prior to the pandemic SIP orders, which was before mid-March 2020 for most states; Phase 1: between late March and late April 2020, which witnessed a rapid change in traffic patterns to a temporarily reduced plateau;

Phase 2: beginning in late April 2020 and extending into winter 2021, which saw a gradual increase in traffic as SIP orders were reversed or ignored; and Phase 3: after the change in the Centers for Disease Control (CDC) guidance in mid-May 2021, when traffic in most U.S. states was similar to the same period in 2019, and most SIP orders and pandemic guidance had ended. I used traffic data (vehicle miles traveled, VMT) from Streetlightdata.com.[1] To estimate fuel use and equivalent GHG emissions, I used average fuel economy and GHG emissions rates for U.S. vehicles, assuming no appreciable change in fleet composition (EPA, 2017).[2] To estimate fuel costs, I used an average gasoline price of $2.59 across the U.S. (Source: USDOE, Alternative Fuels Data Center).[3] I used a California legislative source for information about California's SB1 legislation.[4] Lastly, I used estimated fuel tax rates from the American Petroleum Institute.[5]

## 2 Pandemic Impacts on Travel

### *2.1 Changes in Traffic*

Using daily travel data from Streetlightdata.com, I calculated the change in daily vehicle miles traveled (VMT) for every county in the United States from Phase 0 to Phase 1 (see Introduction for Phase definitions). Streetlightdata uses custom algorithms with cell phone tracking data to estimate how many miles people drive per day. Streelightdata estimated that the total miles traveled in the first week of March 2020 in the United States was 76.5 billion miles, while the total miles traveled in the second week of April 2020 was 42.0 billion miles. This 45% reduction in total miles traveled was reflected in the range of reductions seen across each state (Table 1).

Although traffic (VMT) increased during Phase 2, after the initial dramatic reduction following SIP guidance (early to mid-March 2020), traffic remained reduced in the United States as a whole until January 2021 (Fig. 1a, Phase 3). There are few other datasets available to evaluate total traffic in a large geographic area like the U.S. Apple Inc. collects data from iPhones and other devices about requests for driving directions. They have estimated the relative volume of directions requests per country/region, sub-region, or city around the world, compared to a baseline volume on January 13, 2020.[6] According to these data, the volumes of driving directions

[1] See https://streetlightdata.com.

[2] See https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references.

[3] See https://afdc.energy.gov/data/.

[4] See https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1.

[5] See https://www.api.org/oil-and-natural-gas/consumer-information/motor-fuel-taxes/gasoline-tax.

[6] See https://covid19.apple.com/mobility, accessed 6/7/2021.

**Table 1** Reduction (%) in vehicle-miles traveled for the U.S. states between the first week of March (3/2-3/8, Phase 0) and the second week of April (4/11–4/17, Phase 1)

| State | % reduction VMT (%) | State | % reduction VMT (%) | State | % reduction VMT (%) |
|---|---|---|---|---|---|
| Wyoming (WY) | 31 | Maine (ME) | 40 | Nevada (NV) | 48 |
| Idaho (ID) | 32 | Iowa (IA) | 41 | Florida (FL) | 48 |
| Arkansas (AR) | 34 | West Virginia (WV) | 41 | Delaware (DE) | 48 |
| Oregon (OR) | 34 | Kentucky (KY) | 42 | Minnesota (MN) | 48 |
| Alabama (AL) | 36 | Nebraska (NE) | 43 | Maryland (MD) | 49 |
| Montana (MT) | 37 | Louisiana (LA) | 43 | California (CA) | 49 |
| South Carolina (SC) | 37 | Missouri (MO) | 43 | Pennsylvania (PA) | 49 |
| Utah (UT) | 37 | Virginia (VA) | 43 | Rhode Island (RI) | 50 |
| Mississippi (MS) | 38 | Kansa (KS) | 43 | Connecticut (CT) | 50 |
| North Dakota (ND) | 38 | Wisconsin (WI) | 44 | Colorado (CO) | 52 |
| Washington (WA) | 39 | Indiana (IN) | 44 | Massachusetts (MA) | 52 |
| New Mexico (NM) | 39 | South Dakota (SD) | 44 | Michigan (MI) | 54 |
| Tennessee (TN) | 40 | Texas (TX) | 45 | New York (NY) | 55 |
| Oklahoma (OK) | 40 | Ohio (OH) | 45 | New Jersey (NJ) | 56 |
| North Carolina (NC) | 40 | Illinois (IL) | 45 | District of Columbia (DC) | 65 |
| Arizona (AZ) | 40 | Vermont (VT) | 45 | | |
| Georgia (GA) | 40 | New Hampshire (NH) | 46 | | |

*Data source* Streetlightdata.com

requests in the United States declined rapidly between early March 2020 and mid-April 2020 (Fig. 1b), with an average reduction of 45% for April 1–15, 2020. This reduction is essentially identical to the change in traffic measured as estimated VMT.

Figure 1a shows changes in traffic (vehicle-miles traveled, VMT) between January 1, 2019 and March 31, 2021). The yellow line represents the daily VMT for 2019,

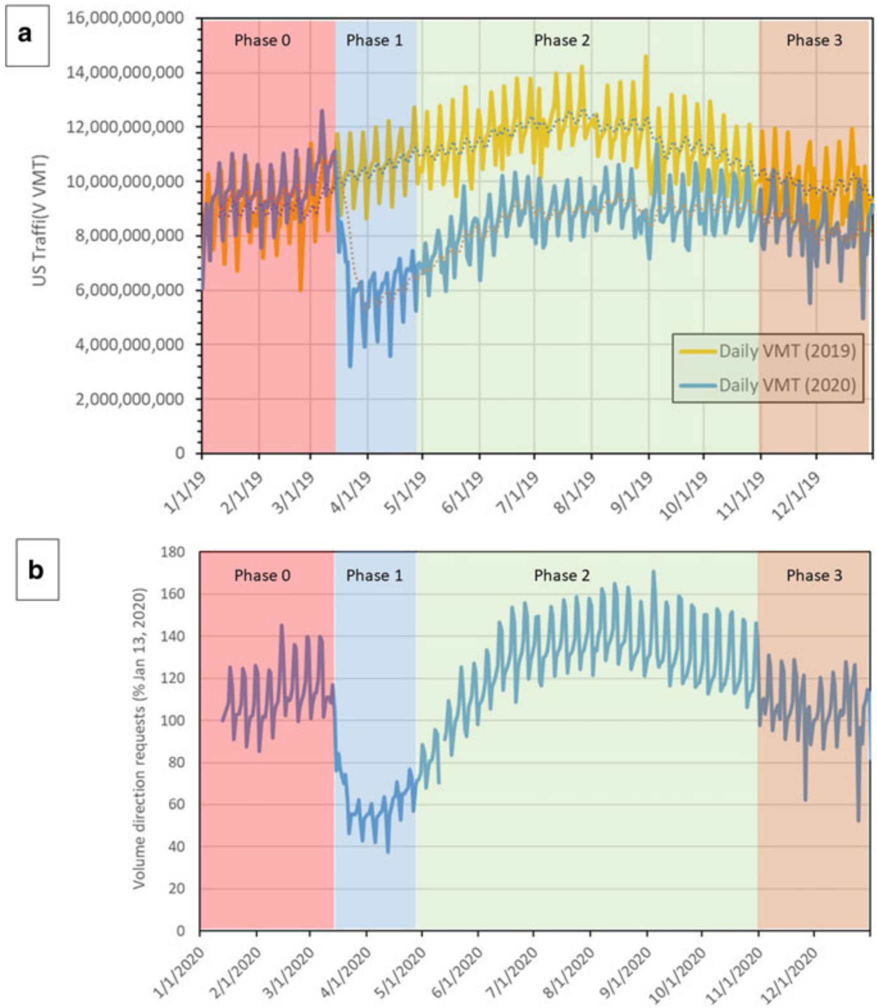


**Fig. 1** Changes in traffic (vehicle-miles traveled, VMT). *Data source* https://covid19.apple.com/mobility (data accessed on 6/7/2021)

the blue line for 2020, and the dotted line represents the 10-day moving average of daily VMT. Short-term variation in daily VMT is due to greater VMT on weekdays (versus weekends), while long-term variation is due to seasonal changes in travel patterns. Figure 1b depicts changes in volumes of requests for driving directions on Apple devices, relative to the volume on January 13, 2020.

The initial rapid reduction in U.S. traffic between early March 2020 and early April 2020 (Phase 1) was replaced by a second phase (Phase 2) of gradual increase in traffic volumes until approximately January 7, 2021, when the 10-day moving average VMT was equal to or greater than the average January VMT in 2019 (Fig. 2a). There were

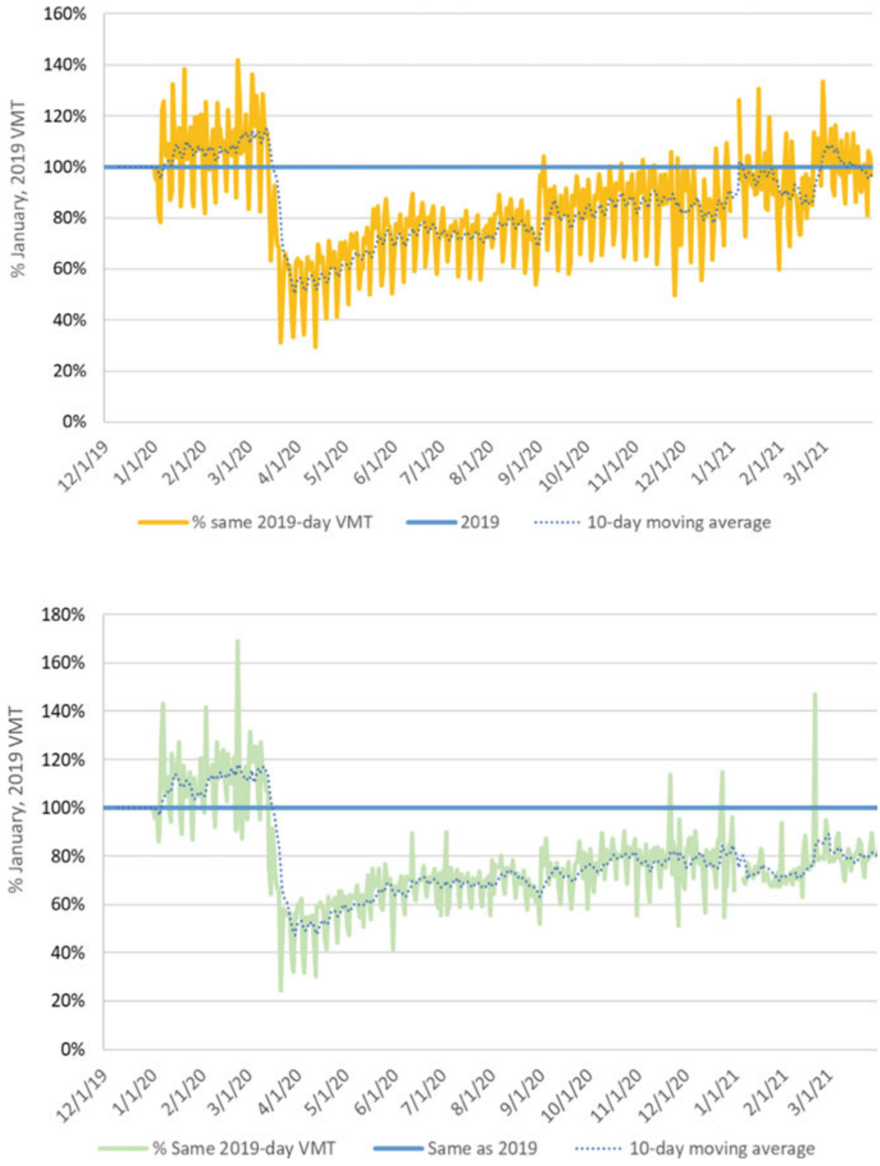


**Fig. 2** Comparison of traffic between the United States (**a**) and California (**b**). *Data source* https://covid19.apple.com/mobility

days before and after that date when daily VMT was greater than the same weekday in 2019, but it appears that traffic had largely returned to pre-pandemic (i.e., 2019) levels for the United States as a whole by early January 2021. In contrast, California's traffic remained depressed by about 20% through March 31, 2021 (Fig. 2b). Other states showed some variation in the timing and amount of increases in traffic during Phase 2, but the overall pattern was similar. It is not obvious why California's reduction was different from the remainder of the United States, and it is possible that it is an artifact of the source of the Streetlightdata VMT data—movement patterns and distances of cell phones.

Figure 2 shows the comparison of traffic between the United States (Fig. 2a) and California (Fig. 2b) on the same weekday in 2019 (e.g., first Monday, 2020 compared with the first Monday, 2019) as a percent of the average of traffic (VMT) in January 2019. The solid line represents the daily VMT in 2020 compared with the same week-day in 2019, while the dotted line represents the 10-day moving average of the values represented by the solid line.

### 2.2 Change in Greenhouse Gas Emissions

The reduction in VMT resulted in a proportional decrease in greenhouse gas emissions from vehicles burning fossil fuels. In the United States, the transportation sector, including personal vehicles, accounts for about 29% of the total GHG per year [12]. These GHGs are usually quantified as "carbon dioxide equivalents" ($CO_2$eq), which reflect the different global warming potential of the various GHG emissions from vehicle fuel combustion. I used average fuel economy rates for U.S. vehicles using information from the Environmental Protection Agency (EPA),[7] which is based on the fleet composition and fuel types. I assumed that the fleet composition did not change from 2019 to 2020 in terms of the proportion of light-duty (e.g., passenger automobiles) and heavy-duty vehicles (e.g., freight trucks). I estimated the GHG emissions equivalent to VMT in Phases 0, 1, and 2, before, during, and after the SIP guidance for COVID-19 mitigation. The total for the first week of March 2020 was 31 million metric tons $CO_2$eq, while for the second week of April 2020, it was 17 million metric tons $CO_2$eq. Because of the nature of the calculation, the 45% decline in ($CO_2$eq) was identical to the reduction in travel VMT. There was variation in degree of reduction in travel and thus in GHG emissions among the states (Fig. 3).

The reduction in travel persisted during April 2020 and then gradually increased, which was reflected in a gradual increase in GHG emissions. Vehicle travel generally increases from year to year, but comparing calculated emissions during the pandemic with the same period during the last pre-pandemic year (2019) is one way to index the savings in GHG emissions that resulted from the traffic reductions.

[7] See EPA (2017) https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references.

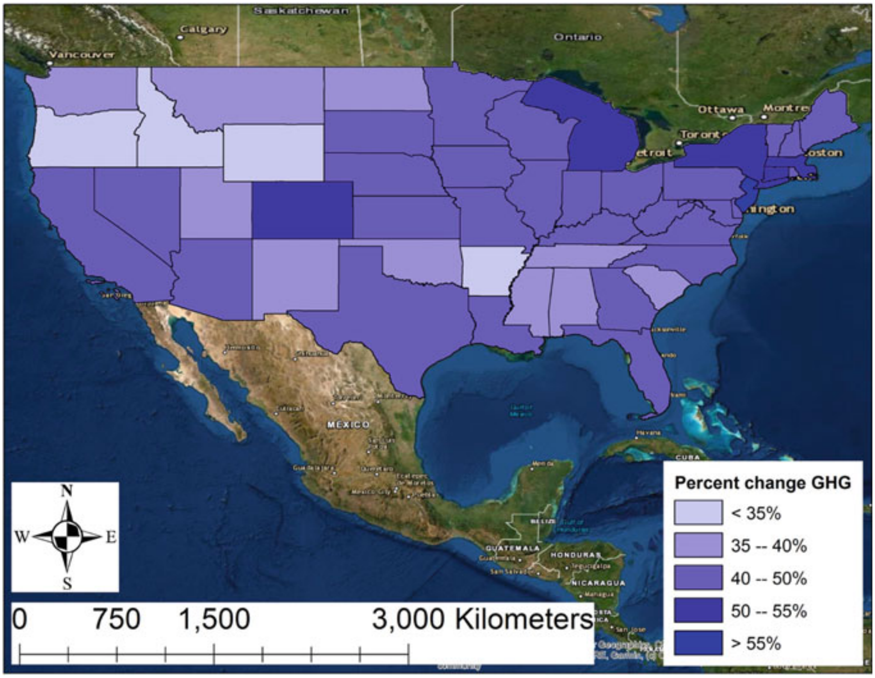


**Fig. 3** Comparison of the percent reduction in GHG emissions (MT $CO_2$-equivalents) from Phase 0 (pre-pandemic) to Phase 1 among the U.S. states. *Data source* Author; secondary data source: EPA (2017), see Footnote 7

The pandemic-related reduction in traffic resulted in an estimated 332 million metric tons fewer GHG ($CO_2$eq) emissions from U.S. vehicle travel that in the previous equivalent period. This represents a 15% decrease in transportation-related annual GHG emissions and a 4% decrease in total annual GHG emissions in the United States (Table 2).

**Table 2** Reduction in vehicle traffic and GHG emissions between the reduced-traffic pandemic period (3/9/2020–1/7/2021) and the equivalent period in 2019–2020

| Period/Year | Pandemic reduction (3/9/2020–1/7/2021) | Equivalent period pre-pandemic (3/9/2019–1/7/2020) | Total reduction cf. 2019 GHG |
|---|---|---|---|
| VMT | $2.50 \times 10^{12}$ | $3.332 \times 10^{12}$ | $-0.82 \times 10^{12}$ |
| GHG ($CO_2$eq) MT | $1.01 \times 10^{9}$ | $1.34 \times 10^{9}$ | $0.33 \times 10^{9}$ |
| Total GHG reduction | | | 4.2% |
| Transportation GHG reduction | | | 14.6% |

*Data sources* Streetlightdata.com; EPA (2017)

### 2.3 *Reduction in Fuel Use and Tax Revenue*

In the first week of March 2020, U.S. daily travel used an estimated 3.4 billion gallons of fuel. Due to reduced daily travel following government guidance, the United States used only 1.9 billion gallons of fuel in the second week of April 2020 at an average gasoline price of $2.59 across the United States.[8] This reduction in use is equivalent to a savings of about $4 billion/week to U.S. drivers. For the sake of simplicity, I used gasoline prices and taxation as a proxy for all fuels, while recognizing that this is imperfect.

Every U.S. state charges a fuel tax, which varies by state. I multiplied the state-specific tax rate by the estimated fuel use per state to calculate the total revenue per week for the first week of March 2020 (Phase 0) and the second week of April 2020 (Phase 1). The state fuel tax revenue was reduced from $1.1 billion per week in March (Phase 0) to $587 million per week in April (Phase 1), a difference of more than $500 million/week. The total reduced U.S. fuel use for Phases 1 to 3 was 37.0 billion gallons of fuel, equivalent to savings to drivers of $95.7 billion and a loss of fuel tax revenue to states of $11.5 billion.

California relies upon a fuel tax triggered by Senate Bill 1 (SB1) in 2017 that potentially can generate $53 billion over 10 years to support highway construction and maintenance and transit improvements to reduce GHG emissions.[9] This source of revenue is intended to support state and local transportation and other projects. The current SB1 excise tax rate is 17.6 cents/gallon (gasoline), and the total CA fuel tax rate is about 63 cents/gallon (gasoline).[10] Diesel fuel has higher rates. The fuel use and SB1 tax revenue for the first week of March 2020 were 377 million gallons and $64 million, respectively. The fuel use and SB1 tax revenue for the second week of April 2020 were 193 million gallons and $33 million, respectively. The Phase 0–1 difference in weekly fuel use and revenue was 184 million gallons and $31 million. The difference between the total CA fuel tax revenue before and after the SIP order (Phase 0–1) was $115 million per week. For the entire Phase 1–Phase 3 traffic-reduction period, the travel reduction would be equivalent to 4.1 billion gallons of fuel not being used and a fuel costs savings to drivers of $10.6 billion and a loss (to the state government) of fuel sales tax revenue of about $2.57 billion.

## 3 Discussion and Conclusion

This chapter provided an overview of how reduced vehicle traffic during the pandemic resulted in an estimated reduction in GHG emissions from the transportation sector in the United States. The estimated reduction includes several important facets: (1) It points to GHG savings that are now "in the bank" in the sense that GHG emissions

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[8] The source of this data is USDOE, Alternative Fuels Data Center, https://afdc.energy.gov/data/.

[9] See https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1.

[10] See https://www.api.org/~/media/Files/Statistics/StateMotorFuel-OnePagers-January-2020.pdf.

were reduced; (2) there is an important potential lesson that reducing VMT can immediately contribute to mitigating climate change; and (3) human behaviors (e.g., less driving) that were adaptive to the pandemic have the potential to contribute to long-term changes that reduce GHG emissions.

The United States and other countries contribute GHG emissions to the atmosphere at an accelerating rate, one which assures large changes in regional climates, sea levels, and even habitability of parts of the Earth. The primary response from governments and academics seems to be to reduce the *net* carbon or carbon-equivalent emissions from industrial and other activities, while maintaining or growing economic and other rate processes [12]. Although there is no evidence that this experiment will work, there has been little focus on other strategies that could rapidly reduce GHG emissions, such as reduced carbon footprint from transportation, in addition to other strategies currently investigated. In this chapter, I addressed the possibly valuable lesson from the pandemic that we could drive less and immediately provide climate change benefits. Although I did not address the lifestyle and workplace changes that accompanied the pandemic and led to less driving, these have been extensively covered in the press and elsewhere.

Government guidance to mitigate the pandemic has primarily consisted of orders to close or limit businesses and non-essential travel by the public. There was a 31–65% reduction in daily travel among U.S. states and the District of Columbia and overall, a 45% reduction in travel across the United States. This indicates that the guidance from the Centers for Disease Control (CDC) and individual states' SIP and similar orders at the municipal scale had a profound effect on daily travel, expressed as miles traveled. This driving reduction resulted in an estimated 45% drop in fuel use, which had inevitable knock-on effects on greenhouse gas emissions and state fuel tax revenue. Residents of U.S. states largely followed government SIP guidance, resulting in the U.S. having sufficient vehicle-related GHG emission reductions over an eight-week period (Phase 0–Phase 1) exceeding the annual target reductions under the Paris Climate Accord (>2%/year reduction) by 2%, for a 4% total annual reduction. This value is very similar to the recently published quantification of the reduction in estimated GHG emissions during the pandemic shut-downs. Le Quere et al. [10] estimated a reduction of 17% of daily global GHG emissions by mid-April, with half coming from surface transport. They also estimated that the total emissions reductions for 2020 were 4–7%.

Because of a sustained reduction in driving, California's reduction in GHG emissions has been greater than the U.S. states' average, putting it on track to get halfway to its 2050 goal for GHG emissions by 2021. Of course, all of these benefits of the SIP orders began to retreat after vaccines allowed normal economic and travel activity to resume, or at least gave the impression that the activity would be safe. This was generally true, except for California, where travel rates remained reduced by as much as 20% through the spring of 2021, compared to the same days in 2019. The continuing reduction could be related to a stronger effect in California of the "work from home" (WFH) strategy that many institutions adopted during the pandemic and which some may be retaining. Although WFH is not new, it rapidly expanded during the pandemic as an adaptation to the reduced travel and contact resulting from the

SIP orders and guidance [2]. Although the WFH strategy holds promise in reducing unnecessary travel and GHG emissions, it poses a risk of exacerbating inequities because of who can work from home and who cannot [2]. For example, ridership on public transit vehicles, which have higher energy efficiency than personal vehicles, plummeted to even lower depths and will take longer to recover, because of fears of transmitting/contracting the virus when in close proximity to other transit riders.

It is possible that the U.S. public is adapting to the multiple unintended consequences of the pandemic response, which may intentionally or unintentionally lead to a reduction in harm from travel and economic activity. The most immediate effect, discussed in this chapter, was the reduction in vehicle distance traveled, which resulted in a reduction in fuel use and fuel costs/taxes. An expected consequence of using less fuel in the United States is a reduction in states' tax revenues from fuel purchases. U.S. states use state and other taxes to maintain and expand highway and road systems. Expanding and otherwise improving road lanes leads to alternating increases in travel and congestion [4, 6, 11]. These tax-fueled expansions lead to greater GHG emissions, assuming most vehicles rely directly or indirectly on fossil fuels. So, an interesting feedback loop created by the pandemic was the reduction in tax revenue, leading to less funds available for road system expansion, leading to reduced GHG emissions. This suggests that during non-pandemic periods, targeting fuel tax revenues could be another control valve on GHG emissions—that is, by limiting fuel tax revenue, the expansion of surface transportation modes that result in GHG emissions would be curtailed. Alternatively, fuel taxes could be re-directed to reductions in total (i.e., not "net") carbon emissions from transportation.

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# Highway Crashes in California During the COVID-19 Pandemic: Insights and Considerations

**Offer Grembek, Praveen Vayalamkuzhi, and SangHyouk Oum**

**Abstract** This chapter describes the results of a short-term analysis of highway crashes in California during the first year of the COVID-19 pandemic. The pandemic has had an unexpected and abrupt influence on the demand for mobility. The effect of this was a drastic reduction in the level of activity on the roads. This level of activity defines the exposure of road users to crash risk and represents a focal variable in the sciences of traffic safety. The rapid rate of change in traffic that occurred during the pandemic, triggered a need to monitor highway safety at a higher frequency than what was previously common in traffic safety studies. We compiled data at the weekly level and analyzed six-week periods. Our analysis shows that the minor injury crash rate per 100 million vehicle-miles traveled (VMT) has gone down from 37.58 per 100 million VMT during the before period to 25.52 per 100 million VMT in the first period after the pandemic. This is a reduction of 32% in the minor injury crash rate per 100 million VMT. In contrast, the more severe and often catastrophic, major injury crash rate per 100 million VMT increased from 4.47 per 100 million VMT during the before period to 5.15 per 100 million VMT in the first period after the pandemic. This is an increase of 14.8% in the major injury crash rate per 100 million VMT. The resulting bifurcation across different crash severity levels indicates that although the overall crash rates dropped, the rate of catastrophic crashes (i.e., fatal and severe) got worse. The main implication of this finding is that a reduction in minor injury crashes does not necessarily correspond to a reduction in major crashes. These findings demonstrate that it is possible to reduce the overall crash rate without making the system safer in terms of fatal and severe crashes, and this should be considered when developing roadway safety programs.

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## 1 Introduction

The COVID-19 pandemic has had an unexpected and abrupt influence on many aspects of our lives. One major impact of the pandemic is a dramatic change in the demand for mobility. Various safe-at-home protocols, which require people to work and learn remotely, have temporarily dissolved the ever-increasing pressure on commute patterns. The remaining commute-related travel was mostly for essential work. The non-commute travel also experienced significant changes due to restrictions related to opportunities for shopping and entertainment. The combined effect of this was a drastic reduction in the level of activity on the roads. This level of activity defines the exposure of road users to crash risk and represents a focal variable in the sciences of traffic safety. Moreover, the sudden change in traffic patterns can also trigger other responses that can affect the safe behavior of road users or the safety of the conditions they travel. This includes both the perspectives of individual road users, who might behave a bit differently under different traffic conditions, and also less congestion and other operational considerations.

The societal impact of traffic safety is massive. In 2016, road crashes in the U.S. claimed the lives of 34,439 people. Of those victims, 23,714 were drivers or occupants of a motor vehicle, 5,987 were pedestrians and 4,738 were motorcyclists, bicyclists, and other non-occupants. The estimated economic cost of all motor vehicle traffic crashes in the United States was $242 billion in 2010 and is undoubtedly higher today [7]. However, despite the overwhelming impact and the catastrophic outcome of fatal and severe crashes, traffic crashes are rare events, if we consider the massive numbers of individual daily trips. Considering this, researchers commonly utilize statistical analysis using data collected over multiple years to systematically study traffic safety. The common range of study periods for safety analyses ranges from three to 5 years of data. However, the rapid rate of change in traffic that occurred during the pandemic, triggered a need to monitor highway safety at a higher frequency than what was previously common in studies about the traffic safety of communities.

This study opens opportunities to evaluate common principles that are agreed upon by safety professionals. For example, the traditional expectation is that when traffic volume drops, the number of crashes will drop as well. The rationale is that with less traffic on the streets, the exposure is lower. While this principle is logical, it overlooks core principles of emerging traffic safety approaches, such as vision zero and the safe system [1, 5, 8]. These approaches are policy innovations to move the needle from our currently unsafe system to a safe system in which no one can be severely or fatally injured. To achieve this, the basic elements of the system are identified with the goal of tapping into the protective capabilities of each element, which include safe roads, safe vehicles, safe speeds, safer users, and post-crash care. These approaches also dictate how these elements need to be fused together to create a safe system. The two core principles in this respect are considering kinetic energy as the focal variable of safety, and recognizing that humans make mistakes [2–4, 6, 9, 10] . The COVID-19 pandemic allows us to compare how the traditional perspective and the novel perspective are aligned with the safety outcomes that we are seeing.

Another common principle that can be evaluated here is the "safety pyramid," which postulates that the most severe (i.e., fatal) crashes represent the top of the pyramid, while the less severe crashes compose a wider layer that represents more crashes. In other words, there is some proportional relationship between different levels of crash severity. Again, this is a valid point, but the natural experiment of the pandemic allows us to examine the situations and if we need to revise our assumptions. With this in mind, this chapter describes the results of a short-term analysis of highway crashes in California during the first year of the pandemic.

The chapter is organized into five sections. First, we present the data that was collected for this purpose and the assumptions it was based on. Next, we describe our data processing and analytical methodology, followed by suggested policy actions within each timeframe. In the next section, we present the results of our analysis across different jurisdictions. And finally, we discuss the findings and the policy implications that can be derived from it.

## 2 Data Sources and Methodology

Traffic safety analysis is commonly comprised of three data types. The first is *transportation safety data,* which is typically sourced from police-reported crashes. It includes the location, date, time, and type of a crash, characteristics of the parties involved, possible presence of intoxication, weather conditions, etc. The second data type is *exposure data*, which approximates the level of activity and is usually based on traffic counts or traffic models. When activity data is not available, it is possible to resort to census or Department of Motor Vehicle (DMV) data sources to represent any population group or licensed road users. Lastly, the third data type, is *infrastructure or land-use data* (e.g., roadway and intersection characteristics, presence of marked or unmarked crosswalks, type of land uses, etc.), which allows for the analysis of the relationship between the built environment and traffic safety.

This chapter is focused on the short-term impact of the pandemic on transportation safety. The roadway infrastructure and land use has not changed during this time and, therefore, data about the built environment was not used in our analysis. Accordingly, the data used here is a combination of safety data and exposure data, as described below.

### *2.1 Crash Data*

The crash data is extracted from police-reported injury crashes that are added to the California Statewide Integrated Traffic Records System (SWITRS) by the California Highway Patrol (CHP). There is a delay related to submitting, processing, and tabulating crash data into SWITRS. The delay is too restrictive for crashes that occur on non-state roads so those were excluded in this effort. Moreover, due to this lag, the data shown may be missing some relevant crashes, particularly those occurring more recently. It is also important to note that while this data is not expected to change, it is considered provisional data until CHP releases the SWITRS Annual Report.

The data displayed in Table 1 was collected at the weekly level for the period between January 6, 2020 and December 28, 2020 and for the corresponding week in 2019 (e.g., Monday March 16, 2020 corresponds to Monday March 18, 2019). The week of March 16, 2020 is highlighted since stay-at-home orders went into effect on March 19, 2020, in response to the COVID-19 pandemic. Our data includes only injury crashes that occurred on the California State Highway System (SHS) during these two chronological segments. The SHS facilities are mostly freeways, but in some jurisdictions, they can also include urban arterials, which are operated by the state.

Table 1 lays out the data as a year-over-year (YOY) comparison between equivalent weeks in 2019 and in 2020. The principles of Vision Zero and the Safe System approach postulate that the fatal and severe crashes are the pertinent ones and need to be monitored separately from other minor crashes. Considering this, the first two columns separate the number of minor injury crashes and the number of Fatal and Severe injuries (labeled as F + SI). The subsequent columns do the same for 2019. The last two columns show the YOY percentage change. The change starts from a 61% decrease in minor injury (March 23, 2020) crashes and slowly changes to a range of 20–30% decrease. We can see that the drop in Fatal and Severe crashes was much smaller and started from a 21% decrease, fluctuating significantly before gradually bouncing back.

A comparison of YOY is not the only way to observe the effect on crashes, however. By looking separately at each of the first two columns, we can also appreciate the longitudinal drop in crashes, from 1,169 minor crashes during the week of March 9, 2020 (before the State-wide stay-at-home orders went into effect) to only 407 during the week of March 23, 2020. Similarly, fatal and severe crashes dropped from 117 to 97.

The data plotted in Fig. 1 can illustrate the longitudinal change in patterns of different crash severity. The fatal and severe crashes are represented by the darker curve and the axis on the left, and the minor injury crashes are represented by the lighter curve and the axis on the right. Figure 1 includes data for 2019 and for 2020. While there are clear fluctuations for both the Fatal + Severe and the Minor Injury curves, the left side of the figure (which mostly represents 2019) has a noticeable overlap. However, two notable differences are observed when we look at the curves during the week of March 16, 2020 (denoted by the vertical dashed line). First, there is a dramatic drop in both curves due to the San Francisco Bay Area Shelter-in-Place order of March 16, 2020 and the overarching California Stay-at-Home order of March 19, 2020. Second, there is a separation of the curves, which shows that the reduction in minor injury crashes was larger and longer-lasting relative to the fatal and severe crashes. Thus, these preliminary observations indicate that the impact of the these stay home orders was not the same across different crash severities.

**Table 1** Police-reported injury crashes on state highways in California. Data Source: CHP's Statewide Integrated Traffic Records System (SWITRS). Data retrieved on September 30, 2021

| Weekly start date 2020 | 2020 | | 2019 | | YOY weekly percent change | |
|---|---|---|---|---|---|---|
| | Minor crashes | F+SI crashes | Minor crashes | F+SI crashes | Minor crashes (%) | F+SI crashes (%) |
| 1/6/2020 | 986 | 111 | 1028 | 114 | −3.9 | −2.6 |
| 1/13/2020 | 989 | 112 | 1202 | 111 | −16.1 | 0.9 |
| 1/20/2020 | 939 | 113 | 1100 | 120 | −13.8 | −5.8 |
| 1/27/2020 | 1049 | 113 | 1162 | 120 | −9.4 | −5.8 |
| 2/3/2020 | 951 | 100 | 1,230 | 86 | −20.1 | 16.3 |
| 2/10/2020 | 1,030 | 126 | 1,168 | 103 | −9.0 | 22.3 |
| 2/17/2020 | 965 | 133 | 964 | 103 | 2.9 | 29.1 |
| 2/24/2020 | 1,068 | 133 | 1,145 | 130 | −5.8 | 2.3 |
| 3/2/2020 | 1,039 | 131 | 1,066 | 105 | −0.1 | 24.8 |
| 3/9/2020 | 1,169 | 117 | 1,120 | 141 | 2.0 | −17.0 |
| 3/16/2020 | 632 | 87 | 1,151 | 108 | −42.9 | −19.4 |
| 3/23/2020 | 407 | 97 | 1,053 | 116 | −56.9 | −16.4 |
| 3/30/2020 | 413 | 82 | 1,017 | 99 | −55.6 | −17.2 |
| 4/6/2020 | 638 | 89 | 1,035 | 122 | −37.2 | −27.0 |
| 4/13/2020 | 388 | 91 | 1,039 | 119 | −58.6 | −23.5 |
| 4/20/2020 | 452 | 116 | 1,059 | 137 | −52.5 | −15.3 |
| 4/27/2020 | 515 | 93 | 1,102 | 133 | −50.8 | −30.1 |
| 5/4/2020 | 573 | 109 | 1,031 | 101 | −39.8 | 7.9 |
| 5/11/2020 | 586 | 97 | 1,256 | 114 | −50.1 | −14.9 |
| 5/18/2020 | 651 | 95 | 1,057 | 114 | −36.3 | −16.7 |
| 5/25/2020 | 594 | 114 | 979 | 126 | −35.9 | −9.5 |
| 6/1/2020 | 643 | 126 | 1,109 | 140 | −38.4 | −10.0 |
| 6/8/2020 | 762 | 108 | 1,159 | 129 | −32.5 | −16.3 |
| 6/15/2020 | 800 | 135 | 1,041 | 152 | −21.6 | −11.2 |
| 6/22/2020 | 813 | 122 | 1,074 | 138 | −22.9 | −11.6 |
| 6/29/2020 | 752 | 117 | 949 | 141 | −20.3 | −17.0 |
| 7/6/2020 | 796 | 126 | 1,077 | 132 | −23.7 | −4.5 |

(continued)

**Table 1** (continued)

| Weekly start date 2020 | 2020 | | 2019 | | YOY weekly percent change | |
|---|---|---|---|---|---|---|
| | Minor crashes | F+SI crashes | Minor crashes | F+SI crashes | Minor crashes (%) | F+SI crashes (%) |
| 7/13/2020 | 762 | 140 | 1,190 | 154 | −32.9 | −9.1 |
| 7/20/2020 | 779 | 146 | 1,105 | 142 | −25.8 | 2.8 |
| 7/27/2020 | 777 | 123 | 1,114 | 141 | −28.3 | −12.8 |
| 8/3/2020 | 800 | 141 | 1,104 | 143 | −24.5 | −1.4 |
| 8/10/2020 | 891 | 124 | 1,110 | 136 | −18.5 | −8.8 |
| 8/17/2020 | 803 | 139 | 1,191 | 151 | −29.8 | −7.9 |
| 8/24/2020 | 835 | 125 | 1,127 | 132 | −23.7 | −5.3 |
| 8/31/2020 | 887 | 141 | 1,124 | 131 | −18.1 | 7.6 |
| 9/7/2020 | 756 | 156 | 1,128 | 127 | −27.3 | 22.8 |
| 9/14/2020 | 840 | 134 | 1,171 | 145 | −26.0 | −7.6 |
| 9/21/2020 | 959 | 162 | 1,129 | 135 | −11.3 | 20.0 |
| 9/28/2020 | 911 | 140 | 1,173 | 154 | −20.8 | −9.1 |
| 10/5/2020 | 903 | 108 | 1,134 | 159 | −21.8 | −32.1 |
| 10/12/2020 | 985 | 149 | 1,152 | 120 | −10.8 | 24.2 |
| 10/19/2020 | 823 | 143 | 1,123 | 151 | −24.2 | −5.3 |
| 10/26/2020 | 989 | 157 | 1,158 | 129 | −11.0 | 21.7 |
| 11/2/2020 | 921 | 144 | 1,231 | 127 | −21.6 | 13.4 |
| 11/9/2020 | 908 | 132 | 1,160 | 122 | −18.9 | 8.2 |
| 11/16/2020 | 932 | 116 | 1,221 | 120 | −21.8 | −3.3 |
| 11/23/2020 | 829 | 136 | 1,184 | 149 | −27.6 | −8.7 |
| 11/30/2020 | 816 | 103 | 1,239 | 108 | −31.8 | −4.6 |
| 12/7/2020 | 816 | 110 | 1,178 | 116 | −28.4 | −5.2 |
| 12/14/2020 | 730 | 119 | 1,196 | 118 | −35.4 | 0.8 |
| 12/21/2020 | 734 | 116 | 954 | 109 | −20.0 | 6.4 |
| 12/28/2020 | 702 | 109 | 740 | 104 | −3.9 | 4.8 |

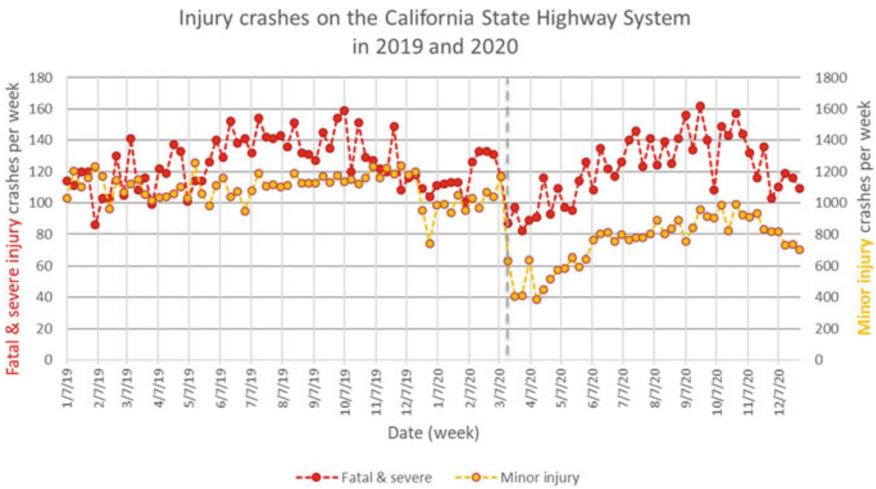


**Fig. 1** Weekly police-reported injury crashes on the California State Highway System before and during the COVID-19 pandemic. *Data source* California Statewide Integrated Traffic Records System (SWITRS)

## *2.2 Exposure Data*

Operational data is commonly used as a form of exposure data in traffic safety. It is typically represented using Vehicle-Miles Traveled (VMT), which are calculated using in-pavement loop detectors. The California Department of Transportation (Caltrans) monitors the flow of vehicles using such loop detectors on the California State Highway System. The data is processed and does not suffer from a reporting lag. The output is available online through the Caltrans Performance Measurement System (PeMS). The data includes all the roadway facilities on the California State Highway System. These vast facilities are freeways, but in some jurisdictions, they can also include urban arterials which are operated by Caltrans. Similarly to traffic safety data, we exported the exposure data for this study for each week between January 6, 2020 and December 28, 2020 and the corresponding week in 2019.

Table 2 summarizes Vehicle Miles Traveled on the California State Highway System; this is a measure of exposure calculated by multiplying the amount of daily traffic by the directional distance. This table also lays out the data as a year-over-year (YOY) comparison between equivalent weeks in 2019 and 2020, with the last column being the YOY percent change. By looking at changes in the VMT just before and after the initiation of stay-at-home orders during the week of March 16, 2020, we can also appreciate the drop in VMT, from 2,570 million VMT during the week of March 9, 2020 (before the stay home orders were initiated) to only 1,804 million VMT during the week of March 23, 2020. By examining Fig. 2, we can see that the change starts on March 23, 2020, with a 37% drop in VMT from the previous year, and it consistently converges back to a drop of about 10% by June 2020.

**Table 2** Exposure Data: Vehicle miles traveled on the California State Highway System before and during the COVID-19 pandemic. Data source: Caltrans Performance Measurement System (PeMS). Data retrieved on September 30, 2021

| Weekly Start Date for 2020 | Vehicle-Miles Traveled (Millions) | | YOY weekly Percent change |
|---|---|---|---|
| | **2020** | **2019** | |
| 1/6/2020 | 2,723.12 | 2,689.28 | 1.3 |
| 1/13/2020 | 2,756.82 | 2,648.92 | 4.1 |
| 1/20/2020 | 2,759.79 | 2,757.30 | 0.1 |
| 1/27/2020 | 2,748.80 | 2,667.42 | 3.1 |
| 2/3/2020 | 2,765.44 | 2,729.04 | 1.3 |
| 2/10/2020 | 2,817.61 | 2,728.67 | 3.3 |
| 2/17/2020 | 2,800.07 | 2,791.92 | 0.3 |
| 2/24/2020 | 2,813.64 | 2,751.28 | 2.3 |
| 3/2/2020 | 2,789.33 | 2,779.12 | 0.4 |
| 3/9/2020 | 2,570.43 | 2,840.22 | −9.5 |
| 3/16/2020 | 2,062.24 | 2,858.41 | −27.9 |
| 3/23/2020 | 1,804.62 | 2,865.38 | −37.0 |
| 3/30/2020 | 1,783.36 | 2,840.23 | −37.2 |
| 4/6/2020 | 1,712.41 | 2,865.43 | −40.2 |
| 4/13/2020 | 1,832.01 | 2,887.58 | −36.6 |
| 4/20/2020 | 1,904.41 | 2,895.55 | −34.2 |
| 4/27/2020 | 1,987.98 | 2,872.63 | −30.8 |
| 5/4/2020 | 2,103.58 | 2,883.71 | −27.1 |
| 5/11/2020 | 2,126.63 | 2,851.26 | −25.4 |
| 5/18/2020 | 2,238.47 | 2,861.59 | −21.8 |
| 5/25/2020 | 2,232.05 | 2,816.82 | −20.8 |
| 6/1/2020 | 2,300.26 | 2,888.54 | −20.4 |
| 6/8/2020 | 2,431.11 | 2,914.86 | −16.6 |
| 6/15/2020 | 2,501.35 | 2,888.87 | −13.4 |
| 6/22/2020 | 2,499.59 | 2,900.37 | −13.8 |
| 6/29/2020 | 2,430.13 | 2,780.64 | −12.6 |
| 7/6/2020 | 2,495.30 | 2,891.99 | −13.7 |
| 7/13/2020 | 2,486.06 | 2,914.37 | −14.7 |
| 7/20/2020 | 2,507.41 | 2,915.13 | −14.0 |

(continued)

**Table 2** (continued)

| Weekly Start Date for 2020 | Vehicle-Miles Traveled (Millions) | | YOY weekly Percent change |
|---|---|---|---|
| | **2020** | **2019** | |
| 7/27/2020 | 2,535.39 | 2,914.10 | −13.0 |
| 8/3/2020 | 2,548.31 | 2,920.36 | −12.7 |
| 8/10/2020 | 2,558.07 | 2,898.30 | −11.7 |
| 8/17/2020 | 2,531.36 | 2,890.24 | −12.4 |
| 8/24/2020 | 2,546.71 | 2,886.82 | −11.8 |
| 8/31/2020 | 2,566.98 | 2,800.77 | −8.3 |
| 9/7/2020 | 2,475.91 | 2,873.06 | −13.8 |
| 9/14/2020 | 2,557.28 | 2,876.22 | −11.1 |
| 9/21/2020 | 2,582.53 | 2,867.18 | −9.9 |
| 9/28/2020 | 2,576.19 | 2,861.75 | −10.0 |
| 10/5/2020 | 2,586.04 | 2,843.22 | −9.0 |
| 10/12/2020 | 2,599.15 | 2,864.92 | −9.3 |
| 10/19/2020 | 2,581.25 | 2,833.36 | −8.9 |
| 10/26/2020 | 2,557.73 | 2,803.18 | −8.8 |
| 11/2/2020 | 2,496.13 | 2,826.48 | −11.7 |
| 11/9/2020 | 2,531.62 | 2,809.71 | −9.9 |
| 11/16/2020 | 2,521.89 | 2,798.89 | −9.9 |
| 11/23/2020 | 2,415.38 | 2,655.73 | −9.1 |
| 11/30/2020 | 2,459.47 | 2,725.49 | −9.8 |
| 12/7/2020 | 2,396.11 | 2,813.44 | −14.8 |
| 12/14/2020 | 2,458.64 | 2,845.80 | −13.6 |
| 12/21/2020 | 2,305.32 | 2,605.68 | −11.5 |
| 12/28/2020 | 2,249.19 | 2,674.12 | −15.9 |

## *2.3 Crash Rates*

It is important to mention that the total number of injury crashes across all levels of severity decreased during the observation period in 2020 (during the pandemic) as compared to the previous year (before the pandemic). This is a desirable outcome, but not sufficient to quantify the traffic safety impact. To better assess the impact

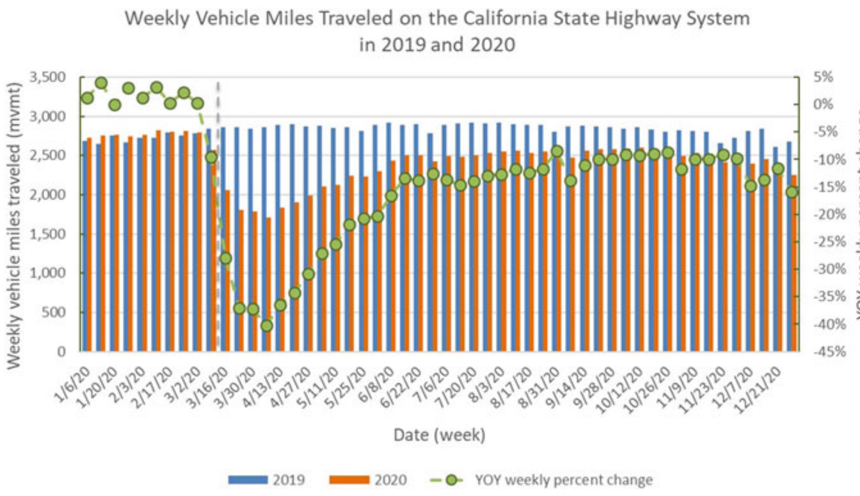


**Fig. 2** Weekly vehicle-miles traveled on the California state highway system before and during the COVID-19 pandemic. *Data source* Caltrans performance measurement system (PeMS)

on traffic safety, we also need to analyze the crash rates by controlling for exposure using VMT.

While this data is technically considered provisional, at this point only minor changes to the data are expected, if any. Considering this, it is already possible to make some important observations by conducting a naïve before-after comparison. The before data is based on the six weeks prior to California's Stay Home orders and include the week of January 6, 2020 through the week of March 9, 2020. The week of March 16, 2020 is excluded since it was a transitional week between the before and after periods. The after data included seven separate six-week periods after California's Stay Home orders. These weeks are considered individual observation points, and the result of this analysis is described in the next section.

## 3 Findings

Table 3 summarizes the results of the six-week observations and analysis of the crash rates across minor injury crashes (two lowest injury levels) and major injury crashes (severe and fatal) for the year 2020 and the pre-pandemic year. The results of our analysis can provide some valuable insights.

The first observation is that the impact on safety was different for different levels of crash severity. Table 3 shows that the minor crash rates in 2020 across all the periods after the initiation of the stay-at-home order are lower than on March 9, 2020 when the rate was 37.58 per 100 million VMT. Note that the rates are also lower in 2020 for the before period than in 2019 (37.79 vs. 41.21), but this difference is much

**Table 3** Injury crash rate on the SHS during 2020 and 2019

| Weekly start date for six-week period | Minor crash rate (crash/mvmt) | F + SI crash rate (crash/mvmt) |
|---|---|---|
| 2/25/2019 | 41.21 | 4.03 |
| 4/8/2019 | 37.79 | 4.05 |
| 5/20/2019 | 37.93 | 4.16 |
| 7/1/2019 | 36.71 | 4.81 |
| 8/12/2019 | 38.39 | 4.86 |
| 9/23/2019 | 39.96 | 4.77 |
| 11/4/2019 | 40.93 | 4.93 |
| 12/16/2019 | 43.11 | 4.40 |
| 1/27/2020 | 34.77 | 4.07 |
| 3/9/20 | 37.58 | 4.47 |
| 4/27/20 | 25.52 | 5.15 |
| 6/8/20 | 28.36 | 4.83 |
| 7/20/20 | 31.52 | 5.27 |
| 8/31/20 | 32.66 | 5.19 |
| 10/12/20 | 34.82 | 5.52 |
| 11/23/20 | 35.77 | 5.48 |
| 12/28/20 | 32.31 | 4.67 |

*Data sources* Caltrans performance measurement system (PeMS); California statewide integrated traffic records system (SWITRS)

smaller than the previous one. However, when we look at the severe crash rates, the impact is reversed. We can see that the F + SI crash rate is higher in each of the after periods. This opposite change in the impact of the pandemic on crash severity is non-intuitive to traditional safety principles, which would expect a more similar effect.

As we continue to examine this, we can more explicitly see the immediate impact and the trend in the longitudinal impact on the two levels of severity in 2020. This can be observed in Fig. 3, which provides a visual illustration of the impact and the bifurcation across different crash severity levels. The chart includes two different curves with a different vertical axis, one for minor crashes and one for fatal and severe crashes.

The minor injury crash rate per 100 million VMT has gone down from 37.58 per 100 million VMT during the *before* period to 25.52 per 100 million VMT in the first *after* period. This is a reduction of 32% in the minor injury crash rate per 100 million VMT. The following *after* periods demonstrate a smaller but noticeable reduction. It can also be observed that the reductions are gradually recovering and slowly moving back up towards the rate of the before period.

In contradiction, the more important, and often catastrophic, major injury crash rate per 100 million VMT has gone up from 4.47 per 100 million VMT during the

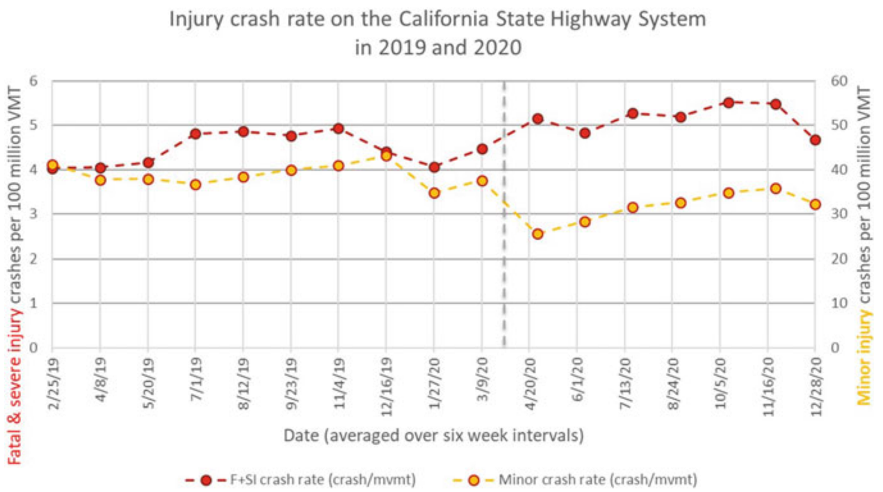


**Fig. 3** Injury crash rate on the California SHS during the COVID-19 pandemic. *Data sources* Caltrans Performance Measurement System (PeMs); California Statewide Integrated Traffic Records System (SWITRS)

*before* period to 5.15 per 100 million VMT in the first *after* period. This is an increase of 14.8% in the major injury crash rate per 100 million VMT. The following *after* periods also demonstrate a smaller but noticeable increase and have stayed somewhat stable.

## 4 Discussion

The findings discussed in the previous section indicate that although the overall crash rates dropped, the rate of catastrophic crashes (i.e., fatal and severe) got worse. There are probably several factors that have led to this outcome. If we use a Safe System lens to evaluate this, we can review the different elements of the system across roads, vehicles, speeds, users, and post-crash care to help us understand this outcome.

We know that the design elements (vehicle and road) did not change during this time. We expect some changes in post-crash care due to COVID-19 protocols. We also expect some changes in user behavior due to the emotional toll of the pandemic, which can include situations of excessive speeding. However, the element which can explain this dramatic change is a systemic change of operational average speed. We suggest that this change in speed is associated with a reduction in traffic congestion during the pandemic and goes beyond the impact of individual speeding events. The lower occurrence of congested periods has the implication of an increase in average speeds and more opportunities for excessive speeding than before the pandemic. Again, while reducing traffic congestion is a desirable thing, the result is that the average amount of kinetic energy for a trip is now higher. In turn, this increases the magnitude of the safety problem. In other words, the roads and vehicles are now expected to contain or control higher levels of kinetic energy. If we combine this with the Safe System principle that expects human error, the outcome is that the consequence of each human error will now be larger. This has additional policy implications for traffic operations, since it might justify coupling congestion mitigation efforts with safety improvements.

This postulation can also explain the reduction in minor crashes. Since there is less congestion, there are fewer human errors during low-speed trips, which commonly lead to minor injury or property damage only. Another practical implication of this finding is that a reduction in minor injury crashes does not necessarily correspond to a reduction in major crashes. If the focus is the ability to prevent fatal and severe crashes, these findings demonstrate that it is possible to reduce the overall crash rate without making the system safer. Accordingly, to reduce fatal and severe crashes, it is critical to make sure that the most pertinent data is used. If all crash severity levels are used together, it can dilute an agency's ability to allocate life-saving resources to the situations that need it the most.

Lastly, the findings here open opportunities to further examine our understanding of the safety pyramid. While the findings do not challenge the existence of the safety pyramid, they do demonstrate that the relationship between different layers of the pyramid is not static. The idea of the crash pyramid does indeed hold when we are looking at a specific crash type (i.e., all else equal) but may not be transferable to other types of crashes. Furthermore, if the causal mechanism of many minor crashes is different from that of catastrophic crashes, one can question the value of using the number of minor crashes as a proxy for major crashes. The policy implications here are again valuable, since we also want to make sure we are focusing our countermeasures on these fatal and severe crashes, as opposed to all crashes.

## Appendix: Data Dashboard

In addition to the efforts to track the crash data, the UC Berkeley Safe Transportation Research and Education Center has made the data available on the center's website. The data was updated daily/weekly as part of a provisional Injury Crashes During COVID-19 dashboard. The dashboard allows users to view the data across three geographical areas for all the state highways in California and covering the two main urban metros. Additional tables include a breakdown by crash severity, primary collision factors, and transportation modes.

The dashboard is shown in Fig. 4 and can be found at https://tims.berkeley.edu/covid19.php.


**Provisional weekly police-reported injury crashes on state highways in California**

Data on this page is updated daily and can be used to monitor the frequency and type of crashes that occur in the weeks prior, during, and after California's stay home order, which went into effect on March 19, 2020 in response to the COVID-19 pandemic.

**Note:**

Provisional crash data are based on police reports of crashes that occurred on state highways. Crashes are added to the California Statewide Integrated Traffic Records System (SWITRS) by the California Highway Patrol (CHP) and we download them from the I-SWITRS website on a daily basis. There is a delay related to submitting, processing, and tabulating crash data into SWITRS. Due to this lag, the data shown on this page may exclude some relevant crashes, particularly those occurring in the most recent two to three weeks. Crash counts for all weeks are revised as new and updated crash data are received. These data do not currently include crashes that occurred on non-state roads.

Last Updated:

— Collisions as of October 20, 2020 from *CHP I-SWITRS*
— Vehicle Miles Traveled as of October 13, 2020 from *Caltrans Performance Measurement System (PeMS)*

Area: California

Table Option: Overall Summary By Primary Collision Factor By Ped & Bike

**Fig. 4** UC Berkeley SAFETREC weekly injury crashes dashboard COVID-19

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# Impacts on Mobility and Travel

# Changes in Active Travel During the COVID-19 Pandemic

**Sean McElroy, Dillon T. Fitch, and Giovanni Circella**

**Abstract** This chapter examines the impact of the pandemic on walking and bicycling using three longitudinal samples of U.S. adults in the time of COVID-19. We use data from a unique longitudinal panel that was created as a combination of research projects conducted during 2018, 2019, and 2020 at the University of California, Davis. Data was collected in a sequence of four waves of data collection to better understand how active travel changed from early lockdown orders through lifts in travel restrictions. Bicycling in all three panels showed examples of an increase in the mode share for commuting at the start of the pandemic along with less of a decrease in the absolute number of trips with this mode, compared to other modes. Through person-level change and changes in mode share, walking showed an increase for non-work travel and daily physical activity during the spring of 2020. The analyses presented in this chapter show how some respondents initially turned to active travel during the early pandemic months, but that active travel generally waned later into the pandemic.

## 1 Introduction

Dramatic restrictions to social gatherings and fear of infection have impacted walking and bicycling (active travel) during the COVID-19 pandemic in a wide variety of

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ways. In addition, the closure or reduced capacity of businesses, schools, and public facilities, in response to social distancing guidelines and lockdown measures, reduced the demand for out-of-home activities. Changes in activity patterns were accompanied by absolute reductions in travel as well as shifts from public transit to more private and socially-distant modes of transportation such as privately-owned cars, bicycles, and walking [1, 11, 28]. Large increases in social and recreational travel have been associated with reported increases in walking and bicycling during the pandemic [41, 46], as well as with surges in the sale of conventional and electric bicycles [3, 15, 24, 25, 30, 45, 47]. However, not all increases in active travel were for recreation. While many former commuters sheltered at home, essential workers continued to travel to work, and often did so through active modes [22, 40].

To meet the demand for and promote active travel, many cities throughout the world took the initiative to expand existing or implement new infrastructure to facilitate the use of these modes. Local governments implemented provisional bicycle infrastructure such as "pop-up" bike lanes or made other improvements that included full or partial street closures ("open streets" or "slow streets") allowing local traffic only, decreased speed limits, automated walk signals, and curb space reallocation [9, 13, 37, 39]. One study that evaluated the impact of new bicycling infrastructure on bicycling rates in 106 European cities using data from bicycle counters found that these projects on average resulted in a 41.6% increase in bicycling volume [27]. Using permanent bike count data, another study found increases in bicycling volume between 5% and 20% in major European countries and select regions in the United States and Canada with most of the increases occurring on weekends, which is consistent with the narrative of more active recreational trips [6, 49]. Similar results were also reported from passively collected smartphone location-based service and cellular data such as Streetlight Data[1] showing an average increase of 13% in bicycling activity between May 2019 and May 2020 in the United States; however, patterns varied by metro area as well as the month chosen for the year-over-year comparison [15, 42].

Despite the many reports and empirical evidence of increases in active travel, there is concern from the public health field that the closure or reduced capacity of out-of-home locations and social distancing have increased sedentary behavior and reduced the capacity for physical activity, especially daily activity [20, 34]. One international online survey found an average decrease of 33.5% in physical activity and a 28.6% increase in daily sitting time [31]. Such observed reductions in physical activity induced by the pandemic could potentially have negative effects on the well-being of many individuals who have become more sedentary, at least in part due to pandemic-related changes [12]. Many studies cite the importance of daily physical activity to boost the immune system to reduce the risk and severity of respiratory viral infections [32, 44]. Further, maintaining regular physical activity can prevent the incidence of comorbidities such as obesity, diabetes, hypertension, cardiovascular disease, and other serious heart conditions for both adults and children [2, 16, 47]. The reduced physical activity associated with the pandemic is of particular concern for

[1] See www.streetlightdata.com.

young children. With historically high prevalence of childhood obesity, the closure of schools and the reduced access to physical activity opportunities such as recess, walking to and from school, youth sports programs, and physical education (P.E.) have likely exacerbated the problem [2, 16].

Although previous research has examined the impact of the pandemic during its early months on active travel, limited research exists on the changes in walking and bicycling over the duration of the pandemic. Another gap in the literature is a discussion of the parallel evidence of increasing active travel and increasing sedentary behavior. Considering the observations of increased sedentary behavior (likely from decreases in walking) and increased physical activity from active travel during the pandemic, this chapter examines the impact of the pandemic on walking and bicycling among U.S. adults.

## 2 Sample Characteristics and Demographics

We use data from a unique longitudinal panel that was created as a combination of research projects conducted during 2018, 2019, and 2020 at the University of California, Davis. Data was collected in a sequence of four waves of data collection, with the first data collection occurring in 2018, as part of the 2018 California Mobility Study[2] (N = 3767), which used a statewide sample of California residents. The second data collection was carried out as part of the 8 Cities Travel Survey (N = 3410), which collected data from a sample of respondents who lived in eight cities across the United States in 2019. The third and fourth data collections were carried out as part of a pandemic-specific study, the COVID-19 Mobility Study[3] (N = 13,658 in spring 2020; and N = 8,029 in fall 2020). The surveys administered as part of that project also collected data for 2019, with a set of retrospective travel behavior questions that were included in the 2020 survey instruments.

The geographic scope in the California Mobility Study and 8 Cities Travel Survey is well defined with sampling conducted in the state of California and eight large metropolitan areas across the United States (Boston, San Francisco, Sacramento, Seattle, Los Angeles, Kansas, Salt Lake City and the District of Columbia), respectively. Due to the recontact of respondents from pre-pandemic survey rounds as well as two other recruitment methods, both COVID-19 surveys share a more diverse geographic scope with respondents from regions across the United States.

All surveys were designed for a longitudinal panel analysis (person-level) and to maintain consistent survey language and structure across the questionnaires, to the extent possible. The survey instruments collected information on a variety of topics including the use of active travel modes, regular travel patterns, activity participation, adoption of work from home and telecommuting patterns, shopping behaviors, use of

[2] For more information, please read the project report for the 2018 California Mobility Study [8].

[3] For more information on the COVID-19 Mobility Study, please visit the project website [38].

**Table 1** Summary of longitudinal panel datasets in the study

| Survey wave | California panel (N = 305) | 8 cities panel (N = 404) | Nationwide panel (N = 2,769) |
|---|---|---|---|
| • 2018 California mobility study (N = 3,767) | ✓ | ✖ | ✖ |
| • 2019 8 cities survey (N = 3,410) | ✖ | ✓ | ✖ |
| • 2020 COVID-19 mobility study (spring 2020; N = 13,658) | ✓ | ✓ | ✓ |
| • 2020 COVID-19 mobility study (fall 2020; N = 8,029) | ✓ | ✓ | ✓ |

shared mobility and emerging delivery services, as well as individual and household-level characteristics, including household size and composition, presence of children, and vehicle ownership.

We grouped responses to these surveys into the three longitudinal panel datasets (California, 8 Cities, and Nationwide) to examine the person-level change in active travel across time periods (Table 1), using repeated observations for the same respondents. It should be noted that we observe a relatively high mode share for transit use in this study at all times (much higher than the U.S. average) because the data collections mainly focused on large metropolitan areas, which are often served by relatively dense, high-quality public transportation networks.

We analyzed demographic characteristics of the entire sample of respondents as well as the demographics of people who bicycle and people who walk to destinations. By comparing the differences between the sample demographics and the demographics of people who bicycle and people who walk, we conclude that our samples seem to represent what has been previously reported about the demographics of people who bicycle and people who walk to destinations in the United States. Both people who bicycle and people who walk to destinations in our samples are more likely to live in urban areas. People who bicycle are more likely to be men, young, and of higher incomes [6]. However, because the data collections include a variety of non-probability sampling techniques limiting the representativeness of our sample (also in terms of unobserved characteristics of respondents), we refrain from making strong inferences about the population at large. Instead, we focus on person-level change, the one major advantage of our study design.

# 3 Findings

## *3.1 Broad Travel Changes*

Figure 1 illustrates the changes in the self-reported commuting behavior identifying the groups of commuters who traveled to work or school (or did not) in each panel dataset. The information for commuting and telecommuting behavior was extracted from the self-reported frequencies of telecommuting and commuting trips reported by the respondents in the survey. Respondents were categorized as *Commuters (only)*, *Telecommuters (only),* or C*ommuters & Telecommuters*, based on their commuting behavior in each time period. The analysis was restricted to only individuals who were workers or students. Members of the latter group (C*ommuters & Telecommuters*) reported they both physically traveled to work or school and worked remotely at least one day a week. Commuting behavior to a physical work or school location was dominant in each panel in the pre-pandemic time periods. Consistent with the information reported by other studies that have analyzed the impacts of the pandemic on transportation, we observed a clear shift to a larger adoption of telecommuting during the early pandemic months in spring 2020, which was associated with a decrease in commuting to a physical work or school location.

While commuting declined overall, the decline was not consistent across travel modes. Walking and bicycling for commute purposes (to either work or school) declined between the pre-pandemic and pandemic time periods in our data, but to a smaller degree than other commute modes. Our data shows that early in the pandemic, the majority of the commuting respondents traveled to work or school in a private vehicle, which is consistent with the usual commuting patterns in U.S. cities. Mode share of private vehicles for commuting further increased during the early months of the pandemic.

The use of active travel modes accounted for a smaller share of commute trips than private vehicles also in Spring 2020. Walking was in general more prevalent than bicycling (personal and shared bikes) during that spring as well as during the other four time periods (Table 2). The lack of decline in active travel commute mode share, especially compared to public transit use which declined considerably, complements the narrative that both active travel and private vehicle modes experienced an increase in the *share* of commute travel because they offered socially-distant travel options.

Walking and bicycling for non-work trips follow a similar trend for both travel modes. When considering non-work trips, mode shares for walking increased for commuters and non-commuters between the pre-pandemic and pandemic time periods, but this increase had largely disappeared by Fall 2020 for non-commuters. As it can be seen in Table 2, the larger increase in walking mainly happened for non-work trips, among those who did not commute during the pandemic. This makes sense, as this group also includes those who switched to telecommuting, and might have looked at non-work walking trips as a source of physical activity during the days they would otherwise spend at home. Indeed, non-commuters have higher shares of walking for non-work trips and, despite the reduction in mode share between Spring

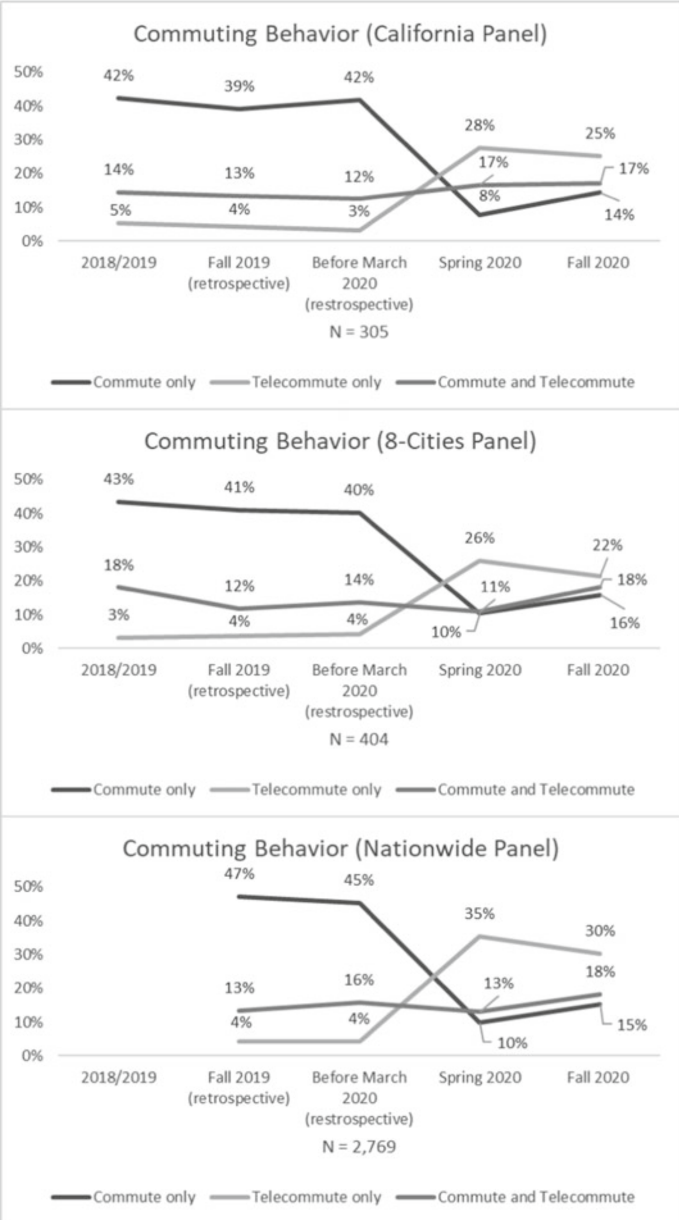


**Fig. 1** Differences in commuting behavior (California, 8 Cities and Nationwide Panels). *Data sources* Authors' surveys

**Table 2** Changes in commute and non-work trip mode share (California, 8 Cities and Nationwide Panels)

| | Trip purpose | Commuter status | Walking 2018/2019 (%) | Walking Fall 2019 (%) | Walking Spring 2020 (%) | Walking Fall 2020 (%) | Bicycling 2018/2019 (%) | Bicycling Fall 2019 (%) | Bicycling Spring 2020 (%) | Bicycling Fall 2020 (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| California panel | Commute | Commuter | 6.8 | 12.1 | 7.9 | 8.7 | 2.0 | 4.6 | 3.7 | 3.0 |
| | Non-work travel | Commuter | 10.0 | 14.0 | 12.8 | 15.6 | 2.9 | 4.5 | 4.3 | 4.2 |
| | | Non-commuter | 21.2 | 25.3 | 44.0 | 31.2 | 6.4 | 4.0 | 6.7 | 6.1 |
| 8 cities panel | Commute | Commuter | 13.4 | 13.7 | 12.5 | 10.4 | 3.9 | 4.3 | 5.2 | 3.5 |
| | Non-work travel | Commuter | 13.8 | 17.8 | 16.0 | 18.2 | 5.7 | 5.5 | 4.2 | 3.9 |
| | | Non-commuter | 24.8 | 25.9 | 43.0 | 32.3 | 3.3 | 2.8 | 6.2 | 3.8 |
| Nationwide panel | Commute | Commuter | | 14.2 | 11.5 | 11.6 | | 4.1 | 4.1 | 4.0 |
| | Non-work travel | Commuter | | 18.5 | 17.3 | 17.5 | | 4.5 | 5.0 | 4.5 |
| | | Non-commuter | | 25.2 | 42.9 | 33.1 | | 3.2 | 6.5 | 4.2 |

*Data sources* Authors' surveys

and Fall 2020, there is some retention of the increased share of walking trips in both groups. The differences in non-work travel mode share between commuters and non-commuters are much smaller for bicycling trips. Nevertheless, changes in bicycling mode share follow similar trajectories to walking for non-work travel.

The prior discussion of the changes in trip frequency for commuting and non-work travel purposes for walking and bicycling provides evidence for a substantial decrease in non-work travel on these modes between Spring 2020 and Fall 2020. This is an observation that might be explained as a combination of the effect of the reopening of in-person activities and the need to work in-person (i.e., a reversal of the early pandemic trends), as well as seasonal effects associated with the colder season, which discourages the use of active modes of travel.

## *3.2 Group-Level Changes in Active Travel*

When merged at the dataset level, changes in walking and bicycling trip frequency reiterate the person-level change profiles. The largest change profile was a decrease in walking for commute purposes, which is apparent in the substantial increase in respondents who either stopped commuting or switched to working from home in Spring 2020 (Fig. 2). This profile was common in all three datasets, especially the increase in respondents who stopped commuting. The less prominent change profile included increases in trip frequency, particularly among workers returning to commuting to a physical work or school location. Individual change profiles for this group included respondents who returned to their previous reported trip frequency along with others who reported similar frequencies to those before the pandemic. Group-level changes in walking for non-work travel were more common than commute travel. Among those who increased their walking for non-work purposes during the pandemic, and differently from bicycling, many maintained or at least did not completely revert to their prior level (or lack) of walking by Fall 2020, suggesting the pandemic may have caused some more lasting effects on walking behavior (Fig. 3). This does not translate into saying that all people who increased their walking early during the pandemic maintained their walking into Fall 2020, though. The most common walking change profile experienced an increase in walking for non-work travel during Spring 2020, at the peak of the pandemic and in-person work restrictions, but then slightly reduced their walking by Fall 2020. Still, they continued to walk more than in their pre-pandemic life. This profile is most apparent in the California and Nationwide panel and appears to complement the many news reports of increases in the use of active modes for non-work travel [29].

Walking trip frequency showed more behavior changes at the dataset level than bicycling for commute and non-work travel. The group of people who showed no behavior change was considerably smaller for walking than for bicycling. This suggests that the barriers to change walking behavior were less strong compared to bicycling. This is not surprising, given the overwhelming evidence that traffic

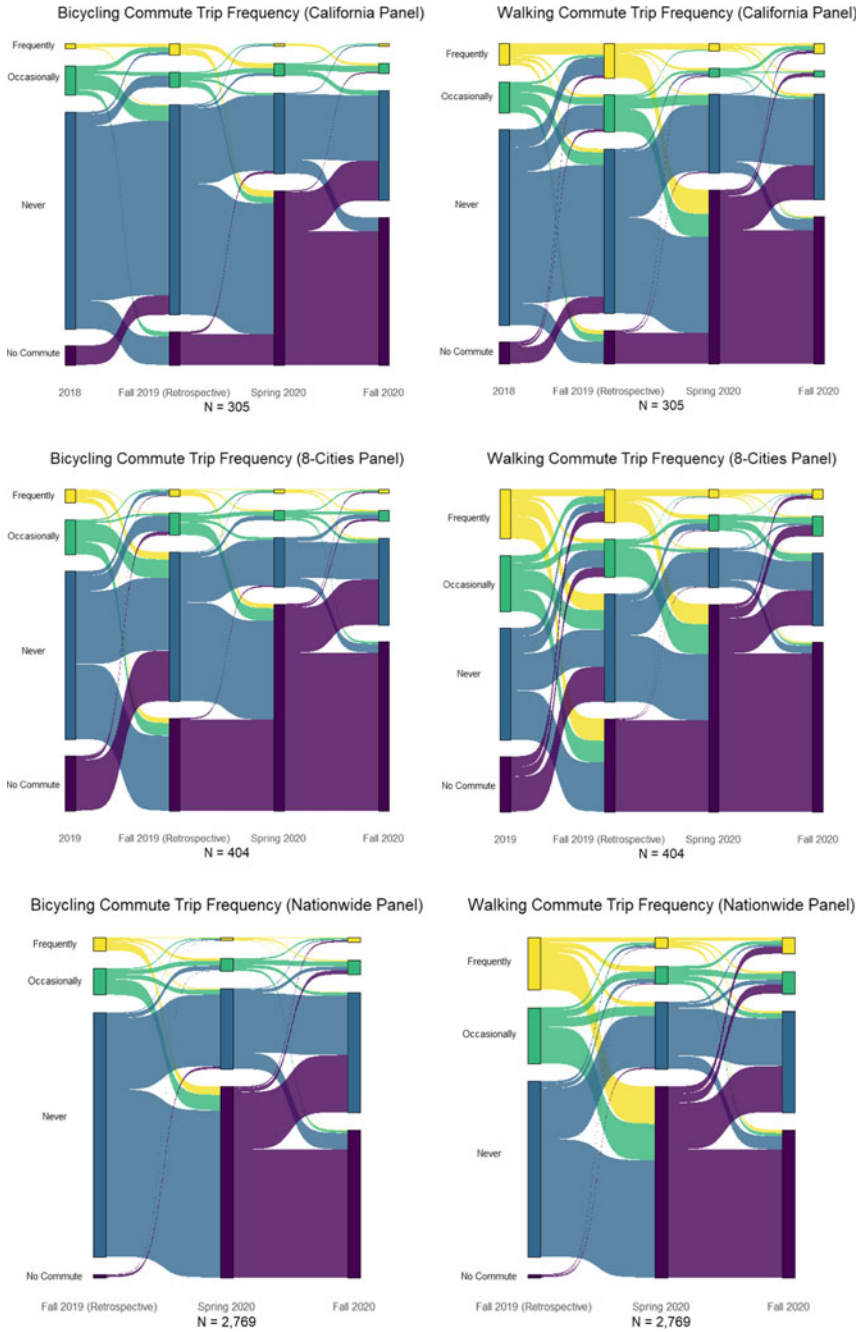


**Fig. 2** Walking and bicycling frequency for commute travel purposes (California, 8 Cities and Nationwide Panels). *Data sources* Authors' surveys

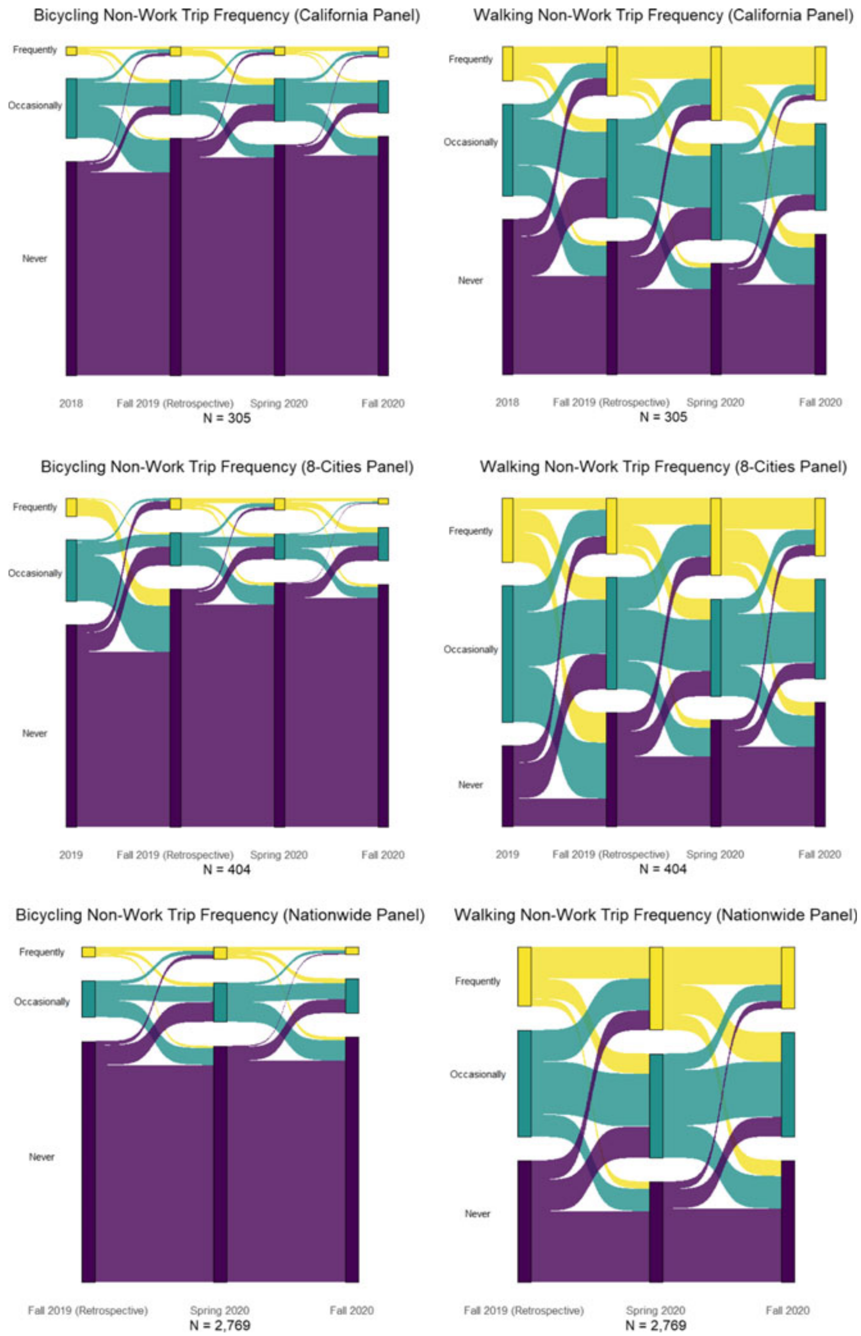


**Fig. 3** Walking and bicycling frequency for non-work travel purposes (California, 8 Cities and Nationwide Panels). *Data sources* Authors' surveys

safety is still a dominant barrier to bicycling in the United States [14, 19, 23, 43]. The most common change in behavior was "no change at all," i.e., people who never rode a bike continued to not ride a bike. This was apparent in all three datasets, particularly for non-work travel (Fig. 2). The second most common change profile was a marked reduction in bicycling. This profile was more common in the 8-cities dataset for both commute and non-work travel and was also present to a small degree in the Nationwide panel, but not so much in the California panel. The third profile showed an increase in bicycling, particularly for non-work travel (Fig. 3). This profile accounts for only a small share of respondents but shows up in all three datasets. This group included individuals who reported never bicycling prior to the pandemic but showed regular bicycling activity during the pandemic. This profile is consistent with the media reports describing bicycling as a booming mode of transportation during the pandemic [24], and an important one for policy implications, since encouraging these individuals to continue to ride their bicycle after the pandemic would lead to environmental and societal benefits. However, the profile of people who increased bicycling for non-work travel already showed some attenuation by the Fall 2020 (Fig. 3). The substantial return to pre-pandemic bicycling levels for many members of this group is particularly evident in the Nationwide panel. This suggests that much of the behavioral change that occurred during the early stage of the pandemic had already reversed by Fall 2020, most likely for the combination of reasons mentioned previously.

While these group-level profiles suggest that certain segments of the population changed travel behavior, due to the small number of individuals who bicycle (especially for commute purposes), we caution against extrapolating more subtle change profiles at the dataset level to the population. For example, a closer look at a less common profile of increased bike commuting during the pandemic in the 8 Cities panel reveals that only ten respondents increased bicycling in spring 2020, six of whom continued using that mode in the fall. This retention of bicycling as a commute travel mode suggests that for some people, the pandemic is likely a primary cause of changing bicycling behavior. However, the evidence remains largely anecdotal, and the degree to which this happens cannot be fully ascertained from the analyses of the data from our study. It should also be noted that in most regions of the United States, active travel tends to be more popular during the warmer months of the year, in particular during spring and summer, than in the colder months of fall and winter. Accordingly, the seasonal differences in the time periods in which the surveys were administered, and the accompanying weather patterns in the select cities represented in each longitudinal sample, at least in part might explain the observed changes in non-work trips during the pandemic months.

### *3.3 Person-Level Mode Substitution*

Commuters who did not switch from public transit to private vehicles possibly chose walking or bicycling as their preferred alternative for a socially-distanced mode of travel during the pandemic months. An examination of the various profiles of mode shifts between public transit and other modes—including bicycling, walking, or driving—as well as shifts between driving and bicycling or walking—reveal similar trends in all three panel datasets. Respondents in each panel are more likely to have decreased their public transit frequency and increased their frequency of driving than to have increased their levels of bicycling or walking as a replacement for public transit. This substitution pattern is expected, considering that many transit trips are made for distances that are more compatible with the use of a private car than with walking or bicycling, in addition to other factors such as concerns about safety when using active modes. Shifts from driving to bicycling or walking were also observed in each panel, even if these mode shifts accounted for a very small proportion of the sample in each panel.

### *3.4 Changes in Daily Physical Activity*

Our Nationwide surveys also tracked active travel, not only in terms of numbers of trips, but also in terms of days and minutes of activity. We first asked respondents to report the number of days that they participated in a physical activity in a week during the pandemic, as well as the number of minutes they spent performing each activity for the days in which they participated in that activity. The various activities presented in the questionnaire are summarized in Table 3. "Total Active Travel" is an aggregate category built using responses from both walking and bicycling activities. Using the measures of days and minutes spent performing each activity, we calculated average daily activity minutes for each activity in Spring 2020 and Fall 2020 for the Nationwide Panel.[4] With this measure we calculated individual change in physically active travel between spring 2020 and fall 2020 for each activity.

Table 3 displays the population-level averages along with the standard deviations, confidence intervals, and the mean person-level differences[5] between the two time periods. Results for the average minutes spent per day participating in each activity indicate an average increase in most forms of physical activity across the two time periods. This suggests that people were increasing their physical activity (on average) well into the pandemic. However, the magnitude of change appears small (less than 2 min) for most activities, except for exercise at a non-home location. While the magnitude of change is small, even small increases in physical activity can have large effects on public health [47].

The most notable change in the average minutes spent per day performing a physical activity was the large increase in exercising at a non-home location, which is

[4] The measure of average daily minutes was calculated by multiplying the number of days in a week the respondent reported doing that activity by the self-reported minutes per day, and dividing the total by 7.

[5] A paired sample t-test was computed to determine the statistical significance of the mean difference between fall and spring.

**Table 3** Average minutes spent per day on each activity, Spring 2020-Fall 2020

| | | Spring 2020 | | | Fall 2020 | | | Mean difference | Standard error of mean difference |
|---|---|---|---|---|---|---|---|---|---|
| | Sample size | Mean | Standard deviation | 95% CI | Mean | Standard deviation | 95% CI | Fall-Spring | |
| Walk to get to and from places | N = 1,044 | 13.3 | 21.9 | 11.9–14.6 | 14.6 | 18.0 | 13.5–15.7 | +1.3 | 0.73 |
| Walk for leisure/exercise | N = 1,980 | 27.6 | 31.8 | 26.2–29.0 | 26.0 | 33.3 | 24.6–27.5 | −1.5 | 0.69 |
| Bicycle to get to and from places | N = 232 | 10.8 | 17.2 | 8.6–13.0 | 10.5 | 13.7 | 8.7–12.2 | −0.4 | 1.22 |
| Bicycle for leisure/exercise | N = 435 | 17.4 | 24.6 | 15.1–19.7 | 17.5 | 27.9 | 14.8–20.1 | +0.1 | 1.24 |
| Total Active Travel | N = 1,980 | 39.7 | 41.1 | 37.9–41.5 | 35.0 | 39.1 | 33.2–36.7 | −4.7 | 0.94 |
| Exercise at home | N = 1,620 | 21.8 | 28.5 | 20.4–23.2 | 20.1 | 25.8 | 18.8–21.4 | −1.7 | 0.73 |
| Exercise at non-home location (e.g., park, beach, gym) | N = 257 | 15.9 | 18.6 | 13.6–18.2 | 21.0 | 28.7 | 17.5–24.5 | +5.1* | 1.72 |

* $P < 0.05$

*Data sources* Authors' surveys

likely associated with the dropping of many restrictions to non-home activities and the end of the stay-at-home orders, after the first stage of the pandemic. While exercising at non-home locations saw the largest average increase, active travel changes were more equivocal. Nearly no change was observed for bicycling, and while walking to get to and from places rose slightly, perhaps due to reopening of activity locations, a similar magnitude in the decline in walking for leisure and exercise suggests that the changes largely canceled out.

We also examined these changes in physical activity by region (West, Midwest, South, and Northeast) to examine the impact of seasonal change. While total active travel (walking plus bicycling) slightly increased on average for the entire sample, this trend was not observed among respondents living in the West or South. Examining the mean differences in total active travel, we see that the South had the largest average decrease (−4.9 min), while the Northeast had the largest and only increase (2.5 min). Specific to walking for leisure/exercise, the West and South had the highest seasonal averages but both regions also had the largest average decrease, whereas only the Midwest experienced a small increase (0.7 min). The only statistically significant mean difference was walking to and from places in the Northeast. Incidentally, this activity saw an increase on average (4.3 min). Lastly, the South appeared to be the most popular region for bicycling, having the highest seasonal averages for bicycling to and from places and bicycling for leisure/exercise, in the spring; however, the mean differences showed decreases for bicycling, walking, and total active travel suggesting that any large increases in the spring were only temporary. These differences by region suggest that some of the changes in walking and bicycling during the various stages of the pandemic might be at least partially explained by travel behavior changes due to weather patterns, but they were also affected by the changes in the pandemic-related policies. This is particularly evident in the increases in total active travel between Spring and Fall 2020 in the Northeast region, one of the coldest regions of the country in the fall, but also a region that experienced stay-at-home orders and strong restrictions to movement during the spring of 2020.

## 4 Transportation Planning and Policy Implications

Results from our present analysis provide evidence for widespread increases in walking and more sparing increases in bicycling during the early months of the pandemic. However, much of the increase reported during the early months of the pandemic was erased or considerably eroded by the fall of 2020. Findings from this analysis suggest that relying on "natural" changes in travel behavior due to the pandemic to increase active travel is not likely to succeed unless specific policies to promote (and/or maintain) certain behavioral changes are implemented. In particular, our results suggest the need for continued or renewed efforts to facilitate the use of active travel modes. Popular strategies that were implemented at the start of the pandemic included full or partial street closures from cities such as Oakland, California that closed 74 miles of city streets to vehicular through traffic [29]. Similar traffic calming projects in other cities, often framed as “Open Streets” or “Slow Streets,” could become permanent features of the built environment to encourage and facilitate the use of walking and bicycling. Traditional traffic calming strategies such as road diets, lowering speed limits, and restricting streets to local traffic are also available as preexisting tools for transportation planners to make the built environment more accessible for pedestrians and bicyclists.

Improving accessibility can also come in the form of increasing pedestrian and bicycling infrastructure through new bike lanes, multi-use trails, and other amenities such as pocket parks or urban plazas. Despite what seemed like a renewed commitment from cities to make streets safer for pedestrians and cyclists, the unfortunate tale of the Slow Streets pilot programs is that many cities such as San Diego and Washington D.C. are planning to or are in the process of removing their pilot programs [36]. This would potentially hurt many of the neighborhoods that could benefit the most from these programs, which tend to be low-income and traditionally underserved from transportation investments. A proper evaluation of these pilot programs is warranted to ensure that successful experiments are not disregarded. In addition to transportation planning solutions, another avenue for encouraging the use of active travel modes is through more direct incentives such as the Electric Bicycle Incentive Kickstart for the Environment Act [17] and the Bicycling Commuter Act of 2019. Rebates, tax incentives, and other monetary incentives may help encourage more active travel. Similarly, disincentives for car use such as pricing parking, reducing parking minimums, congestion pricing, car-free zones, etc. are likely to support active travel. Policy measures of this type may encourage people to change their automobile-centered travel and also help support larger policies like increasing transportation funding for active travel.

## 5 Conclusions

This chapter presented findings from the analysis of three longitudinal datasets on the use of active travel modes for commuting, non-work travel, and daily physical activity. We observed an overall decrease in the share of commuters between the pre-pandemic survey waves in 2018 and 2019 and the early months of the pandemic in Spring 2020. Consistent with other studies, all travel modes including walking and bicycling experienced a decrease in the number of trips for commuting to work and school at the start of the pandemic. Bicycling in all three panels showed examples of an increase in the mode share for commuting at the start of the pandemic, along with less of a decrease in the absolute number of trips with this mode, compared to other modes. The popularity of walking was observed in our data through our analysis of the broader changes in travel, person-level change, changes in mode share (with an increase of the mode share of walking for non-work travel during Spring 2020), and daily physical activity. However, because of seasonal differences in our two “during” COVID-19 waves, and the confounding impacts of the pandemic’s travel limitations that in certain regions acted in the opposite direction of the seasonal variation, it is difficult to determine the lasting change in active travel from the analysis of our data.

The analyses presented in this chapter show how active travel could be serving as an important source of physical activity for respondents who initially turned to these modes during the early pandemic months. However, this phenomenon could also be complemented by increases in sedentary behavior associated with work from home and increased indoor activities, which were not measured in this study (we did not measure all types of physical activity).

The increase in non-work travel during the early pandemic months was a result of the new adoption of active travel during this time by people who were not active travelers before, combined with small increases in trips from pre-pandemic active travelers. Whether this added active travel overcame the potential increase in sedentary behavior brought on by the pandemic remains to be seen. Our analysis stops short of providing a post-pandemic effect, but the trends in declining active travel during 2020 are worrisome and suggest that this component of travel behavior change from the pandemic may be fleeting. While the present analysis only presents broader trends in the use of active travel modes, further analysis of these data—as well as the analysis of additional waves of data collected during the following stages of the pandemic, and beyond—can reveal the unique factors that affect changes in active travel use. Further, the inclusion of spatial variables in future analyses can provide objective measures of the impacts of the built environment on these behavior changes.

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# Adoption of Telecommuting and Changes in Travel Behavior in Southern California During the COVID-19 Pandemic

**Jai Malik, Bailey Affolter, and Giovanni Circella**

**Abstract** One of the major impacts of the COVID-19 pandemic on society has been the massive adoption of telecommuting, and its related changes in travel choices. Using data collected in the greater Los Angeles region in the Fall 2020, this chapter examines the topic through the analysis of the changes in travel behavior among workers who adopted telecommuting in some capacity versus workers who did not telecommute during the pandemic. We analyze data from a cross-sectional survey conducted among 4,045 local residents to examine key sociodemographic characteristics of these two groups and their changes in travel behavior. We observe some major demographic differences between the telecommuting and non-telecommuting respondent groups, with non-telecommuters more likely to be non-white, younger, and with lower household income than telecommuters. At the time of the data collection, all groups reported lower average trip frequency across all travel modes and trip purposes, and reduced vehicle-miles traveled (VMT) as well. However, we observed high average monthly frequency of use of private vehicles and active travel modes for non-commute travel, in some cases indicating an increase from the previous year during the same period, as travelers avoided shared modes of travel during the pandemic.

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## 1 Introduction

The COVID-19 pandemic disrupted many aspects of life as we know it. Shelter-in-place orders and social distancing policies affected the way that individuals worked, studied, socialized, and attended to necessities such as grocery shopping and other essential services. Travel behavior associated with these activities changed in response to such pressures. While essential workers were still required to attend their jobs in-person, travel demand changed as an important portion of the work-force switched to telecommuting. Also, in other sectors, many activities moved to online/remote formats such as telehealth and online schooling. Gig economy services, including DoorDash, UberEATS, and Instacart allowed many to not travel at all in order to receive the food and grocery items they needed [2, 4, 5], these services increased in popularity during a time when demand for on-demand passenger services dropped. As more people stayed at home, their patterns of engagement in recreational activities also changed. For instance, Molloy et al. [6] noted that highly-educated individuals, who worked from home during the pandemic, engaged in more long-distance travel for recreational/leisure purposes.

Even before the pandemic, the relationship between telecommuting and mobility has been a topic of interest among researchers [9, 11]. But during the pandemic, individual patterns regarding the involvement in in-home activities and remote work have evolved rapidly. In a study conducted via an online panel as part of the American Trends Panel, the Pew Research Center surveyed a representative sample of working adults throughout the United States with at least one primary job. As of December 2020, 71% of those who said their job duties could be performed from home were telecommuting, while only 20% of them had been telecommuting before the pandemic. Those who did not or could not telecommute during the pandemic were more likely to be Hispanic or Black, have low to middle income, and not have a college degree. Conversely, Asians were the most likely to report having a job wherein some or all duties could be performed from home [8]. Analyzing data from a survey administered in Chicago, [10] highlighted how the percentage of employees who telecommuted full-time (5 days a week) increased majorly from 2019 to 2020, from 15% in 2019 to above 55% in 2020 in their sample. While results from studies based on the analysis of data collected with online surveys during the pandemic are likely to overestimate the impacts of remote work (and overrepresent teleworkers), the findings highlight a clear trend toward increased telework and telecommuting during the pandemic. Whether part of these increased telecommuting patterns will continue once the pandemic is over is a pending research question, with important implications on the use of transportation in future years.

In the early stages of the pandemic, vehicle-miles traveled in California (and in other parts of the country) saw a sharp decline when shelter-in-place orders rolled out around mid-March 2020. With telecommuting still in place for many employees, the vehicle miles traveled (VMT) began to rebound within 80%–100% of the baseline VMT in the summer of 2020, and then back to as low as 60% of the VMT baseline toward the end of the year, in December 2020 [8], when a new peak in the pandemic again reduced activity participation. The pandemic also brought a major shift in travel mode choice, due to the perceived threats of transmission of the virus and the need for social distancing. More personal, isolated modes such as walking, bicycling, and the use of personal vehicles took precedence over shared modes of transportation including public transit, ride-hailing and ride sharing, and micromobility services such as shared e-scooters and/or e-bikes. This was due in part to the perception that these shared modes of travel posed a higher risk of transmission [1, 10]. Even as overall VMT recovered during the summer months of 2020, public transit saw a much slower recovery, and has still not yet recovered to its pre-pandemic level in many areas [3], with rail services in particular still experiencing low ridership in the later stages of the pandemic.

In this chapter, we build on this literature by focusing on the greater Los Angeles region and investigating the differences in the travel behavior of telecommuters vs. non-telecommuters. We analyze responses to a Fall 2020 online survey administered in the Southern California Association of Governments (SCAG) region to investigate how travel behavior changed among telecommuters and non-telecommuters during the early stages of the pandemic. The focus on a specific region (the greater Los Angeles area) as opposed to an entire state or nation is advantageous as the pandemic response policies have varied greatly by the city, state, and country over the course of the pandemic. Accordingly, analyzing data from one region helps ensure that all individuals in the study region were subjected to somewhat similar response policies, with only minor local intraregional differences at the county or city level.[1] In this chapter, we focus on measures of travel behavior change, as defined by variables concerning changes in monthly trip frequency by travel mode and trip purpose, weekly distance driven, and shopping activity, and relate them to the telecommuting status, residential location, vehicle ownership, and sociodemographic characteristics of the respondents.

## 2 Data Sources and Methods

To examine travel behavior patterns during the pandemic, this chapter uses responses from an 88-question cross-sectional COVID-19 mobility survey administered in Fall 2020. The survey instrument included questions about travel behavior in Fall 2019 (retrospectively provided by the respondents at the time of completing the survey) and Fall 2020, i.e., pre-pandemic versus during-pandemic time periods. In addition, the survey collected information from the respondents on individual and household sociodemographics, individual attitudes and preferences, employment, home, and household composition, and changes in vehicle ownership.

[1] Some of the COVID-19 response policies varied somewhat among the six counties (Los Angeles, Orange, San Bernardino, Imperial, Riverside and Ventura) that constitute the greater Los Angeles area.

Even though the survey was conducted in Fall 2020, individuals were asked to recall their behavior in Fall 2019 (before the pandemic). Asking respondents to recall behaviors from the past can certainly introduce a measurement error. By Fall 2020, respondents may have been unable to report accurate behaviors from Fall 2019. While a component of this study included the collection of longitudinal data among respondents from previous surveys administered in 2018 and 2019 (for whom a full comparison of travel behavior choices before and during the pandemic could be possible), the number of cases with repeated observations was relatively small. Thus, the longitudinal component of the dataset would not allow conducting meaningful statistical analyses. Thus, we had to rely on retrospective answers provided at the time respondents participated in the survey during the pandemic to reach meaningful conclusions about the effects of the pandemic on telecommuting adoption and travel behavior changes among various groups. Thigpen [12] assessed the measurement validity of retrospective questions by comparing data collected over four years with corresponding retrospective data. He reached the conclusion that retrospectively-collected behavioral data are much closer to prospectively-collected data for behavioral choice variables than for variables measuring individual attitudes. Furthermore, as the reliability of recollection decreases over time, the association of prospectively and retrospectively-collected data within five years was found to be sufficient enough to support the validity of the results from the analysis of retrospective behavioral data.

The survey was administered online as part of a larger study focusing on the impacts of the pandemic on travel in the entire United States. Respondents were recruited through three main channels—online opinion panels, convenient sampling (e.g., with recruitment through social media platforms and listservs) and recall of the participants from previous surveys administered in 2018 and 2019. Out of the 3,716 respondents in the dataset used for this study, we recruited 2,963 through a commercial online opinion panel. The provider, Qualtrics, maintains an online opinion panel composed of individuals who agree to participate in surveys in exchange of incentives such as gift cards and airline miles. Our research team set quotas so that the final sample collected through this recruitment channel mimics the census distributions for key demographic variables of the population in the Southern California Association of Governments (SCAG) region: age, gender, household income, race, ethnicity, and employment status. Since we did not have access to the number of individuals initially contacted through the opinion panel, it is difficult to compute a response rate for this channel. An additional group composed of 498 respondents was recruited through a link with an invitation to participate in the study that was posted on university websites, shared through the email listservs of professional organizations and partner agencies, and advertised on social media platforms (Facebook and Instagram). For this recruitment as well, it is difficult to estimate the response rate as we don’t know how many individuals actually might have seen the survey links through the various channels. Finally, the remaining responses in the dataset are from individuals who participated in previous surveys administered by the research team. The research team maintains a panel of respondents who have participated in various surveys conducted since 2015 in various regions of the United States, Canada, and other countries. For this recruitment channel, we sent emails inviting the respondents

**Table 1** Distribution of respondents versus population by county in the region of study

| | Survey responses | | Population | |
|---|---|---|---|---|
| | *n* | % | *N* | % |
| Ventura county | 201 | 5.4 | 655,715 | 4.5 |
| Los Angeles county | 1785 | 48.0 | 7,894,558 | 54.0 |
| San Bernardino county | 399 | 10.7 | 1,610,447 | 11.0 |
| Orange county | 794 | 21.3 | 2,486,016 | 17.0 |
| Riverside county | 503 | 13.5 | 1,856,391 | 12.7 |
| Imperial county | 34 | 0.9 | 129,617 | 0.9 |

*Data Source* Authors' survey

from the previous surveys to participate in this study. We offered an incentive in the form of a $10 gift card from a retailer of choice for each completed response. The overall response rate for this channel, which included respondents living all over the United States and Canada, was approximately 35%, with 255 respondents who resided in the greater Los Angeles region by the time they completed the survey. A special focus in this survey was to recruit respondents living in the greater Los Angeles region, in partnership with the Southern California Association of Governments. The analyses presented in this chapter focus only on the respondents living in this region. Table 1 shows the total number of survey responses from each county, compared to the population of the county, and their respective proportion of the region as a whole.

To examine the degree to which the survey demographically represents the population in the region, Table 2 compares various key characteristics of the 3,716 survey respondents with the 2019 1-year estimates from the American Census Survey for the SCAG region.

At the time of the data collection our attempt was to broadly mirror the distribution of respondents in the study region. However, some groups were overrepresented and others underrepresented. First, by study design, residents in Los Angeles County were under-sampled, while the residents of lower-density counties in the region were sampled with a higher sampling rate, to allow meaningful analyses to be conducted for all sub-regions. Further, the sample has a greater proportion of females than in the regional population of SCAG. Similarly, there is a greater proportion of respondents in the 35–64 age category than in the population. There is a striking difference in the amount of Hispanic survey respondents when compared to the population as well. Hispanic respondents make up only 24% of the survey sample, whereas they represent over 46% of the population of the SCAG region. This is mainly a limitation of the data collection method, as well as the lower response rate among minorities. Our primary source of data collection method is online opinion panels. Most commercial online opinion panels in the United States require a minimum level of proficiency in English to enroll and are in general less popular among minority groups. This leads to a lower representation of Spanish speakers and individuals with Hispanic ethnicity in opinion panels, which is reflected in the lower proportion of individuals

**Table 2** Demographic distribution of the Fall 2020 sample versus SCAG population

| | SCAG survey responses | | SCAG population |
|---|---|---|---|
| | *N* | % | % |
| Gender | | | |
| Male | 1471 | 39.6 | 49.0 |
| Female | 2225 | 59.8 | 51.0 |
| Prefer to self-describe | 20 | 0.5 | N/A |
| Age | | | |
| 18–34 years old | 1363 | 33.9 | 32.6 |
| 35–64 years old | 2026 | 49.8 | 34.6 |
| 65+ years old | 656 | 16.1 | 32.8 |
| Ethnicity | | | |
| Hispanic | 882 | 23.7 | 46.7 |
| Non-hispanic | 2834 | 76.2 | 53.3 |
| Race | | | |
| White, alone | 2392 | 64.4 | 73.4 |
| African American, alone | 182 | 4.9 | 7.3 |
| Asian, alone | 586 | 15.8 | 14.1 |
| Other, alone | 411 | 11.1 | 1.9 |
| Two or more races | 145 | 3.9 | 3.3 |
| Neighborhood type* | | | |
| Rural | 117 | 3.1 | – |
| Small town | 217 | 5.8 | – |
| Suburban | 1968 | 52.9 | – |
| Urban | 1414 | 38.0 | – |
| Educational | | | |
| High school or less, or vocational degree | 1720 | 46.3 | 40.5 |
| Bachelor's degree or Higher | 1996 | 53.7 | 59.5 |
| Annual household income | | | |
| Less than $50,000 | 1303 | 35.1 | 31.8 |
| $50,000 to $100,000 | 1197 | 32.2 | 39.9 |
| More than $100,000 | 1159 | 21.1 | 28.3 |
| Prefer not to answer | 57 | 1.5 | N/A |

*Self-reported neighborhood type not asked in ACS
*Data Sources* Authors' survey; American Community Survey (ACS) 2019, one-year estimates

with these characteristics in the sample. Further, online opinion panels often tend to overrepresent groups (e.g., women) who tend to have higher response rates than other groups, when participating in surveys. In order to counterbalance some of the limitations of the use of online opinion panels for the recruitment of participants, the research team plans in the future to conduct a follow-up data collection to correct these sampling and response biases.[2]

The main focus of this analysis requires the definition of two specific groups of respondents in the survey. In particular, we are concerned with the change in work-related as well as non-work travel behavior patterns for employed telecommuters and employed non-telecommuters. First, to determine telecommuting status, respondents were asked for their current employment status. Employees were classified as those who work full time, part time, have multiple jobs, or are in an unpaid working arrangement. Those who answered affirmatively to any of these options were then asked where they were performing their job duties as of Fall 2020, and on how many days per week they did so. Choices included telecommuting, working at a regular work site, and at other work locations outside of the home. Respondents were also asked about their weekly frequency with which they participated in work-related online meetings via technological platforms such as Zoom, Skype, or Microsoft Teams. These same questions were asked again of every survey respondent in reference to their Fall 2019 work patterns. Respondents were only eligible to answer how many days they telecommuted, if they had first responded that they had the *option* to telecommute back in 2019.

For the purpose of this analysis, we classify telecommuters as those who work or perform job duties from home 1–7 days a week. The frequency of telecommuting is divided into *light telecommuting* (i.e., telecommute, or TC, 1–2 days a week), *most of the workweek* (TC 3–4 days), or *entire workweek* (TC 5+ days a week). Between Fall 2019 and Fall 2020, there is a clear shift among the majority of workers in our sample from working in-person at a job facility to working at home (see Fig. 1).

Trip frequency (for different mode choices) and trip purpose are discussed further in the results and discussion sections. To compare responses for telecommuters and non-telecommuters, frequency values were assigned to each response, and we examined the mean values of each category. For each trip mode choice, the options available for respondents were: "not available," "available but did not use," and then "I used it…" "less than once a month," "1–3 times per month," "1–2 times per week," "3–4 times per week," and "5 or more times per week." The questions about trip purpose frequency were very similar. However, there was no "not available" option.

[2] In addition to the online opinion panel channel, we will recruit respondents through a combination of letter invitations and printed questionnaires mailed to the home address of a group of stratified randomly selected households in the region. All surveys in the 2021 data collection wave will be also translated into Spanish, and we will use higher sampling rates to recruit more respondents in communities that are traditionally characterized by lower response rates, including minorities and Spanish-speaking Hispanic communities in the SCAG region. Further, we plan to use a set of weights to correct any remaining deviation from representativeness of the population in the region. However, data from the 2021 round of data collection were not available yet for purposes of analysis at the time of writing.


**Fig. 1** Distribution of number of days of telecommuting among employed respondents during both 2020 and 2019 ($n = 2{,}213$). *Data Source* Authors' survey

The options given for trip purpose frequency were "I have not done this," and then "I have done this…" "less than once a month," "1–3 times per month," "1–2 times per week," "3–4 times per week," "5 or more times per week." For the analysis, each answer was converted into an approximate trip frequency per month. For example, if a respondent used a certain mode of travel "1–3 times per month," their responses were assigned a frequency value of two trips (on average) per month, as two is the midpoint of that category. Similarly, weekly frequency values were multiplied by 4 to yield a monthly frequency. Those who left these questions blank were excluded from the analysis, but those who answered "not available" or "available but did not use" for the travel modes were labeled with a 0 frequency for that mode in the analysis. "Less than once a month" responses were assigned a frequency of 0.5 times/month.

## 3 Results and Discussion

The following analysis provides insights into the travel behavior patterns of those who were employed in Fall 2020, those who were employed in Fall 2019, or both. There is a difference in the number of employed versus unemployed respondents at the two points in time. Approximately, 9.4% of the 2,442 employed respondents in 2019 stopped working in 2020 (employed = 2,213). These groups were further divided into those who telecommuted versus those who did not. Some respondents did not telecommute in 2019, but did so in 2020 and vice versa (see Fig. 1). Nearly 22% of the respondents reported telecommuting at least once a week in Fall 2019. That number was roughly 62% in Fall 2020. This is most likely an overestimation of the actual telecommuting employees in the SCAG population. Recall that we recruited respondents through online channels only, which may lead to an upward bias in the estimates of telecommuters in the SCAG region. In the final dataset of employed respondents living in the SCAG region, 27.3% of respondents in the sample lived in households that make less than $50,000 per year, and 34.2% in households that make between $50,000 and $99,999. Most respondents identified as women (59.8%) and were primarily from the Los Angeles, Orange, and San Bernardino counties, three of the most populous counties in the region.

### 3.1 Sociodemographic Characteristics

Telecommuters were more likely to be non-Hispanic, white, have higher income, and be over the age of 34. Those 18–34 years old, and those making less than $100,000 per year were more likely to be non-telecommuters in both 2019 and 2020. In both years, those with a Bachelor's degree or higher education were more likely to telecommute, whereas those who had a high school education or less were more likely to not telecommute. The majority of those who telecommuted in 2019 did so just for 1–2 days per week in 2019. However, in 2020, 38% of employed respondents reported telecommuting 5+ days per week.

### 3.2 Residential Location and Distance from Work

Residential location type (i.e., urban, suburban, or rural), distance from work, and average weekly vehicle-miles traveled are pertinent when considering the differences in telecommuting status during the pandemic. There is currently an active discussion in the scientific and planning communities about the relationship between telecommuting and the propensity to live further away from the main workplace. Further, transportation researchers wonder whether residential location is a facilitator or consequence of the ability to telecommute, and whether this leads to an increase or decrease in VMT among the telecommuting population, and whether these changes/shifts will persist after the pandemic is over, leaving potentially lasting effects on work culture, travel behavior, and residential choices [2, 7, 13].

Full-time teleworkers were more likely to be living in non-urban locations in both 2019 (49.2%) and 2020 (53.2%) as compared to partial telecommuters in both years. In 2020, 53.5% of non-telecommuters reported living in a suburban location, and 36.3% in an urban area. The proportion of non-telecommuters living in either a small town or rural area was greater than that of telecommuters (11% vs. 4%). Thirty-eight percent of telecommuters and 36% of non-telecommuters lived within five miles or less of their workplace. About 93% of all non-telecommuters and 88% of telecommuters lived within 30 miles or less of their workplace (Fig. 2).

During the pandemic, the non-telecommuting group had a mean VMT of 115.2 miles per week, while the mean VMT for telecommuters was just 65.4 miles per week. T-tests confirmed that the differences between the VMT of the two groups were statistically significant at the 0.05 level. This question was asked only for Fall 2020, so this comparison could not be carried out with the 2019 data. Additionally, respondents were asked not to consider any miles driven while on the clock, if the nature of their job required driving, like trucking or driving for a ride-hailing company. Not surprisingly, employed individuals tended to have a higher mean VMT than the average respondents in the region.

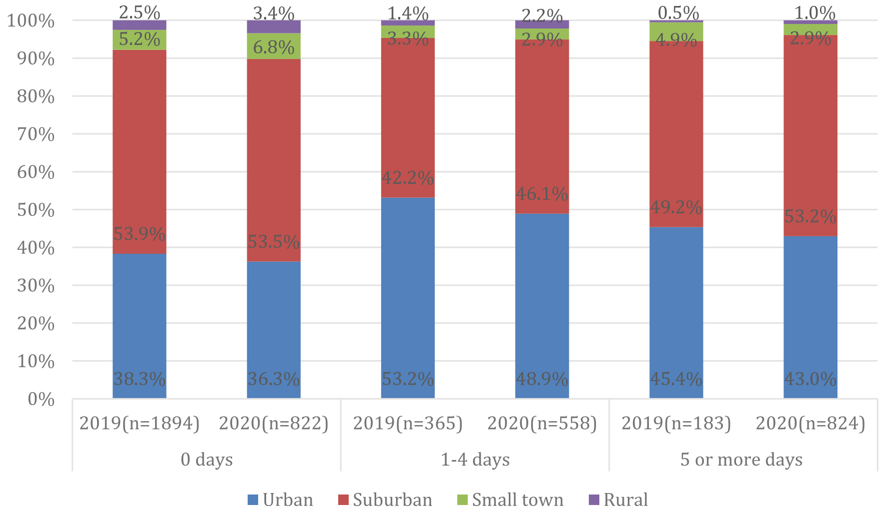


**Fig. 2** Distribution of home locations of non-telecommuters, partial- and full-telecommuters in 2019 and 2020 ($x$-axis: number of days of telecommuting). *Data Source*: Authors' survey

### *3.3 Vehicle Access*

The majority of both telecommuters and non-telecommuters reported having access to a vehicle, which is consistent with the high vehicle ownership rates observed in the study region. Roughly 96% of both telecommuters and non-telecommuters in 2020, reported having access to a vehicle in their household. Telecommuters with access to a vehicle on average drove 67.1 miles per week, while telecommuters without vehicle access reported an average of 21.6 miles per week. These differences were also statistically significant at the 5% level. The difference in VMT by vehicle access for non-telecommuters was even more pronounced with an average of 118.7 miles for those with a vehicle, and 14.8 miles for those without access to a vehicle.

Low-income employed respondents were more likely to not have access to a vehicle, and also more likely to work in-person. Not surprisingly, though, there were other sociodemographic dimensions at play, and vehicle access was not necessarily a direct impact of telecommuting status, but rather a covariate (or a predictor of it). As shown in Fig. 3, nearly 10% of telecommuting respondents with household income lower than $50,000 did not have access to a vehicle in the household but only 6% of low-income-non-telecommuters did not have access to a vehicle. The situation was reversed for high-income households (those with income higher than $100,000), where only 1.1% of telecommuting respondents did not have access to a vehicle, while 1.4% of non-telecommuters in that income category did not have access to a vehicle.

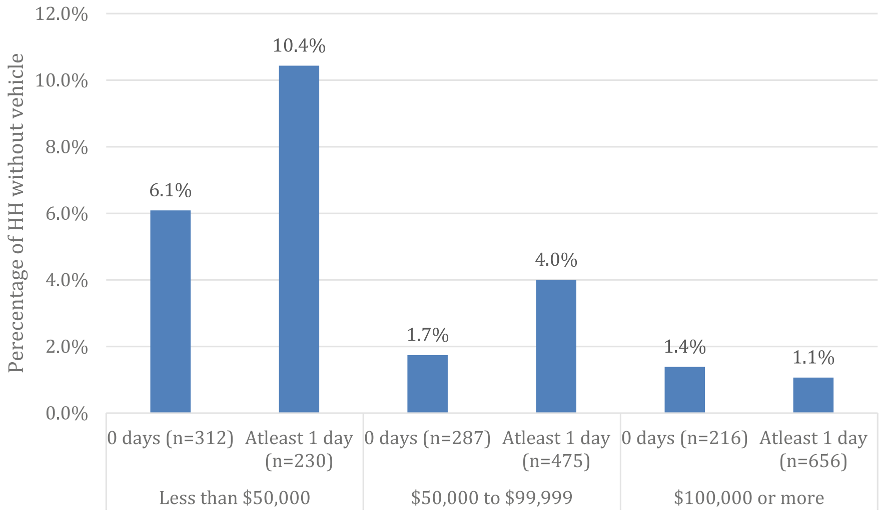


**Fig. 3** Percentage of telecommuters vs. non-telecommuters without access to a vehicle in the household divided by income category. *Data Source* Authors' survey

## *3.4 Trip Frequencies by Mode*

To examine trip frequencies by mode and purpose, responses were broken up into three categories based on telecommuting status: non-telecommuters, partial telecommuters (those that both telecommute and commute to work in-person), and full-time telecommuters (those who work as full-time telecommuters).

### 3.4.1 Non-Commute Purpose

In terms of mode choice, there were statistically-significant differences in the mean monthly frequencies of travel by various modes among telecommuters and non-telecommuters in both Fall 2020 and Fall 2019. In the survey, respondents were asked about the frequency with which they used specific travel modes. For the purposes of this analysis, we grouped the main travel mode categories as active modes (including walking and bicycling), personal vehicle use (aggregated individual categories of carpooling or single-occupancy car use), public transit (rail or bus services), carsharing, and other miscellaneous modes. Respondents were asked to report their mode use separately for non-commute and commute purposes. Total travel was determined for each respondent, as a summation of all travel modes to determine changes and differences in total travel. For non-commute travel, total travel frequency in Fall 2020 was greater among telecommuters than non-telecommuters. Total trip frequency decreased in 2020 across all telecommuting respondent groups compared to 2019.

As shown in Table 3, telecommuters had a greater mean frequency for non-commute trips via active modes, transit, ride-hailing, and carsharing. Mean trip frequency via bus was greater than rail for both telecommuters and non-telecommuters in Fall 2020 (not shown in Table 3, since "bus" and "rail" were merged into "public transit"). Telecommuters reported more trips by walking than non-telecommuters in both years, though the proportion of walking trips increased in 2020 regardless of telecommuting status. Walking was the most prevalent active mode in percentage of total trips. The greatest increase in walking was among full-time telecommuters, at a 67% increase in trip frequency proportion of total trips. The proportion of personal and shared bike trips decreased for both the telecommuter and non-telecommuter groups. Private vehicle use declined among all groups, but the proportion of vehicle trips increased among all groups, with partial telecommuters seeing the highest increase, followed by full-time telecommuters and lastly non-commuters.

#### 3.4.2 Commute Purpose

The use of public transit, active mode of travel, ride-hailing, and carsharing/shuttling declined among non-telecommuters. However, non-telecommuters reported higher number of trips made by private vehicles. Similar to non-commute travel, walking was consistently reported as accounting for the highest proportion of total trip frequency in the active transportation category, among all telecommuting groups in both 2019 and 2020. Walking decreased for non-telecommuters and partial telecommuters, but increased slightly among full-time telecommuters. It is important to note that full-time telecommuters reported a very low total trip frequency average for commute purposes. This is consistent with expectations that virtually no commute travel would occur for this group, except for special circumstances. Telecommuters also reported higher mean frequency of bus and rail use for commute purposes when compared to non-telecommuters in both 2019 and 2020.

The most popular mode choice for telecommuters was still private vehicles. They also reported higher trip frequencies using non-private modes of transportation than non-telecommuters.

### *3.5 Trip Frequencies by Purpose*

Respondents were also asked about the frequency at which they took trips for specific travel purposes. Options for non-commuting trip purposes included "social visits with friends/relatives," "concerts/sporting events," "errands," "travel done for the purpose of sightseeing or for the sake of itself," "recreational bicycling, walking, or going to the park," or "traveling to/from the airport."

The average total trip frequencies (all purposes combined), for all groups, declined from 2019 to 2020. However, the trip purpose categories that saw the largest decline

**Table 3** Monthly trip frequency by travel mode and trip purpose ($N = 2{,}213$)

| | **2019** | | | **2020** | | |
|---|---|---|---|---|---|---|
| | Non-telecommute | Telecommute (partial) | Telecommute (full time) | Non-telecommute | Telecommute (partial) | Telecommute (full time) |
| Mode Choice | | | | | | |
| Commute | | | | | | |
| Total | 25.78 | 32.55 | 27.63 | 17.29 | 17.63 | 2.81 |
| Active | 3.89 | 6.20 | 5.00 | 1.88 | 3.80 | 0.94 |
| Transit | 2.37 | 4.11 | 2.82 | 0.93 | 1.71 | 0.37 |
| Private vehicle | 17.01 | 14.50 | 10.78 | 14.89 | 11.29 | 2.09 |
| Ride-hailing | 0.72 | 1.57 | 0.96 | 0.44 | 0.99 | 0.22 |
| Shuttle | 0.63 | 1.68 | 0.94 | 0.31 | 1.03 | 0.17 |
| Other | 1.48 | 3.37 | 3.36 | 0.40 | 1.37 | 0.25 |
| Non-commute | | | | | | |
| Total | 23.11 | 31.58 | 25.36 | 17.54 | 23.01 | 18.63 |
| Active | 4.05 | 6.91 | 6.22 | 3.21 | 5.50 | 5.72 |
| Transit | 1.48 | 3.40 | 2.03 | 0.95 | 1.83 | 0.73 |
| Private vehicle | 14.06 | 13.64 | 13.04 | 12.37 | 12.05 | 10.32 |
| Ride-hailing | 1.29 | 1.79 | 1.29 | 0.44 | 1.05 | 0.38 |
| Carsharing | 0.45 | 1.46 | 0.70 | 0.25 | 0.89 | 0.34 |
| Other | 1.44 | 3.22 | 2.36 | 0.98 | 1.81 | 1.09 |
| Trip Purpose | | | | | | |
| Social | 8.55 | 9.97 | 9.34 | 3.32 | 5.29 | 2.24 |
| Errands | 4.02 | 4.32 | 4.73 | 2.40 | 2.58 | 2.19 |

(continued)

**Table 3** (continued)

| | **2019** | | | **2020** | | |
|---|---|---|---|---|---|---|
| | Non-telecommute | Telecommute (partial) | Telecommute (full time) | Non-telecommute | Telecommute (partial) | Telecommute (full time) |
| Mode Choice | | | | | | |
| "For Fun" | 2.10 | 2.73 | 2.23 | 1.05 | 1.55 | 0.86 |
| Recreation | 6.02 | 6.77 | 8.21 | 5.79 | 6.82 | 7.62 |
| To/from Airport | 0.84 | 2.07 | 1.48 | 0.54 | 1.13 | 0.39 |

*Data source:* Authors' survey

***Note:*** Full-time telecommuters are making non-zero commute trips. We assume that even though these individuals replace the commute to the main office with home-based telecommuting, they are still making some other work-related trips or trips related to another job/business among all telecommuting statuses were trips made for social purposes—with the largest reductions observed among non-telecommuters (−61%), followed by partial telecommuters (−47%) and full-time telecommuters (−76%). In both 2019 and 2020, full-time telecommuters reported highest average trip frequencies for recreational travel such as walking, biking, or going to the park (~8 trips per month). In 2020, non-telecommuters reported the largest percent decrease of all groups with an average of 5.79 trips per month; full-time telecommuters dropped to about 7.62 trips per month (one less monthly trip, in terms of averages), and partial telecommuters remained more or less at the same level. In 2019, the average errand trip frequency was the greatest among full-time telecommuters (~5 trips per month), and declined the most to almost twice trips per month, on average.

Self-reported VMT for non-telecommuters had a higher average mean than that for telecommuters. Nevertheless, further examination is necessary to understand the relationship between VMT and trip frequency. Perhaps, the total number of trips was indeed higher but the estimated VMT was lower for telecommuters because they tended to stay closer to their place of residence, and were more available or likely to make short trips. This may also relate to residential locations and density. The majority of 2020 telecommuters lived in urban or suburban settings, while a higher proportion of non-telecommuters (10.7%) reported living in a small town or rural area as compared to telecommuter respondents (5.1%).

Consistent with the current understanding of travel behavior during the pandemic, we also observed a major difference in total trip frequency between 2019 and 2020. Non-telecommuters saw a steeper decline in total trip frequency by purpose and mode choice when compared to telecommuters. Further examination is necessary to understand why there were significantly higher means for commute travel among telecommuters, when logically, commute travel should have diminished. One explanation is that travel frequency does not necessarily make up for the whole travel volume. Distance and time spent are also indicators. Many small trips might be a result of needing to gather equipment or resources that are typically kept at the office and necessary for job tasks. Alternatively, telecommuters may have to come into the office for short periods of time to conduct certain tasks, while still having the profile of full-time telecommuters. Therefore, respondents' own interpretation of their telecommuting status and what constitutes commute travel may be at play in the results.

## 4 Conclusions

We conducted this analysis with the aim of improving the understanding of travel behavior changes among commuters and telecommuters in the greater Los Angeles region during the COVID-19 pandemic. We observed key differences among telecommuting (including both full-time and partial telecommuters) and non-telecommuting respondents in terms of both sociodemographics and travel behavior. In general, the proportion of individuals who engaged in forms of remote work and telecommuting increased dramatically in 2020 as a result of the pandemic. All else equal, our analysis highlighted that telecommuters were more likely to have higher income, be white and non-Hispanic, and in the age group of 35–60 years old. Non-telecommuters tended to be younger, making less than $100,000 per year, and held less than or equivalent to a Bachelor's degree. Non-telecommuters were more likely to live in rural or small-town settings. Average VMT was higher for non-telecommuters, despite lower average rates of vehicle access than among telecommuters. Trip frequency decreased as a result of the pandemic.

We are aware of a few limitations of our analysis. The sample collected in this first stage of our study was not fully representative of the SCAG population, and our recruitment channels have likely introduced some sources of bias in the sample. For example, similarly to what other researchers did during the pandemic, we administered the survey online, which automatically excluded respondents who did not have access to Internet, or were not familiar with online surveys. This may have led to the overrepresentation of telecommuters in our sample. Additionally, our analysis was restricted to descriptive statistics and univariate comparisons of behavioral variables with sociodemographic variables. Previous research has shown that individual behaviors (including telecommuting and travel behavior) also depend on the built environment and individual attitudes. Our research in the future will incorporate these variables into analyses using econometric models. Further, our survey included many retrospective questions asking respondents to report their behaviors for one year prior to the data collection. This may have introduced some degree of measurement error. However, previous studies (e.g., Thigpen [12]) found responses to retrospective questions reliable enough to conduct meaningful analyses of self-reported individual behaviors.

One important finding in this chapter is that telecommuters made more social and recreational trips than non-telecommuters. This finding has planning and policy implications. For example, in the last few years, telecommuting has been often promoted as a travel demand management strategy, which could help reduce total travel (and car travel, in particular). This rebound effect, (i.e., higher number of non-work trips made by telecommuters, compared to non-telecommuters), must be considered while estimating the effect of telecommuting on total VMT and congestion levels. We also found that telecommuters were more reliant on non-private modes of transportation (e.g., public transportation, bike sharing, active mobility) than non-telecommuters. However, the use of all modes, in absolute value, declined during the pandemic. The question still remains whether the decrease in use of certain shared mobility options such as e-scooters/ bikes and ride-hailing services was due to the fear of COVID-19 transmission, or a lack of infrastructure as companies pulled their services out of rotation in certain areas.

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# Impacts of the COVID-19 Pandemic on Telecommuting and Travel

**Michael G. McNally, Rezwana Rafiq, and Md. Yusuf Sarwar Uddin**

**Abstract** This chapter examines changes in telecommuting and the resulting activity-travel behavior during the COVID-19 pandemic, with a particular focus on California. A geographical approach was taken to "zoom in" to the county level and to major regions in California and to "zoom out" to comparable states (New York, Texas, Florida). Nearly one-third of the domestic workforce worked from home during the pandemic, a rate almost six times higher than the pre-pandemic level. At least one member from 35% of U.S. households replaced in-person work with telework; these individuals tended to belong to higher income, White, and Asian households. Workplace visits have continued to remain below pre-pandemic levels, but visits to non-work locations initially declined but gradually increased over the first nine months of the pandemic. During this period, the total number of trips in all distance categories except long-distance travel decreased considerably. Among the selected states, California experienced a higher reduction in both work and non-workplace visits and the State's urban counties had higher reductions in workplace visits than rural counties. The findings of this study provide insights to improve our understanding of the impact of telecommuting on travel behavior during the pandemic.

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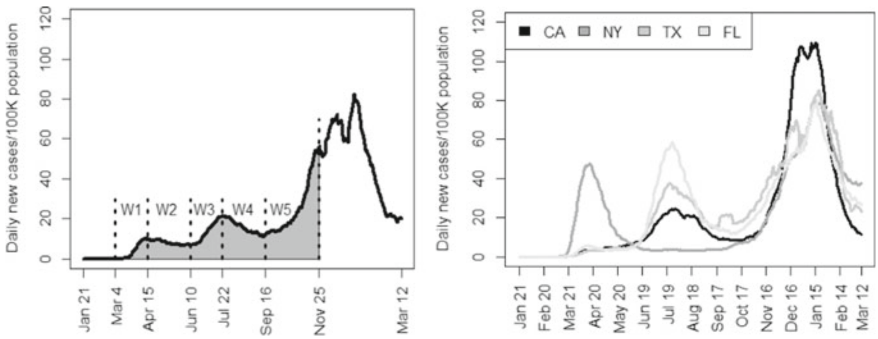
## 1 Introduction

The COVID-19 pandemic has created extreme disruption in our regular day-to-day schedules and triggered massive changes in activity-travel behavior. Due to social distance practices and activity-travel restrictions imposed by the pandemic, telecommuting—also known as working from home or telework—has become a widespread reaction, with significant increases in 2020 compared to prior years [4, 5, 8]. A recent survey estimates that between February and May 2020, over one-third of the American labor force replaced in-person work with telework, which resulted in the share of remote workers nearing 50% of the nation's workforce [6]. In addition to work, other daily routines also changed: in-person grocery/restaurant visits were impacted by increased takeout/delivery, in-store visits were largely replaced by online shopping, and in-person social interactions often became virtual social visits. These changes in activity participation contributed to changes in travel behavior during the pandemic. This chapter reports on observed changes in telecommuting and travel, with a particular focus on California (CA). To understand the breadth and depth of change, a geographical analysis was taken. First, a disaggregate approach involved "zooming in" to major regions and counties in California and, second, an aggregate approach of "zooming out" to comparable states[1] including New York (NY), Texas (TX), and Florida (FL).

Figure 1 depicts daily new COVID-19 cases per 100 K population from January 2020 to March 2021 in the United States and the selected states. The ebb and flow in daily new infection cases suggest that the pandemic passed through a series of waves over this period.




A. Selected time windows for U.S. B. Infection rates for selected states

**Fig. 1** Daily new COVID cases per 100 K population from January 2020 to March 2021. *Data Source* The New York Times [16]

[1] These states are the four most populous in the United States and have received significant media focus throughout the pandemic due in part to disparate policy orientations. CA and NY are blue (electorate majority Democrats); TX and FL are red (electorate majority Republics) based on the 2020 U.S. presidential election.

New York experienced a severe early hit of the pandemic whereas California reached the highest peak among the four states later in the year (Fig. 1B). The first 10,000 confirmed cases appeared later in California (after 68 days) than in the other three states. In contrast, New York reached the first 10 K and 100 K cases rapidly (after 20 and 33 days, respectively). California was the first state to impose a stay-at-home order for residents except for those with essential jobs and needs [15].

We analyzed nine months of pandemic data from March 4, 2020 through November 25, 2020. To observe changes in behavior, including changes in telecommuting, visits to work and non-work places, and average distance traveled during this period, we defined five-*time windows*. The shaded area in Fig. 1A defines the selected windows and their respective start and end dates. The overall national pattern of new COVID cases between the start of the pandemic to just before the start of the November holiday season was defined by three periods of significant increase and two periods of decrease in daily new cases. This national pattern did not necessarily reflect regional trends. Furthermore, given the time lag between COVID-19 exposure and the appearance of symptoms, the endpoints for each window were not precisely defined. Nevertheless, these windows appear quite suitable for the aggregate analyses proposed.

This exploratory study provides a descriptive analysis of the impacts of telecommuting during the pandemic using data from multiple sources (i.e., big data). We believe that such an examination using big data is essential to understanding the changes in telecommuting and the associated changes in activity-travel behavior, and consequently for informed policy analysis. After describing the data sources, three interrelated analyses are presented. First, in Sect. 3, an assessment of the level of telecommuting in California before the pandemic provides a baseline for analysis. Second, in Sect. 4, the changes in telecommuting during the pandemic are presented. Third, in Sect. 5, the changes are presented in activity visits and travel distance in California with reference to the selected states. Finally, the findings and policy discussion are provided.

## 2 Data Sources

These analyses merged datasets drawn from the following sources:

- The New York Times COVID-19 data repository [16];
- MTI COVID-19 Impact Analysis Platform [13];
- Google COVID-19 Community Mobility reports [11];
- U.S. Census Bureau [18];
- Bureau of Transportation Statistics [7];
- 2017 National Household Travel Survey [9];
- Household Pulse Survey 2020–2021 [17].

The New York Times dataset contains state- and county-level data (cumulative COVID cases and deaths) since the first domestic case in January 2020. For the

MTI dataset, selected data was extracted from their publicly available web platform including state- and county-level data beginning on January 1, 2020. MTI data categories included mobility and social distancing, COVID and health, economic impact, and vulnerable population statistics. MTI utilized privacy-protected mobile device location data representing person and vehicle movements [20].[2]

The Google COVID-19 Community Mobility report presents traveler location for geographic areas worldwide including the United States. The report categorizes activity places in a set of standard types, including groceries and pharmacies, retail and recreation, parks, transit stations, workplaces, and residential. The data shows the relative changes in visits to categorized places compared to a pre-pandemic baseline. The baseline represented a *typical* value for each day of the week and was defined as the median value for the five-week period from January 3, 2020 to February 6, 2020 [11].

We obtained county socio–economic and location data from the U.S. Census Bureau [18] and the EPA Smart Location database (2014). Travel data was obtained from the Bureau of Transportation Statistics [7] and included trips by distance as well as the number of people staying at home at aggregate national, state, and county levels from January 2019 to March 2021. We defined trips as movements, by any mode of travel, that end with a stay of at least 10 min at an anonymized non-home location [7].

We used the 2017 National Household Travel Survey (NHTS) to identify the sociodemographic characteristics of workers who either worked from home or who had the option to work from home before the pandemic. This dataset provides sociodemographics and travel information for residents in all 50 states and the District of Columbia. It contains trip data for a pre-assigned 24-h period for all individuals in each household. The Census Pulse Survey 2020–2021 [17] was also used for telework behavior data during the pandemic. This survey includes data on travel behavior collected during phase 2 (August 13–October 26, 2020) and phase 3 (October 28, 2020–March 29, 2021).

## 3 Telecommuting in California: Pre-Pandemic

California is the most populous and by area the third-largest state in the United States. We divided the state's 58 counties into four broad regions: two that are predominantly metropolitan (the Bay Area and Southern California) and two that are predominantly rural (Central California and Northern California). Figure 2a maps the regions while Fig. 2b, and Fig. 2c depict population density and proportion of workers in telecommutable jobs, respectively. Density provides a measure of both the potential for pandemic infections as well as a measure of potential pandemic response when combined with the proportion of workers in telecommutable jobs. The opportunity for workers to adopt telecommuting depends on the availability of

[2] See: https://data.covid.umd.edu/.

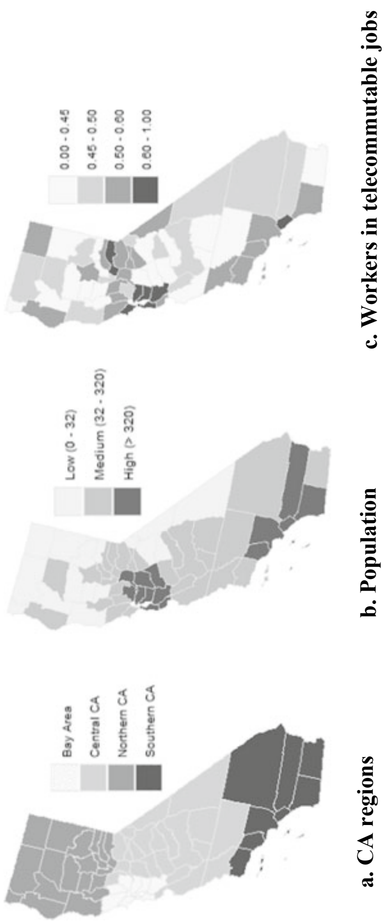



**Fig. 2** California counties by major regions, population density (per mi$^2$), and workers in telecommutable jobs (%). *Data Source* U.S. Census Bureau [18]

**Table 1** Sociodemographic characteristics for California regions

| Sociodemographic characteristics | United States | California | California | | | |
|---|---|---|---|---|---|---|
| | | | Bay area | Southern CA | Central CA | Northern CA |
| Median annual income (in 1000 USD) | 51.6 | 64.4 | 96.7 | 68.8 | 61.0 | 51.1 |
| Full-time (weekly work-hour > 35) (%) | 57.6 | 52.4 | 59.6 | 53.6 | 51.7 | 49.3 |
| Workers in telecommutable jobs (%) | 46.6 | 50.0 | 60.5 | 52.2 | 47.9 | 46.6 |
| Households with computing device (%) | 83.4 | 89.2 | 93.6 | 91.2 | 89.5 | 85.8 |
| Households with internet access (%) | 77.3 | 84.7 | 91.2 | 87.2 | 84.8 | 80.4 |

*Data Source* U.S. Census Bureau [18]

resources including income, occupation type, internet access, and the availability of computing devices. Table 1 provides the pre-pandemic resource levels for each of the defined regions, for California, and the United States.

Median annual income was considerably higher in California than the national average, particularly in the Bay Area, but the percentage of persons in full-time jobs was lower than the national average (52.4% vs. 57.6%). A higher portion of households had access to the internet and computing devices in California than nationally. Rural California households had lower internet access than metropolitan households, although even this lower level was higher than for the nation. A higher portion of California workers were in telecommutable jobs, particularly in the Bay Area and Southern California (telecommutable jobs are jobs in "management, business, science, arts" and "sales and offices" based on the U.S. [18] occupation codes). The county distribution of workers in telecommutable jobs (Fig. 2c) shows that metropolitan areas had a higher portion of these jobs than rural areas.

Table 2 provides California's population distribution over sociodemographic characteristics based on the 2017 NHTS data, split by (a) all workers in the NHTS CA sample, (b) workers who worked from home, and (c) workers who had the option to work from home. The sociodemographics of individuals who work from home (or had the option to) differed slightly from the general worker population distribution. Household income, education, and occupation are key correlates for people working from home (or having options to do so). People who worked from home were more likely to be higher educated, had higher income, and worked in professional, managerial, technical, sales, and services positions. Hispanics and Blacks had lower levels of working from home than Whites.

**Table 2** Sociodemographics of workers who worked from home pre-pandemic

| Household and personal characteristics | NHTS CA all workers (%) | Workers who worked from home (%) | Workers had option to work from home (%) |
|---|---|---|---|
| | $N = 25{,}546$ | $N = 4{,}176$ | $N = 3{,}706$ |
| *Household income* | | | |
| <$25–$50 K | 29.30 | 30.43 | 14.17 |
| $50–$100 K | 29.18 | 24.14 | 21.30 |
| >$100 K | **41.52** | **45.43** | **64.53** |
| *Household size* | | | |
| 1–2 | 35.51 | 40.72 | 47.72 |
| 3 and above | **64.49** | **59.28** | **52.28** |
| *Educational qualification* | | | |
| College degree or less | **52.74** | 43.47 | 22.69 |
| Bachelor or higher degree | 47.26 | **56.53** | **77.31** |
| *Hispanic/Race status* | | | |
| Hispanic | 36.18 | 27.05 | 22.28 |
| White | **59.81** | **62.67** | **64.35** |
| Black | 5.50 | 4.59 | 4.12 |
| Asian | 14.17 | 14.62 | 18.47 |
| *Occupation* | | | |
| Professional/managerial/technical/sales/services | **75.52** | **83.79** | **89.58** |
| Other jobs | 24.48 | 16.21 | 10.42 |

*Data Source* 2017 National Household Travel Survey [9]
*Note* Table 2 depicts population-weighted values

## 4 Impacts of the Pandemic on Telecommuting

What changes occurred in telecommuting practice in California during the pandemic and how did these changes compare with selected reference states? We consider three analysis perspectives: (1) changes in workplace visits, (2) changes in the proportion working from home, and (3) substitution of in-person work with telework.

Our analysis considers county-level pandemic impacts over the defined time windows during the first nine months of the pandemic (see Fig. 3). COVID cases first appeared in southern counties and progressively spread to central California attaining a presence throughout the state by the last time window. By Window 3 the majority of counties recorded infection rates higher than two confirmed cases per day per 10 K people (cf. Fig. 3A).

Figure 3B depicts the associated reductions in workplace visits (relative to the baseline) across California counties. During Window 2 (April 15–June 10, 2020),

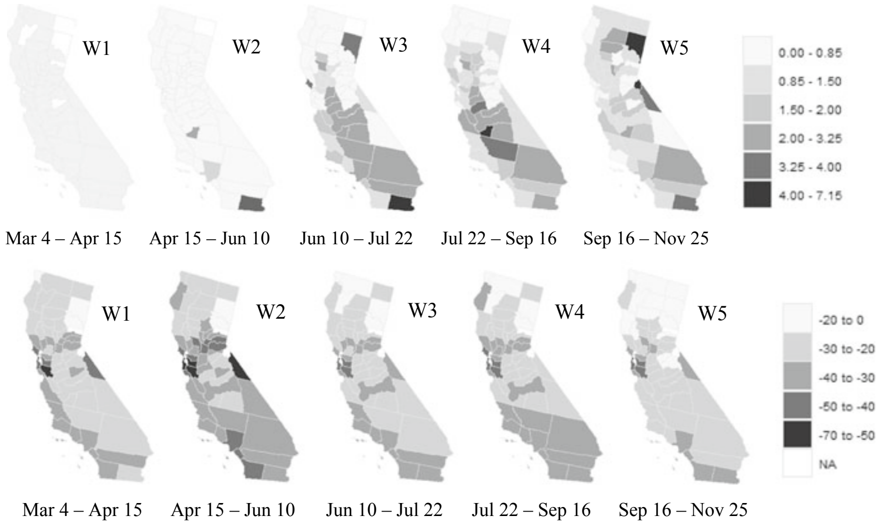



**Fig. 3.** **A** New infections per 10,000 population for California counties for time-windows. **B** Changes in workplace visits (versus pre-pandemic) for time-windows. *Data Source* The New York Times [16] and Google LLC [11]

most counties had their highest changes in workplace visits (at least a 30% reduction) and in subsequent windows, changes in workplace visits diminished and the overall level began to approach baseline values. Most rural counties in Northern California reached baseline visits by Window 5. Urban counties with a higher fraction of workers in telecommutable jobs and a higher fraction of households with internet access experienced higher reductions in workplace visits than rural counties.

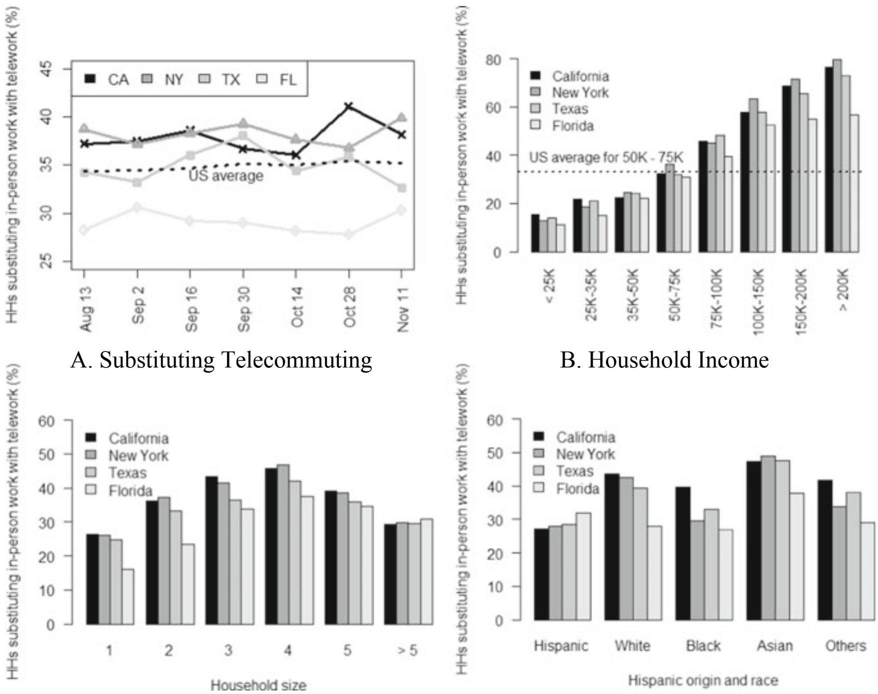
The changes in the portion of the workforce working from home (WFH) and the changes in work and non-workplace visits are shown in Table 3. Over one-third of workers (35.7% in California and 33.1% in the United States) worked from home during the pandemic, a rate nearly 6 times greater than pre-pandemic. Considering out-of-home work and non-work participation, a 30% reduction in work and a 28.7% reduction in non-work visits were observed in California during the pandemic. Among the four selected states, California experienced a higher reduction in both work and non-workplace visits.

The increased adoption of working from home and the significant reduction in workplace visits imply that a considerable fraction of workers were able to substitute in-person work with telework. Insights drawn from the Census Pulse Survey data (2020–21) are displayed in Fig. 4. Figure 4A shows the percentage of households where "at least one adult substituted some or all of their typical in-person work with telework because of the coronavirus." Nearly 35% of U.S. households reported such substitutions, and California and New York had higher levels of substitution than did Texas and Florida. Figure 4B, C, D shows the substitution rates across household sociodemographic indicators (household income, household size, and

**Table 3** Changes in telecommuting and activity-travel during the pandemic

| Variables | | US | CA | NY | TX | FL |
|---|---|---|---|---|---|---|
| Working from home (%) | Pre-COVID | 4.7 | 5.7 | 4.2 | 4.6 | 5.9 |
| | During COVID | 33.1 | 35.7 | 36.3 | 35.9 | 35.5 |
| | Change (%) | 608.7 | 526.3 | 764.3 | 680.4 | 501.7 |
| Unemployment rate (%) | Pre-COVID | 3.5 | 3.9 | 3.7 | 3.5 | 2.8 |
| | During COVID | 8.3 | 12 | 12 | 8.8 | 9.5 |
| | Change (%) | 140.1 | 207.7 | 224.3 | 151.4 | 239.3 |
| Change in workplace visits (%) | Change (%) | −24.3 | −30.0 | −28.5 | −24.4 | −26.1 |
| Change in grocery visits (%) | Change (%) | 1.6 | −3.7 | 1.3 | −2.7 | −7.9 |
| Change in recreation visits (%) | Change (%) | −10.8 | −25 | −17.7 | −11.6 | −19.2 |

*Data Source* Maryland Transportation Institute [13] and Google LLC [11]
*Note* Pre-pandemic is January 3–February 6, 2020 and during-pandemic is March 4–November 15, 2020




A. Substituting Telecommuting B. Household Income

C. Household Size D. Ethnicity / Race

**Fig. 4** Households with at least one adult substituting in-person work with telework from August to November 2020 [17]. *Data Source* Household Pulse Survey, U.S. Census Bureau. *Note* The start dates of seven bi-weekly survey periods are shown in Fig. 5A ethnicity/race). In each selected state, households with higher income switched to telework in higher numbers than did lower-income households, which suggested that higher income, white-collar workers and with more household resources had a greater ability to replace in-person work with telework. Larger households (with three or four members) had a higher level of substitution compared to smaller households. White and Asian households had a higher level of telework substitution compared to other races in all states but Florida, and Hispanic households in Florida more frequently adopted telework compared to Hispanics in California.

## 5 Impacts of the Pandemic on Activity and Travel

The increase in telecommuting during the pandemic corresponded to a decrease in activity visits: there were fewer visits to workplaces and non-workplaces associated with work commutes. This decrease in activity participation corresponded to a reduction in trips. Figure 5 shows the *relative* changes in activity visits by land-use types: workplace, grocery and pharmacy, retail and recreation, and parks, throughout the study period (March 4–November 25, 2020). The daily new infections for 100 K population during the same period (darker shaded area) are also shown in this figure.

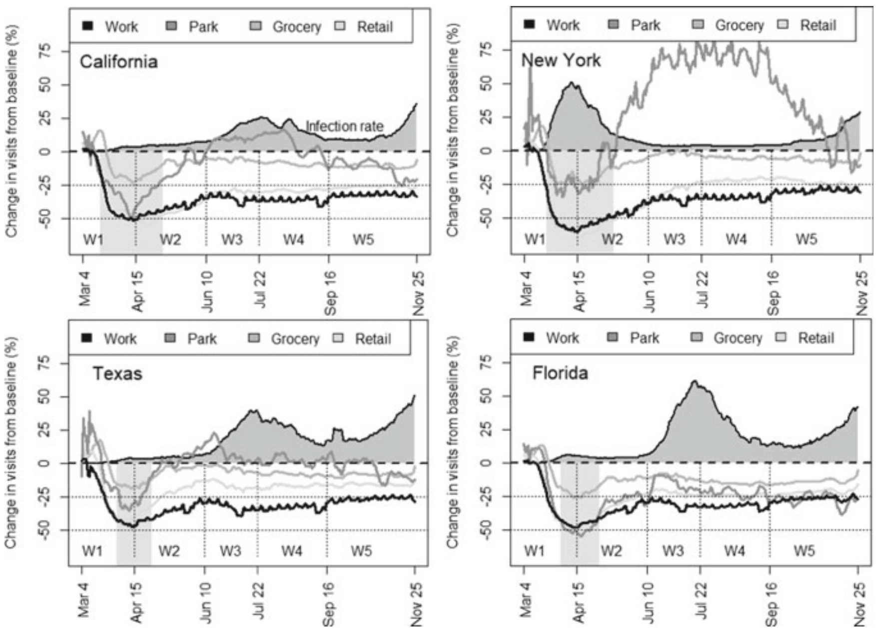



**Fig. 5** Changes in visits versus baseline travel and daily new cases per 100 K population (dark shaded area). *Data Source* Google LLC [11]. *Note* Changes in visits are shown as a seven-day moving average

The lighter shaded regions identify the duration of the first stay-at-home order for each state.

The sharp decline in the change in visits to activity places in the first time window (the initial shock period) corresponded to most states issuing their first stay-at-home order. This decline was followed by a rise after the lockdown period (producing a V-shape). In California, visits to workplaces and to retail and recreation locations declined substantially from the baseline in the first window and remained lower than the baseline throughout the study period compared to the other states (the percentage change in visits from the baseline remained below −25%). Grocery and pharmacy visits and visits to parks, however, started to rise after the initial dip and then approached the baseline level. Park visits occasionally exceeded the baseline, especially during summer (Windows 3 and 4). Among the selected states, New York experienced a high surge in park visits, due in part to severe increases in COVID-19 infections in early 2020, which was followed by low daily new infections through the summer that may have led to increased travel, especially to parks and outdoor spaces.

Changes in activity participation contributed to changes in the number of trips. Based on BTS 2020 data, Fig. 6 shows the percentage change in the number of trips by state in 2020 relative to the same day in 2019. Here, trips are categorized based

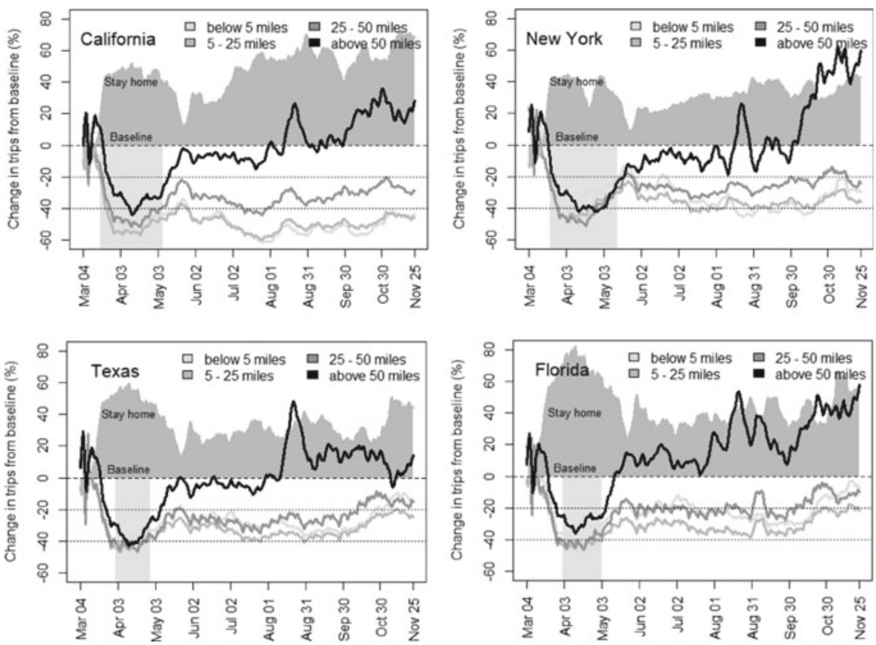



**Fig. 6** Changes in the number of trips with respect to baseline travel and change in the fraction of people staying at home (dark shaded area). *Data Source* Bureau of Transportation Statistics [7]. *Note* Changes in trips are shown as a seven-day moving average

on trip distance: (a) short distance trips (below 5 miles), (b) trips 5–25 miles, (c) trips 25–50 miles, and (d) long-distance trips (greater than 50 miles). Figure 6 also shows the percentage change in population staying home compared to the baseline.

Similar to the changes in activity visits, a V-shape pattern was observed in the changes in trips during the initial outbreak. Trips in all distance categories decreased considerably during the lockdown followed by an increase at the end of this period. The levels were then stable for the remainder of the year except for long-distance trips (over 50 miles). Long-distance trips declined in the first pandemic window but then successively increased to reach and occasionally exceed the baseline frequency. There was a noticeable spike in long-distance trips in mid-August in all four states, which may be due to a reported increase in summer automobile vacations. Among the selected states, California had a considerably higher fraction of people staying home and also had greater trip reductions from the baseline (about −40% per day since March 2020). Texas and Florida had considerably shorter first stay-at-home order durations (about 4 weeks) compared to California and New York (about 6–7 weeks), which might be a reason for a smaller reduction in trips from their respective baselines.

In Table 4, we examine *aggregate* measures of travel before and during the pandemic in California relative to the United States as a whole. In California, both the average numbers of work and non-work trips per person per day were significantly lower during the pandemic than before (based on a Wilcoxon signed-ranks non-parametric test). In California, the average person mile traveled (PMT) during the pandemic did not show statistically-significant changes relative to the baseline. For the United States, the average number of work trips decreased but non-work trips increased. As a result, the average number of all trips, as well as PMT, increased (cf. Table 4). According to seasonally adjusted vehicle mile traveled (VMT) data, however, the average VMT decreased by about 13% in 2020 from 2019 (Federal Highway Administration, 2019–2020). There is a limitation in making a direct comparison between the increase in PMT and the reduction in VMT in the United States during the pandemic. PMT is calculated for trips using all modes, whereas VMT is computed only for motor vehicle trips. According to Apple Mobility Trends Reports [2], walking increased by 24% during the pandemic from the baseline volume on January 13, 2020. These data require further study.

## 6 Summary and Policy Implications

This exploratory study analyzed the impacts of the COVID-19 pandemic on telecommuting and travel in the United States with a particular focus on California. The analysis "zoomed in" to four regions of California and "zoomed out" to three comparable states including New York, Texas, Florida to better position the aggregate analysis results for California. The findings of this study are summarized by general and California-specific observations.

**Table 4** Trips and PMT before and during the pandemic in the United States and California

| | Pre Pandemic | W1 | W2 | W3 | W4 | W5 | During Pandemic |
|---|---|---|---|---|---|---|---|
| | Jan 3–Feb 6 | Mar 4–Apr 15 | Apr 15–Jun 10 | Jun 10–Jul 22 | Jul 22–Sep 16 | Sep 16–Nov 25 | Mar 4–Nov 25 |
| *United States* | | | | | | | |
| No. of work trips per person/day | 0.53 | 0.51 | 0.44 | 0.43 | 0.43 | 0.46 | 0.45 |
| No. of non-work trips per person/day | 2.84 | 2.61 | 2.87 | 3.01 | 3.24 | 3.11 | 2.99 |
| No. of total trips per person/day | 3.36 | 3.12 | 3.31 | 3.44 | 3.68 | 3.57 | 3.45 |
| Person-mile traveled (PMT) | 44.52 | 36.72 | 40.00 | 50.11 | 51.26 | 48.68 | 45.70 |
| *California* | | | | | | | |
| No. of work trips per person/day | 0.47 | 0.43 | 0.35 | 0.33 | 0.34 | 0.37 | 0.36 |
| No of non-work trips per person/day | 2.74 | 2.43 | 2.57 | 2.69 | 2.77 | 2.74 | 2.65 |
| No. of total trips per person/day | 3.20 | 2.86 | 2.93 | 3.02 | 3.11 | **3.11** | 3.01 |
| Person-mile traveled (PMT) | 40.44 | 30.80 | 33.95 | 45.01 | 47.50 | 43.95 | **40.64** |

*Data Source* Maryland Transportation Institute [13]
*Note* A Wilcoxon signed-ranks non-parametric test was applied to assess differences between sequential windows. Window 1 and during-pandemic values are compared with the pre-pandemic baseline. All values were significantly (at the 5% level) different except for the two values in "bold." All the data shown are for the year 2020.

## 6.1 General Observations

- Nearly one-third of the U.S. workforce worked from home during the pandemic, a rate about 6 times higher than pre-pandemic.

- About 35% of domestic households saw at least one member replace in-person work with telework. Higher-income households and White and Asian households had higher proportions of in-person work replaced by telework.
- There were sharp declines in work and non-work visits during the initial outbreak period (March–April 2020). After the initial sharp decline, however, both grocery/pharmacy and park visits increased, approaching baseline levels during the analysis period.
- A reduction in activity participation produced a reduction in the number of trips in all distance categories throughout the year, except for long-distance trips which declined only during the initial outbreak.

## *6.2 State-Specific Observations*

- California and New York had higher levels of telework replacing in-person work than what was observed in Texas and Florida.
- California had a considerably higher fraction of people staying home with respect to its baseline compared to the selected comparison states.
- Among the four states, California experienced a higher reduction in both work and non-workplace visits. California urban counties experienced higher reductions in workplace visits than its rural counties.
- Similar to reduced activity participation, California had greater trip reductions relative to the baseline as did the comparison states.

It is unclear whether the observed changes in telecommuting and activity-travel behavior will continue after the pandemic ebbs. There have been numerous media reports of both employers and employees preferring telecommuting over commuting, at least some of the time. Using survey data, Conway et al. [8] anticipated that the trend of working from home was likely to continue post-pandemic. They surveyed reasons for work productivity changes for those who started telecommuting finding that the top reason for increased productivity was "no commute time," whereas the top reason for decreased productivity was "distraction at home." Based on an Australian survey, Bech and Hensher [4] found that for many respondents working from home was a positive experience and that these individuals expressed interest in continuing to telecommute after the pandemic. Other research suggested a potential increase in telecommuting over the next 2 years [1], based on lower travel/commute costs, more time savings, and higher sustainability impacts. These studies suggest that the telecommuting practice is likely to continue and, in some cases, may even grow in the post-pandemic future. A recent poll from the American Institute of Architects revealed that 56% of firms expected to have their employees work from the office and suggested that future workplaces may reflect a hybrid mixing of in-person and telework [12].

It can be anticipated that changes will occur in our work arrangements after the pandemic ebbs. If telecommuting does continue at current levels or in a hybrid manner, there will be some advantages and challenges. Working from home can improve peak hour congestion and reduce commuting time and cost. Barrer et al. [3] estimated that total time savings in the United States due to telework, measured by the time saved by not commuting to workplaces, was about 10 billion hours (as of mid-September 2020). They also noted that one-third of the savings was put back into the primary job and the rest was spent in leisure and household activities.

There are some potential challenges in the adoption of working from home arrangements. Firms would need to provide logistics, engagement, training, and coordination of remote workforces as well as robust cybersecurity infrastructure [12]. Workers who work remotely could live anywhere. Working from home would likely decrease spending at local service businesses near former workplaces. Consequently, these service workers may bear the economic impacts [19]. Workers may prefer to move from urban residences to outlying areas to gain space needed for dedicated workspaces at home. This may raise demand for larger homes in suburban areas and thus may impact the housing market [10]. Offering childcare closer to home may be another challenge of telecommuting [14]. Considering these factors, it is critical to fully consider how the post-pandemic workplace may be different than today's workplace. The nature of whatever forms of work emerge will impact activity-travel behavior and the transportation systems that accommodated pre-pandemic mobility.

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# The Impacts of Bus Use on COVID-19 Dispersion

**Henry Bernal and David Brownstone**

**Abstract** This research examines how bus use impacts the transmission of the COVID-19 virus in urban areas, focusing on the evolution of the COVID-19 pandemic in Los Angeles County. Using data from the Los Angeles County Metropolitan Transportation Authority on station-level ridership in October 2019, April 2020, and October 2020, we impute station-level ridership for other months in our data and map these to 231 Countywide Statistical Areas (CSAs) in Los Angeles County, which are used by the Los Angeles Department of Public Health to report community COVID-19 transmission. We obtain CSA-specific COVID-19 case counts between March 16, 2020 and January 31, 2021 to create a monthly panel of bus ridership and COVID-19 cases. After using a dynamic panel regression, our findings provide no evidence that increased ridership levels or trip lengths are associated with higher incidence of COVID-19 at the CSA level in Los Angeles County in the period between June 2020 and January 2021.

## 1 Introduction

This paper investigates the links between COVID-19 transmission and bus use in the region served by the Los Angeles Metro system. Los Angeles bus use declined dramatically at the beginning of the pandemic. Some of this decline was clearly caused by stay-at-home orders designed to slow down the spread of the disease. Additionally, the widespread fear that crowded buses could spread and transmit the virus across neighborhoods led to large drops in transit ridership, even before stay-at-home orders were formally announced. However, because Los Angeles has more low-wage "essential" workers who depend on buses to get to their jobs, compared to other

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cities such as New York [7], decline in bus use in many Los Angeles neighborhoods was less drastic than in other parts of the country.

Ideally, establishing a causal link between bus use and COVID-19 transmission would require random assignment of commute trips to either bus or a safe alternative like a single-occupancy car. We could then track infections across the bus and car groups to measure the impact of bus use. However, this experiment is impossible to carry out in practice. The next best alternative is based on Granger [10], and this is equivalent to causality if the underlying prediction model is correctly specified. We first fit the best possible predictive model of COVID-19 transmission without using any information about bus use, and then we add bus use information to this model. If adding bus use information improves the predictive ability of the augmented model, then we will say that bus use "causes" COVID-19 transmission. Based on this analysis, we did not find any evidence that knowing bus use improves our ability to predict COVID-19 transmission in the Los Angeles Metro system area. This is consistent with the claim that mitigation measures (including mandatory mask wearing and improved ventilation) were successful in stopping the spread of COVID-19 on LA Metro buses. Since our data stop before the spread of the Delta variant or the rollout of vaccinations, we do not know whether our conclusion still holds.

Section 2 of this chapter summarizes the literature on COVID-19 transmission as well as early research on the role of transportation modes in COVID transmission. Section 3 offers a description of the data sources used in our analysis, while Section 4 describes the methods used to analyze the relationship between bus ridership and COVID-19 transmission in Los Angeles County. Section 5 presents the results of our analyses, and Section 6 offers a discussion of possible interpretations and ramifications of our findings.

## 2 Literature Review

The main transmission mechanism of COVID-19 is through transmissions from individuals who either experience an asymptomatic infection or who later experience symptoms [2, 28]. It is also well-documented in the literature that COVID-19 is better spread in indoor settings [20]. Mitigation measures such as face covering mandates and capacity restrictions were believed to reduce COVID-19 transmission and prevent infections within weeks after their introduction in areas where such mandates were imposed [14, 24, 26]. Furthermore, transmission in indoor settings can also be mitigated through adequate ventilation where air exchanges are frequent [4], as well as in spaces where thermal destratification (i.e., warmer, contaminated air rises to the ceiling of a ventilated space) is better encouraged [3].

Some early epidemiological literature studying the 2003 SARS epidemic points to a relationship between transit use and transmission. Wang [25] provides a rather bleak outlook for transit use in Taipei, finding an immediate ridership decline of 1200 trips for each new SARS case that was announced in its underground rapid transit. Further, Wu et al. [27] found that taking a bus or riding the subway in Beijing more than once a week was a potential risk factor for contracting SARS. More recently, an investigation of a COVID-19 outbreak following a Buddhist worship event in China found that a large portion of the infected individuals contracted the virus through airborne transmission while riding a bus to the event [23]. However, Hu et al. [13] show evidence that transmission is heavily dependent on passenger density, seat spacing, and co-travel time (the time that passengers are aboard with other passengers). Hence, transmission can be reduced if measures are taken to reduce passenger density by increasing spacing between seats and minimizing co-travel time.

The argument that elevated transit use or high population density directly translates to increased rates of community spread of COVID-19 is contentious. For instance, Hamidi and Hamidi [11] find no evidence of a direct link between subway ridership and community COVID-19 cases in New York City, offering an alternative hypothesis that transmission of COVID-19 is more strongly linked to racial and socio-economic factors. This does seemingly contrast McLaren [18], who uses county-level data to find that disparities in COVID-19 deaths among African Americans are correlated with areas where public transportation use is high, although these numbers are based on Census data that pre-date the pandemic. This hypothesis is echoed by Fathi-Kazerooni et al. [9], who use turnstile data from the New York City subway finding a high correlation between subway ridership and COVID-19 deaths between March and May 2020, detectable across all boroughs. To the best of our knowledge, this is the first study to investigate a dynamic causal link between subway use and COVID-19 transmission in a large metropolitan area. We find no causal link between bus use and COVID-19 transmission in Los Angeles, and this is likely due to differences in the periods examined, mitigation measures, and less crowding compared to New York subways.

Some existing research shows correlations between transit use, COVID-19 infections, and demographics. Hu and Chen [12] note that following the onset of the pandemic in Chicago, wealthier, better-educated areas saw larger declines in transit ridership than areas with lower income and educational attainment. There is also research and press headlines supporting the hypothesis that neighborhoods and cities with high percentages of people of color were far more likely to see higher death rates and more infections per capita [6, 22]. Moreover, increased susceptibility to COVID-19 among ethnic and racial minorities can be traced to these groups representing a disproportionate share of occupations categorized as essential in the pandemic [21].

## 3 Data

We constructed a panel of monthly COVID-19 cases and average weekly bus ridership within Countywide Statistical Areas (CSAs) in Los Angeles County (we will refer to these areas as "neighborhoods"). We supplemented these data with sociodemographic variables like the ones used in McLaren [18] on race and ethnicity, as well as variables about income, education, commuting, population, and household density.

### 3.1 COVID-19 Data

Our data on COVID-19 cases comes from the Los Angeles County Public Health agency and provides weekly counts of new cases for 236 neighborhoods in LA County from March 2020 through January 2021 [17]. We obtained historical data for each CSA for each week between March 16, 2020 and January 31, 2021. We aggregated COVID-19 cases at the CSA level to monthly frequency because of some reporting discrepancies or irregularities. This aggregation removed negative case numbers in the weekly data. These were likely due to data corrections that resulted in a case assigned in a certain CSA and being reassigned to another. Using a larger time unit reduced possible noise from reporting lags or periodic case reporting backlogs.

### 3.2 Transit Ridership Data

Data on transit ridership are from the Los Angeles County Metropolitan Transportation Authority (Metro) [15, 16]. First, we used ridership data at each bus stop for the months of October 2019, April 2020, and October 2020. Second, we used ridership on each bus line (not disaggregated by stop), as well as passenger miles traveled, which were available monthly beginning October 2019 and ending in December 2020.

Because geographic dispersion of bus ridership was only known for three specific months, we imputed the CSA-specific bus ridership for the remaining months. Using the stop-specific data, bus stops were mapped to CSAs, and ridership numbers within CSAs were added to obtain CSA-level ridership in October 2019, April 2020, and October 2020. We then used ridership and passenger miles numbers by line in the remaining months to generate estimates of the share of ridership that each CSA comprises within each line, as well as estimates of the share of ridership that each line comprises within a specific CSA. These ridership shares were then used to estimate CSA-level ridership in months outside those for which stop-level ridership was available. Additionally, we estimated passenger miles traveled for all months between October 2019 and December 2020 (see Sect. 4.1 and the Appendix for a detailed description of bus ridership imputations).

Metro is by far the largest transit provider in Los Angeles County, but there are 66 additional transit operators serving cities other than Los Angeles. LA Metro provides bus service that overlaps the service areas of some of these agencies, so it is likely that our data underestimate bus utilization in some neighborhoods served by multiple transit agencies. Our key results rely on differences in bus utilization and COVID-19 cases, so if bus utilization from other agencies changes proportionally with changes in LA Metro bus utilization, our results are still valid. LA Metro also provides some bus service in parts of Orange and Ventura counties, and we excluded these data from our analyses.

### 3.3 Demographic Data

To supplement our data on bus ridership and COVID cases at the CSA level, we use geographic information software (ArcGIS) to impute demographic data. We draw our data from two sources: the first is ESRI's demographic estimates using up-to-date Census estimates, and the second is the 2018 5-year American Community Survey (ACS) [8]. We categorize our demographic variables into four main groups: race and ethnicity, income and education, commuting, and population and density.

(1) *Race and Demographics*—We examine four minority groups defined by the Census: "Hispanic or Latino"; "Black or African American" (abbreviated as "Black"); "American Indian or Alaska Native", (identified as "First Nations"; and "Asian"). These data were obtained from ESRI's 2020 estimates and imputed at the CSA level.
(2) *Income and Education*—We examine two key income measures: median household income and households below the poverty line. Data on educational attainment and median household income were obtained from ESRI, while data on poverty were obtained from the ACS and imputed using geographical information software.
(3) *Commuting*—We obtained commuting information using ACS data for those who drive alone to work and those who rely on public transit.
(4) *Population and Density*—We obtained data from ESRI for total population and total number of households within a CSA. The quotient of these two variables then gave a rudimentary estimate of the average household density within a CSA.

### 3.4 Descriptive Statistics

Figure 1 shows how these cases are distributed across neighborhoods and across time. There was a clear wave of new cases in June and July 2020, followed by a much larger wave in November, December, and January, and there was a lot of variation in cases across neighborhoods during these peaks. We also collected bus boardings and trip length information from Los Angeles Metro and aggregated these data into the same neighborhoods defined by the Los Angeles County Public Health agency (see detailed explanation later in the chapter). Figure 2 shows the distribution of bus boardings and alightings per 100,000 population across these neighborhoods by month. The steep decline in March and April 2020 is followed by a slow recovery to levels well below pre-pandemic usage. Figure 3 shows a map with the CSAs included in our analysis.

Table 1 shows the distribution of the variables used in our analysis for the full sample and the smaller sample used for estimating the models described in the Results section. The estimation sample excludes all neighborhoods with no Metro bus boardings as well as those with not enough monthly observations to support the lags in our preferred dynamic model. We also excluded all observations with

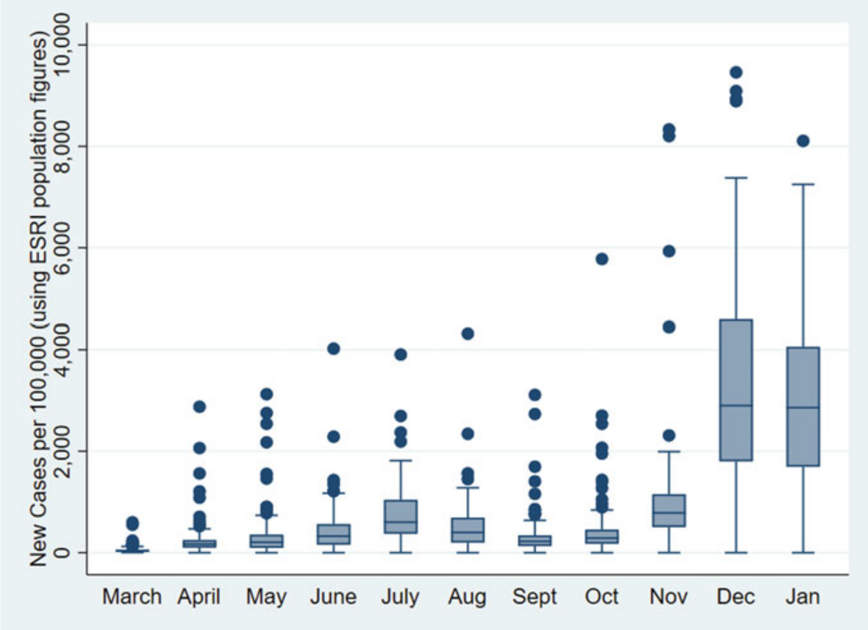


**Fig. 1** Distribution of new COVID cases across neighborhoods by month beginning March 2020. *Data Source* Los Angeles County Public Health. *Note* The shaded rectangles show the area between the 75th and 25th percentile of the distribution across neighborhoods, and the "whiskers" are drawn at the 97.5th and 2.5th percentile. The dots represent "outlier" observations outside of the central 95% of the distribution. The plots exclude 0.29% of the observations that were above 10,000 new monthly cases per 100,000 population

bus boardings per 100,000 population greater than or equal to 400,000 (about 2% of the full sample) because they had undue influence on the precision of estimated parameters; Fig. 3 shows the included and excluded neighborhoods. These exclusions account for the large differences in the average bus boardings across the full and estimation sample. Generally, the two samples are quite similar. The neighborhoods in the estimation sample have somewhat higher population, lower median income, and slightly more households below the poverty line.

## 4 Methodology

### *4.1 Imputing Bus Ridership*

To estimate ridership in each CSA for the months for which we did not directly obtain stop-level ridership, we first computed the share of riders from each line that board and alight in each CSA. To give an example, suppose that a bus line passes through

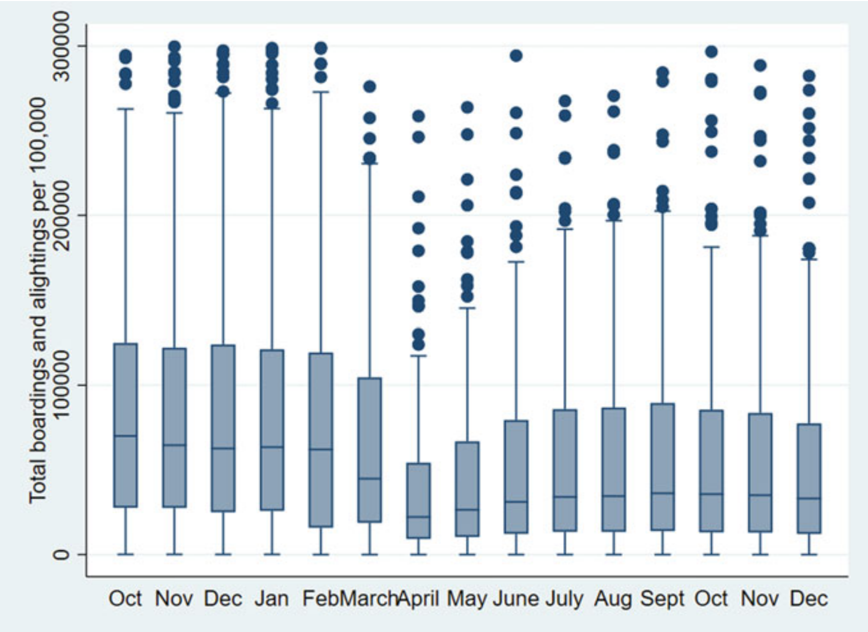


**Fig. 2** Distribution of average weekly bus boardings and alightings across neighborhoods by month beginning October 2019. *Data Source* Los Angeles County Metropolitan Authority (Metro) [16]. *Note* The plots exclude 6% of the observations that were above 300,000 boardings and alightings per 100,000 residents. We also exclude data from stops outside of Los Angeles County

two CSAs—neighborhoods A and B—and totals 1000 average weekly riders in April 2020. We find that 400 riders board and get off in neighborhood A, and the remaining 600 do so in neighborhood B. In that case, 40% of the line's ridership comes from neighborhood A and 60% from B. Because we know the ridership of each line for each month, we can then recover the number of riders that use each line within each neighborhood.

Now suppose we know that 900 riders boarded the same bus line in May 2020. To obtain estimates of May's ridership, we assign 40% of that ridership to neighborhood A, or 360 riders, and the remaining 540 riders to neighborhood B. We then update the neighborhood shares in the next month for which stop-level ridership numbers are available, which is October 2020. Finally, we take the sum of riders from each line within each neighborhood to recover CSA-level ridership. The only exception to our updating rule was March 2020, where the neighborhood shares from April 2020 were used instead of the neighborhood shares calculated from October 2019 data. Here, we use forward interpolation because of the shocks to transit ridership that occurred from the beginning of the pandemic and the initial issuance of stay-at-home orders from the county and state.

Next, we impute a measure of average passenger miles, which we use as a proxy for exposure to COVID-19 while riding transit. Due to data limitations, we are required

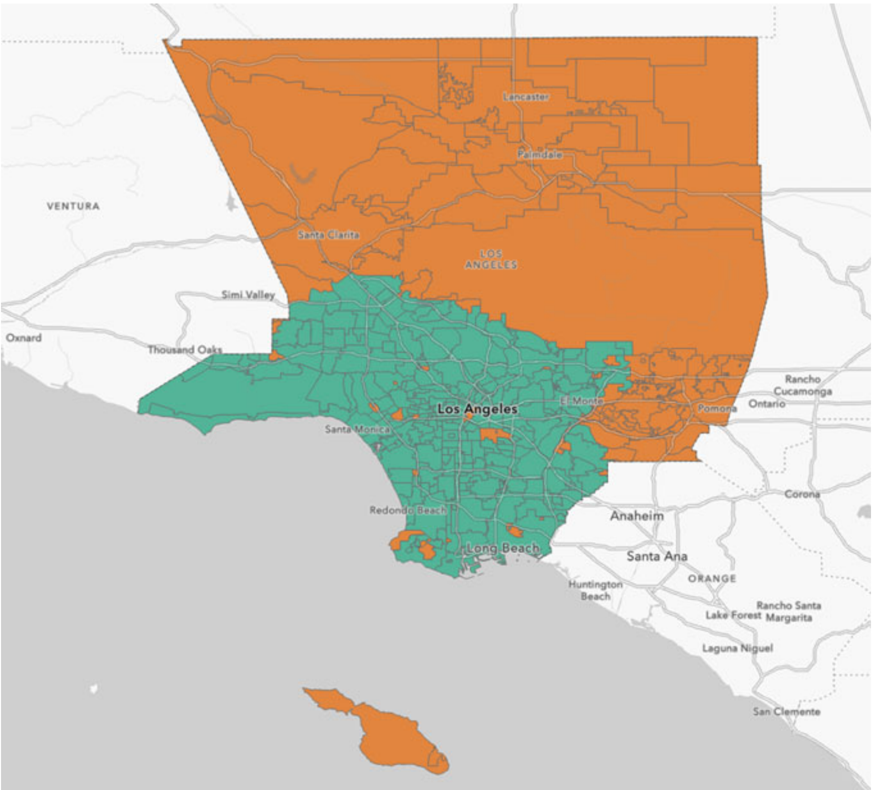


**Fig. 3** Map of Included (green) and Excluded (orange) Neighborhoods. *Data Source* Authors

to make a key assumption: because passenger miles are only available for each line and are unknown at the stop-level, we assume that the distribution of passenger miles within each line does not depend on the neighborhood where riders board or alight (i.e., we assume the average miles traveled by passengers do not change regardless of where along the line they get on or off the bus). Because we have inferred the share of riders from each line pertaining to each CSA, we multiply the average passenger miles by each neighborhood's share of riders from each line and then add these numbers for each line passing through each CSA. Doing this gives a monthly estimate of the average passenger miles within each CSA, since passenger miles data are available monthly. (See Appendix for more detailed description of the imputation process.)

**Table 1** Descriptive statistics

| | Full sample | | Estimation sample | |
|---|---|---|---|---|
| Demographics sample sizes | $N = 329$ | | $N = 231$ | |
| Variable | Mean | Std. Dev | Mean | Std. Dev |
| Average COVID cases* | 970 | 833 | 918 | 446 |
| Total population | 30,904 | 42,638 | 36,175 | 43,319 |
| Total number of households | 10,139 | 14,439 | 12,091 | 15,106 |
| Household density | 3.18 | 0.97 | 3.08 | 0.74 |
| Fraction of Hispanic descent | 0.43 | 0.27 | 0.45 | 0.28 |
| Fraction non-Hispanic Black | 0.090 | 0.144 | 0.109 | 0.164 |
| Fraction Native American | 0.002 | 0.002 | 0.002 | 0.001 |
| Fraction Asian | 0.135 | 0.143 | 0.143 | 0.150 |
| Median household income | 81,830 | 38,662 | 76,491 | 37,715 |
| Fraction households below poverty line | 0.046 | 0.028 | 0.052 | 0.028 |
| Fraction without high school diploma | 0.069 | 0.055 | 0.076 | 0.057 |
| Fraction high school graduates | 0.126 | 0.047 | 0.121 | 0.045 |
| Fraction with GED | 0.012 | 0.008 | 0.011 | 0.006 |
| Fraction with some college | 0.130 | 0.042 | 0.122 | 0.034 |
| Fraction with associate degree | 0.049 | 0.020 | 0.045 | 0.016 |
| Fraction with bachelor's degree | 0.160 | 0.093 | 0.166 | 0.098 |
| Fraction with graduate degree | 0.095 | 0.082 | 0.098 | 0.084 |
| Fraction who drive alone to work | 0.343 | 0.073 | 0.349 | 0.062 |
| Fraction who take public transit to work | 0.025 | 0.028 | 0.032 | 0.031 |
| *Covid-19 Variables sample sizes* | 3465 | – | 2496 | – |
| New monthly cases* | 964 | 1732 | 917 | 1314 |
| Cumulative cases* (first lag) | 2022 | 2897 | 1955 | 2400 |
| *Bus variables sample sizes* | 2548 | – | 2496 | – |
| Bus boardings/alightings* (first lag) | 154,229 | 1,357,613 | 66,336 | 80,370 |
| Average bus trip miles (first lag) | 3.68 | 1.59 | 3.69 | 1.59 |
| * per 100,000 population | – | – | – | – |

*Data Sources* Los Angeles County Public Health; LA Metro; 5-year American Community Survey (ACS), 2018

## 4.2 Empirical Approach

Recall that we need to specify a dynamic model to predict monthly COVID-19 cases for each CSA. We then want to test whether excluding bus utilization variables significantly reduces the predictive accuracy of the model. Our analysis is based on the general dynamic panel data model:

$$y_{it} = \sum_{j=1}^{3} \alpha_j y_{i,t-j} + \mathbf{x_{it}}\beta_1 + \mathbf{w_{it}}\beta_2 + \nu_i + \epsilon_{it}, i = 1, \ldots, N, t = 1, \ldots, T_i$$

Here, $y_{it}$ is our new cases per 100,000 residents in CSA $i$ and month $t$, while $y_{i,t-j}$ represents the $j$-th lag of new cases per 100,000 residents; in our model, we use a maximum of three lags (note that a lag is simply the previous month's new COVID-19 cases). Furthermore, we incorporate monthly dummy variables (with values 0 or 1 for each month in our panel) for the exogenous covariates $\mathbf{x_{it}}$ and bus system usage variables as the endogenous covariates, $\mathbf{w_{it}}$. We will first fit the model without the bus system variables and then see if adding them improves its predictive power.

This model can be estimated by running a regression on the differences from the group means for each neighborhood $i$ since then the unknown neighborhood-level effects, $\nu_{i,}$, drop out. Unfortunately, this "fixed effects" estimation makes it impossible to identify the impact of any time-invariant variables such as sociodemographic information. An additional problem is that taking differences from group means induces correlation across the errors over time, and this also makes the lagged dependent variables correlated with the new error term. This would lead to "bad" estimates of $\beta_2$ (our parameter of interest), and our model describing a spurious relationship between transit ridership and COVID-19 cases at the CSA-level.

The current technique for dealing with these problems is to use the instrumental variable estimator developed by Arellano and Bond [1] together with clustered (or robust) parameter covariance estimators to deal with the error correlations. We also looked at fixed effects panel data estimators, which require the stronger assumption that the lagged variables are uncorrelated with the time-varying error terms. These estimates had lower standard errors but led to similar empirical conclusions.

## 5 Results

We begin by first examining the correlations between COVID-19 cases (using December 2020 data), demographics, and bus system utilization data. Table 2 shows regressions with and without bus system variables. Both regressions were fit using observations from 231 neighborhoods that were also used in the dynamic panel data models described later. Our final sample excluded five observations corresponding to very high values of bus boardings and alightings per 100,000 population (more than 400,000). Including these outlying observations did not change the coefficient estimates but did lead to very high and unstable residual and parameter covariance estimates. We use this same sample throughout this section.

Note that although both average bus boardings and alightings and average bus trip miles are statistically significant, their inclusion only increases the $R^2$ from 0.90 to 0.91. The coefficients of the demographic variables are as expected. Neighborhoods with higher numbers of residents per household, lower income and lower education are associated with higher COVID-19 cases. Neighborhoods with a higher proportion

**Table 2** Regressions on average monthly cases between June 2020 and January 2021 per 100,000 population

| Variable | Without Bus variables | | With Bus Variables | |
|---|---|---|---|---|
| | Coeff | *t*-statistic | Coeff | *t*-statistic |
| Mean boardings/alightings per 100,000 | – | – | 0.001 | 2.8 |
| Mean average bus trip miles | – | – | −24 | −3.3 |
| Total population | 0.003 | 2.3 | 0.003 | 2.4 |
| Total number of households | −0.009 | −2.1 | −0.008 | −2.1 |
| Household density | 276 | 5.8 | 287 | 6.2 |
| Fraction of Hispanic descent | 437 | 3.6 | 436 | 3.8 |
| Fraction non-Hispanic Black | 85 | 0.9 | −52 | −0.5 |
| Fraction Native American | −10,761 | −1.1 | −9407 | −1.0 |
| Fraction Asian | −594 | −6.6 | −603 | −7.0 |
| Median household income | −0.002 | −2.4 | −0.001 | −1.8 |
| Fraction households below poverty line | 1838 | 2.8 | 1446 | 2.2 |
| Fraction without high school diploma | 1214 | 2.3 | 911 | 1.7 |
| Fraction high school graduates | 2299 | 4.9 | 2338 | 5.2 |
| Fraction with GED | −1155 | −0.6 | −1596 | −0.8 |
| Fraction with some college | 348 | 0.6 | 553 | 1.0 |
| Fraction with associate degree | 292 | 0.3 | 712 | 0.8 |
| Fraction with bachelor’s degree | 953 | 2.8 | 863 | 2.6 |
| Fraction with graduate degree | 610 | 1.4 | 538 | 1.2 |
| Fraction who drive alone to work | 48 | 0.2 | 13 | 0.1 |
| Fraction who take public transit to work | 179 | 0.4 | −459 | −0.9 |
| Intercept | −663 | −2.1 | −615 | −2.0 |

*Data Sources* Los Angeles County Public Health; LA Metro; 5-year American Community Survey (ACS), 2018.

of Hispanic residents are associated with higher COVID-19 cases, while those with a higher proportion of Asian residents are associated with lower cases.

The cross-sectional regressions only show partial correlations, and without strong unrealistic additional assumptions do not imply anything about causality. A better approach is to take advantage of the panel nature of our data to see whether the bus system variables can improve dynamic forecasts of COVID-19 infections. Table 3 shows the results of estimating our preferred models using dynamic panel data models estimated with 1,560 observations across 231 CSAs (from June 2020 to January 2021). These estimates allow for unrestricted correlations between the unknown neighborhood-level effects, $\nu_{i,}$, and the included variables. The standard errors are clustered on neighborhoods to allow for the possibility of autocorrelated errors within a neighborhood.

**Table 3** Dynamic panel data models for new monthly COVID cases per 100,000 residents. *Note*: All variables except month dummies and bus trip miles are per 100,000 population and standard errors are clustered by neighborhood. January is the excluded category for the time indicator variables.

| Variable | Forecast without bus variables | | | Full Forecast Model | | |
|---|---|---|---|---|---|---|
| | Coeff. | Std. Err | $t$ | Coeff. | Std. Err | $t$ |
| New monthly cases (first lag) | −0.50 | 0.09 | −5.5 | −0.53 | 0.15 | −3.4 |
| New monthly cases (second lag) | −0.83 | 0.15 | −5.5 | −0.83 | 0.19 | −4.3 |
| New monthly cases (third lag) | −1.55 | 0.25 | −6.3 | −1.55 | 0.48 | −3.2 |
| Cumulative cases per 100,000 (first lag) | 0.68 | 0.04 | 16.5 | 0.70 | 0.06 | 11.5 |
| Bus boardings/alightings (first lag) | – | – | – | −0.002 | 0.003 | −0.9 |
| Average bus trip miles (first lag) | – | – | – | −155 | 129 | −1.2 |
| June (= 1 for June 2020) | −801 | 157 | −5.1 | −799 | 171 | −4.7 |
| July | −445 | 141 | −3.1 | −445 | 141 | −3.2 |
| August | −784 | 129 | −6.1 | −755 | 129 | −5.9 |
| September | −955 | 148 | −6.5 | −965 | 163 | −5.9 |
| October | −892 | 145 | −6.2 | −902 | 134 | −6.7 |
| November | −1150 | 151 | −7.6 | −1156 | 153 | −7.6 |
| December | 615 | 114 | 5.4 | 621 | 153 | 4.1 |
| Intercept | 1218 | 183 | 6.6 | 1898 | 433 | 4.4 |

*Data Sources* Los Angeles County Public Health, LA Metro.

Our best forecasting model without using bus system utilization data estimates is shown in the first three columns of Table 3. This model requires three lags of monthly COVID-19 cases per 100,000 population (as indicated by the highly significant coefficients on these lagged variables); we also found a significant impact of the lagged value of cumulative COVID-19 cases per 100,000. The lagged values of COVID-19 cases as well as cumulative COVID-19 cases are endogenous. We use further lags and levels of these variables together with other exogenous variables as instrumental variables, following Arellano and Bond [1]. We also include a full set of month indicator variables to account for any policies (such as stay-at-home orders or mask mandates) that impact all neighborhoods. The pattern of the estimated month effects is consistent with a peak in July 2020 and a much larger peak in December 2020 and January 2021, which closely corresponds to the peaks of COVID-19 cases in Los Angeles County. The implied dynamics of COVID-19 infections show a small positive impact from last month's cases since the sum of the first lag of new and cumulative cases is positive. This and the positive impact of lagged cumulative cases is likely due to direct transmission within the neighborhoods and reporting lags. The negative impact of cases from 2 to 3 months earlier is likely due to these people having immunity and thus reducing the pool of those who can get infected.

The remaining three columns of Table 3 add lagged values of bus boardings and alightings as well as average trip miles to the previous model. These variables are separately and jointly statistically insignificant at conventional significance levels. More importantly, the coefficients of the predictive model are essentially unchanged.

The overall $R^2$ is 0.89 for both models, and this shows that there is no evidence that bus use had any impact on COVID-19 transmission for this sample. These findings are robust to additional specifications of the estimating equation and additional lags being incorporated into our dynamic panel regression. We also fit models based on Blundell and Bond [5] estimators with the bus system variables treated as endogenous. The empirical results are the same as in Table 3.

Although about 40% of the residual variation in the models in Table 3 is due to variation in the unobserved neighborhood-level effects, $\nu_i$, we could not find any significant interactions with these effects and the demographic variables described in Table 2. We used Monte Carlo simulations to recover the distribution of a regression of the mean residuals within each neighborhood on that neighborhood's demographic characteristics. We also tried fitting a generalized correlated random effects model (see [19]), which makes stronger assumptions. This resulted in statistically significant but small negative coefficients for the fraction of Native American residents and the fraction of residents with a postgraduate degree. Once the dynamics of COVID-19 transmission are modeled as in Table 3, the cross-sectional correlations shown in Table 2 are negligible.

## 6 Conclusion

The results described in this paper are consistent with the hypothesis that bus system utilization in the Los Angeles Metro service area had no impact on COVID-19 transmission during the June 2020 through January 2021 period. Metro mandated wearing masks for all passengers during this period, and our results are consistent with the hypothesis that mask wearing was effective. Of course, we do not know how our results would change if Metro did not require masks for all passengers. Before concluding that bus transit use is not a factor in COVID-19 transmission, it would be useful to carry out careful contact tracing investigations using virus sample genetic sequencing to pinpoint the source of COVID-19 infections. Countries like Taiwan and South Korea have carried out such investigations, and it would certainly be useful to do more in United States and other countries.

Approximately 40% of the residual variation in our models of COVID-19 transmission is due to the variation in neighborhood factors that do not change between June 2020 and January 2021. We tried several methods to explain these factors using a large set of demographic variables but found essentially no correlations. This implies that the cross-sectional correlations frequently noted in press reporting (also in Table 2) are all due to these correlations not accounting for the dynamics of COVID-19 transmission. Of course, the neighborhoods we are forced to use are quite large, and our aggregate demographic measures may well obscure important effects for some subgroups.

Our analysis could be usefully improved by extending our panel data further over time. We could account for vaccinations by adding them to the 2 and 3 months lagged values of current cases. It would be useful to include other geographically detailed mobility measures in the model to distinguish between cases potentially caused by bus use and other types of mobility. Although we did not find much evidence of heterogeneity related to demographic differences in the unobserved time-invariant panel effects, there may be important heterogeneity in the dynamics of COVID-19 transmission across the neighborhoods.

The Los Angeles Metro bus system lost about one-third of its riders from November/December 2019 to November/December 2020. Many of these riders likely left because of fears about catching COVID-19 while riding buses. Our results suggest that these fears might not be justified if Metro's COVID-19 mitigation strategies are followed. While increasing vaccination rates should reduce transmission on buses, the emergence of the Delta variant clearly increases transmission risk. This suggests that it is not prudent to drop mandatory mask policies if COVID-19 is widely circulating among the population served by bus transit.

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## Appendix: Technical Description of Bus Ridership Imputations

To estimate ridership in each CSA for months where we did not directly obtain stop-level ridership, we first compute the share of riders in CSA $i$ conditional on commuting on line $l$, from the most recent stop-level data, which is provided for month $t*$. This share will be denoted $s_{(i|l)t^*}$. Then, we use monthly per-line ridership data to infer ridership specific to each line and CSA, which will be denoted $B_{il}$. Finally, to obtain overall CSA-level ridership, the sum of all values $B_{il}$ is taken across all lines $l$ passing through CSA $i$.

$$s_{(i|l)t^*} = \frac{B_{ilt^*}}{B_{lt^*}} \tag{1}$$

$$B_{it} = \sum\nolimits_l B_{lt} s_{(i|l)t^*} \tag{2}$$

Equation (1) shows how the share of riders in CSA $i$ that comprise line $l$ is computed, using the most recent month $t$*, before month $t$, for which ridership $B_{it}$ is known. Equation (2) shows how known values of $B_{lt}$ are multiplied by $s_{(i|l)t^*}$ and then added across all lines $l$ to give the total average weekly boardings for month $t$ and CSA $i$.

Next, we impute a measure of average passenger miles to use as a proxy for exposure to COVID-19, while riding transit using a few assumptions, which are mostly related to data constraints. Because passenger miles are available for each line, we assume that the distribution of passenger miles within each line is independent of the CSA $i$ where riders are boarding and alighting. We will denote line-specific average passenger miles for month $t$, $\overline{x_{\mathrm{lt}}}$. Unlike for imputing bus ridership, to impute the passenger miles, we obtain the share of CSA ridership hailing from line $l$, which we denote $s_{(l|i)t^*}$. Doing this allows us to compute imputed passenger miles as follows:

$$\overline{x_{it}} = \sum\nolimits_{l} \overline{x_{(l|i)t}} s_{(l|i)t^*} = \sum\nolimits_{l} \overline{x_{lt}} s_{(l|i)t^*} \tag{3}$$

Equation (3) shows that by assuming $\overline{x_{(l|i)t}} = \overline{x_{lt}}$, the computation of $\overline{x_{it}}$ turns into a simple expected value computation using the conditional estimated values of the probability of a rider from CSA $i$ choosing to commute on line $l$, using the most recent data from month $t$*. Assuming that passenger miles on line $l$ are independent of the CSA where riders board and alight would not be required if the conditional values $\overline{x_{(l|i)t}}$ were known.

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# Responses and the Future

# Impact of COVID-19 Pandemic Management Policies on Public Transportation Systems

**Yiduo Huang and Zuo-Jun Max Shen**

**Abstract** During the COVID-19 outbreak, the risk of infection is not neglectable in a public transportation system. To satisfy the demands while controlling the spread of COVID-19, public transportation agencies have proposed various rules, such as increasing train frequency and requiring face coverings. In this chapter, we summarize newly developed evaluation methodologies, and evaluate the impacts of COVID-19 policies. We also present key findings regarding the impacts of different policies using these new methods. We find that the goal of stopping the pandemic coincided with minimizing the total delay when the service area was homogenous in infection rate. For heterogenous cities, minimizing the risk is equivalent to minimizing weighted travel time, where the weight is the infection rate. We also find that the results obtained from different models could be different due to their assumptions on the lost demand. If the demand is elastic, closing part of the system can prevent the spread of the pandemic, otherwise, closing will lead to longer waiting time, higher passenger density, and infection risk.

## 1 Introduction

During the COVID-19 pandemic, public transportation systems worldwide have faced significant challenges while gradually recovering from the total shutdown, including drops in passenger ticket revenue and the risk of spreading COVID-19. We have been studying COVID-19 in public transportation systems for the past few months [4]. According to a report published in September 2020 by the American Public Transportation Association [15] and other reports [16], public transit systems across the U.S. are safe for travel owing to the applied response measures

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(see also Chap. 15), and as of mid-August 2020, there has been no direct evidence of outbreaks of COVID-19 linked to intracity public transit. However, there could be new cases related to public transit that have not been identified by contact tracing. In China, public-transportation-related outbreaks have been found on intercity buses in Zhejiang [17] and Hunan [9, 10].

Local governments and public transportation agencies have implemented various COVID-19-related policies during the recovery phase to control the spread of the pandemic, such as reducing service frequency and reducing network coverage. For example, in the Bay Area, the Bay Area Transit reduced the frequency from 15 to 30 min on certain lines [1]. The New York City Metropolitan Transit Authority (MTA) canceled overnight subway services during May 2020 [11, 19]. And in Washington D.C., the Washington Metropolitan Area Transit Authority (WMATA) closed 19 stations in April 2020 [20].

However, it is not entirely clear which policies are needed, or the extent to which they should be implemented. Policies should be able to prevent COVID-19 transmission, comply with social distancing rules, and promote safe travel, but policies also need to be budget-friendly.

This chapter summarizes COVID-19 policy evaluation methodologies and policy suggestions based on scholarly works published in 2020 and early 2021 worldwide, and also presents some results obtained by our model [4]. The reviewed literature can be classified into two categories: (1) research combining epidemic and transportation models and (2) research without transportation models.

Transportation models include traffic demand models, route choice models, and/or delay estimation models. In studies considering COVID-19 and transportation models, some researchers [7, 9, 12–14, 18] have considered the risks of COVID-19 while building public transportation models. Using this approach, it is possible to quickly evaluate the impacts of different policies and provide additional insights into the COVID-19 risks in public transportation systems. The disadvantage of this type of work is that it usually requires many assumptions regarding the pandemic and passenger route choice properties. If these assumptions are incorrect, the results may be incorrect.

Studies without transportation models (e.g., [3, 6, 9, 10, 17, 21]) are usually based on background knowledge of statistics/biostatistics and epidemiology. Researchers have evaluated policies implemented in 2020 and provided policy suggestions using data-driven approaches such as regression analysis and causal inference. This approach, however, is not able to explain the mechanisms behind the correlations identified in the data analyses or make predictions since the analyses are based on existing data.

Notably, many of the above works have not been peer-viewed and verified, owing to the novelty of the problem. We introduce these studies and results because they may provide valuable suggestions for policymakers, and their methodologies are helpful when evaluating new COVID-19 policies for public transportation systems. Nevertheless, readers should be cautious, as some assumptions may not be applicable to public transportation systems in general. New results are being released daily owing to the efforts of both transportation and epidemiology researchers, and thus our summary might not be complete.

In Section 2, we introduce the model framework of the first approach. In Section 3, we briefly introduce the methods of some studies using the second approach. In Section 4, we summarize all policy evaluation results obtained from both approaches, and discuss some insights from these results that could be useful when formulating new policies. Lastly, we present our conclusions in Section 5.

## 2 Evaluating and Optimizing Policies by Combining COVID-19 and Public Transportation Models

### *2.1 Model Framework*

We know that COVID-19 contraction in public transportation systems occurs when a susceptible passenger encounters an infectious passenger. Studies that combine COVID-19 and transportation models typically address the following issues:

1. Contact tracking: How many infectious passengers were each susceptible to encounters? How long have they stayed together? Where did they meet?
2. Pandemic mechanism: Given the contact history, how many susceptible passengers contracted COVID-19 after staying in the exact location with an infectious passenger for a period?

In other words, contact tracking helps us identify passengers' contact histories in the transportation system, and the pandemic mechanism helps us predict the risk of COVID-19 in the system given such contact histories. A public transportation model can usually solve the first issue, and epidemic models play critical roles in addressing the second issue.

### *2.2 Contact Tracing*

As COVID-19 is transmitted via contacts between individuals, the first task is to track the passenger contacts inside the system. Contact occurs when two passengers stay in the exact same vehicle or on the same platform for a certain period. The intensity of the contact depends on the duration and the character of the contact. The longer the passengers spend together, the higher the risk. If this contact occurs in an open outdoor space or with both persons wearing mask, the risk will be lower. To track possible contacts, we can consider (1) a data-based approach, (2) multiagent-simulation-based approach, and (3) network-flow-based approach.

Data-Based Approach

A data-based approach does not make assumptions regarding passenger route choices. This type of model uses real-world data such as smart card data [8, 12] and automatic passenger count (APC) data [7] to directly track contacts.

Smart card data can be obtained easily for public transportation systems and maintains a record of boarding/alighting for each bus and the number of entrances/exits at train/metro stations. APC records the number of boarding/alighting events. In a bus system, passengers' contacts can be identified directly using smart card data [12], as passengers must tap the smart cards when boarding, and each tap corresponds to a unique passenger ID. The APC data is more challenging to use, as we only know the aggregated data, i.e., the passenger flows at each station. To estimate an encounter network using APC data, Kumar et al. [7] adopted a matrix reconstruction algorithm to identify the passenger flow matrix using APC data.

It becomes much more challenging to track encounters in a metro/train system, as the smart card data usually only provides entry/exit information at stations. We can match individual trips to trains with mild assumptions regarding passenger behaviors. For example, Liu et al. [8] assumed that for passengers' swiping-out behaviors, passengers from the same vehicle will form a cluster, then they recovered their contact history using clustering and matching algorithms.

Multiagent Simulation-Based Approach

As mentioned in the previous section, when it is difficult to get exact trajectories, assumptions must be made regarding passenger route choices. We can run a multiagent simulation to achieve this task. For example, Qian et al. [13] ran a simulation model for the New York metro system. They constructed a network based on the observed metro network layout, demand profile, mobility patterns, and smart card data. Talekar et al. [18] generated travel demand data using a synthetic city based on Mumbai, and ran a cohorting strategy for transit users.

Network-Flow-Based Approach

When the number of passengers becomes more evident and the network becomes more complicated, multiagent simulations may take a long time to run. In such cases, we can aggregate the agents into groups and use a network-flow-based approach to reduce the computational complexity. Another benefit of using a network-flow-based model is that the model can be extended to determine the optimal network design and control plan(s). With decision variables such as the frequency of buses/trains, we can use mathematical programming to find the optimal design. In contrast, it is almost impossible to find the optimal design based on a simulation model, as the computational complexity is too high.

Luo et al. [9, 10] used a metapopulation model to estimate travel reproduction numbers under different policies. They assumed that the route choices for passengers remained the same (for example, if 50% of passengers traveled from station A to B using line 1 at 8:00 AM before the pandemic, then 50% of the passengers will also take line 1 during the pandemic). Qian and Ukkusuri [14] used a deterministic queuing network to model an intracity mobility pattern. They assumed that the departure rate $g_i$ (probability that people leave their residential area), split ratio $m_{ij}$ (probability that people move from region $i$ to region $j$), and arrival rates were known. Therefore, the equilibrium state had a closed-form solution, the commuting pattern was deterministic and stable, and the contacts between different groups could be traced according to the flow intensities.

We propose another approach based on time–space passenger flow [4]. We can build a time–space passenger flow network where each platform at a time step is a node. Passengers are assumed to choose their route based on boundedly rational conditions, namely, their route choice cannot be much worse than the shortest path in the network. We can then solve a multi-commodity network flow problem to determine the route choice for each passenger, thus tracking all contacts.

### *2.3 Pandemic Mechanism*

With passengers' encounter histories, we can apply a modeling framework for infectious diseases to the transportation system. During the pandemic, a population can be split into groups according to health conditions, such as under the susceptible-infectious-recovered (SIR) and susceptible-exposed-infectious-recovered (SEIR) approaches. The number of new infections is defined as the difference between the susceptible (S) population from time $t$ to time $t + 1$. Since the time interval is too small for population growth or immigration to take effect, the change in S population is determined by the pandemic. Some studies [9, 10, 12, 18] have used SEIR population splitting, whereas others [13] have used SIR population splitting. With fewer components, SIR models are usually easier to implement but cannot reflect the less-infective incubation period of COVID-19.

Once the contact intensity between susceptible passengers and infected passengers is known, different pandemic mechanisms can be applied to estimate the number of new infections. A pandemic mechanism is a set of equations describing how each group's size evolves, given its contact history. There are two mechanisms that have been used in policy evaluation models for public transportation during the pandemic: (1) individual-level mechanisms based on contact networks and (2) group-level mechanisms based on compartmental models in epidemiology.

For agent-based contact tracking models [12, 13, 18] (data-based and multiagent simulation-based contact tracking), we can build an individual-level contact network. A contact network is an undirected weighted graph where each node is a passenger, and a link is a contact between two passengers. The weight of the link represents the intensity of contact. For example, if passengers A, B, and C were in the first bus together for 30 min; passenger B, D, and E were in the second bus for 20 min; and passengers D, E, and F were in the third bus for 15 min, their contact network is shown in Fig. 1.

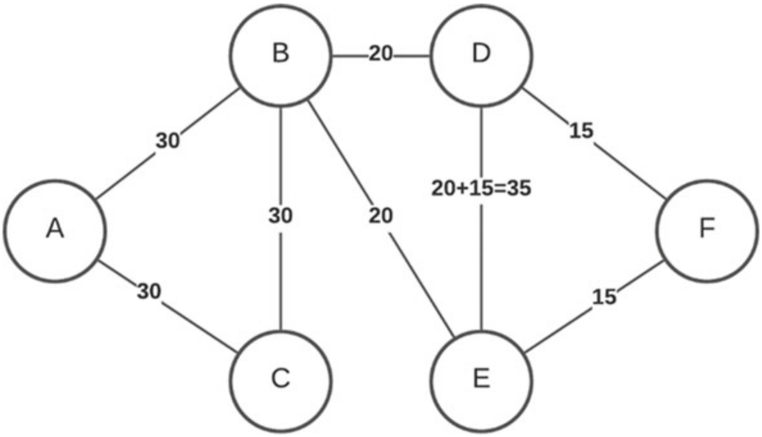


**Fig. 1** A contact network example

Once we have constructed the contact network, the probability of contracting COVID-19 can be modeled as a non-decreasing function of the contact intensity. This approach is useful but cannot be applied to crowded or large-scale systems because the model is agent based, and the number of nodes will increase rapidly when analyzing a large system.

Another approach is the aggregated-level epidemic model used in network-flow-based contact tracking [9, 10, 14]. In this type of approach, the dynamics of COVID-19 are modeled as a set of differential equations, where the derivative of the susceptible (S) population indicates the number of new infections. Like the individual-level model, the expectation of new infection number is a non-decreasing function of the contact intensity. We have also developed a model [4] based on a combination of compartmental models in epidemiology and space–time traffic flow networks.

## 3 Evaluating Policies Without Transportation Models

For studies without transportation models, we can still evaluate the policies implemented in 2020, based on historical data. Each of these studies addressed one policy, without considering a transportation model; there was no general framework. In this section, we introduce the methods for evaluating the different policies without models. Many of these studies were data driven, and the effect of public transportation policies was learned from historical data without considering the actual network structures. Studies without pandemic data usually focused on one aspect of the pandemic, such as, for example, the probability to be infected on a 1-h bus ride or the effectiveness of surface cleaning using fluid flow analysis.

During the pandemic, some cities closed their public transportation systems. To evaluate the effectiveness of line closures or reducing capacity policies, Islam et al. [6] used an interruption time series regression model to evaluate several policies (including closures of public transportation lines) using data from 149 countries/regions in the first 5 months of 2020. Physical-distancing interventions (stay-at-home order/lockdowns) were used as a natural experiment. Fathi-Kazerooni et al. [3] studied the correlations between subway usage and New York City cases using linear regression with L1 regularization. They predicted the number of daily deaths and number of new cases using a long short-term memory neural network and arithmetic moving average models.

To evaluate the effectiveness of physical distancing, some researchers studied COVID-19 outbreak cases in the context of layouts of bus seats. Shen et al. [17] studied an outbreak of 128 passengers on two buses on January 19, 2020 in Zhejiang, China, whereas Luo et al. [9, 10] studied an outbreak on January 22, 2020 in Hunan, China. Yang et al. [21] performed a high-resolution computational fluid dynamic analysis on a coach bus to simulate the dispersion of droplets.

# 4 Policy Evaluation Results and Suggestions

## *4.1 Policy Results*

Impact of Preventive Measures in General

Preventive measures include wearing masks, applying disinfectants, and restricting the capacities of buses and trains. When evaluating policies based on combining COVID-19 and public transportation models, preventive measures such as wearing masks will affect the transmission rate parameters. According to Mo et al. [12], the epidemic would fade out if the transmission rate of the transportation system was less than 10% of the current value. Luo et al. [9, 10] observed a similar result and indicated that we should decrease the infection rate as much as possible. Although these results are not specific enough, it is known that implementing social distancing measures and other preventive measures helps stop the spread of COVID-19; thus, these measures should be maintained until most of the population is immune.

Impact of Restriction on Capacity

According to social distancing rules, buses and trains have been run at reduced capacity across the U.S. There are two possible types of policies for restricting capacity: (1) line-based control, which restricts the total number of passengers on each vehicle (and is easier to implement) and (2) region-based control, which restricts the total number of passengers traveling between two districts. Line-based control has been applied in almost all bus systems throughout the U.S. according to CDC's [2] social distancing guidelines. Region-based control can be achieved by limiting the ticket sales for certain origin–destination pairs or closing stations in certain regions. In Wuhan China, the authorities provided reservation-based service, which limited the origin–destination flow intensity in March 2020 [5].

For the first type of strategy, where we restrict the number of passengers on board, our model [4] shows that if we do not give up passenger demand (i.e., passengers can wait for the next available train), the timetable is optimal, and capacity is high, the number of new cases will not change significantly (i.e., the number is not sensitive). Nevertheless, new cases will rise quickly if the capacity is low and we cut the capacity further, because, in this case, passengers cannot board a fully loaded train during peak hours but will have to wait on the platforms for the next train, leading to crowd gathering. The simulation by Kumar et al. [7] showed a similar result, namely, the risk was higher when the capacity was lower, and the risk was less sensitive to the capacity when the capacity was higher. Mo et al. [12] showed that if we assume that passenger demand is lost when reducing capacity, the COVID-19 infections will decrease because some passengers will simply give up their trips. They showed that this strategy is not as effective as closing bus/train lines.

Different models showed different results due to their assumptions on the impact in demand. If the demand remains in a similar level after reducing capacities, our model's assumption is more realistic, and we should not further reduce capacities with limited budget. Otherwise, reducing capacity will help preventing the spread of COVID-19. The elasticity in demand is a complicated problem itself and is city-specific. It is possible that the total demand remains the same, if we only close one line or two, as passengers would go to the nearest open line/stations after line/station closure. Policymakers need to study historical data to find out the demand pattern.

For the second type of strategy, the model by Luo et al. [9, 10] showed that if we restrict travel between different regions in a city according to their optimal control scheme, the effect can be significant. From the results, it seems evident that we should implement such a policy in areas with the largest outflow. Fathi-Kazerooni et al. [3] showed that in New York City, the number of COVID-19 cases and subway usage were strongly correlated, and that each borough showed a different correlation. It is tempting to conclude that we should restrict entrance capacities for different stations in New York City according to their correlations. However, the correlation alone is not enough to support such a policy, as correlation does not imply causation, and the data-driven research did not provide a transportation model to explain the mechanism(s) of these correlations. Also, such policy is more difficult to implement than the first type of capacity restriction policy.

Impact of Cutting Budgets

Our model [4] shows that if we cut the budget, then the manager cannot run enough trains/buses. Therefore, people will have to use a limited number of trains, which will lead to an increase in COVID-19 cases. We also observe that the number of new cases is less sensitive to the budget, if the capacity constraints are not tight, namely, when the capacity is large. Therefore, if we observe that buses/trains are empty even during peak hours, cutting the budget will not result in a surge in COVID-19 cases, but cutting the budget when the buses/trains are crowded will significantly increase the COVID-19 infections in public transportation systems.

### Impact of Closing Bus/Train Lines

Some cities closed train/bus lines during the pandemic to control the spread of COVID-19 and cut budgets. According to our research [4], assuming that passengers choose the shortest alternative stations if lines are closed, we should either (1) close most of the lines and stations so that most passengers have no access to the system or (2) open all lines and stations while adjusting the timetable to an optimal state. The first approach affects the experiences of most users. Therefore, we only recommend opening all lines and stations while adjusting the timetable. Mo et al. [12] showed that we can reduce the reproduction rate by 15.3% by closing the top 40% of high-demand routes, and that this approach is more effective, if we close the high-demand lines first. This result is different from ours, as they did not optimize the timetables of these lines accordingly.

Similar to capacity policies, we need to evaluate the impact in demand to determine which result we should use. If the total demand remains almost the same after closing lines, and passengers are forced to use nearby stations of unclosed lines, our model's assumption will be more realistic, and agencies shouldn't close any line or station. If these passengers use other modes of transportation or they give up traveling, the assumptions by Mo et al. [12] will be more accurate, and agencies should close high-demand lines.

Some systems were entirely shut down during the pandemic, like bus systems in Wuhan in 2020 [5]. However, the data-driven study by Islam et al. [6] showed no evidence that public transport closures had an additional effect on the number of cases when four other physical distancing measures were implemented, thus shutting down the entire system would not help much.

### Impact of Departure Time Flexibility

During the COVID-19 pandemic, people are being encouraged to take less crowded trains/buses by avoiding peak hours. Mo et al. [12] showed that by changing the time flexibility from 0 to 110 min, the equivalent reproduction rate decreased by only 2.2%. Although demand flexibility can help prevent COVID from spreading, the effect is slight, and we are not sure what kind of policies can increase the time flexibility of passengers.

### Impact of Quarantine and Hospitalization

During the pandemic, passengers who have contact with infectious passengers are quarantined, and symptomatic passengers are hospitalized, if a contact tracing program is being implemented. The quarantine and contact tracing in the U.S. are based on self-reports. Susceptible people are notified if their cell phone has been found to be close to infectious people. According to Mo et al. [12], the reproduction rate is less sensitive to the recovery rate, and even if the recovery rate becomes 100 times the current value, we still cannot eliminate COVID-19 in public transportation systems.

However, different test and quarantine policies may have a huge impact. Mo et al. [12] found that a "k-core" isolation strategy is more effective than any other region-based or route-based policies, and this strategy is most efficient when k is 4. In the contact network, the degree of one vertex represents the number of contacts that person has. Therefore, we should pay attention to influential passengers (vertex with higher degree). k-cores are the maximal connected subgraphs that all vertices have a degree higher than k, which can be obtained by iteratively removing vertices of degree less than k.

The original k-core policy by Mo et al. [12] suggests that governments should isolate all passengers in k-cores no matter if they are infected or not, which is not practical. However, we can modify this policy into a k-core test-isolation policy. We suggest that governments mark passengers in k-cores as "high-risk," test them more frequently, and remove them from the system as early as possible. This can be as effective as the k-core policy proposed by Mo et al. [12] since isolating susceptible passengers cannot help stopping the virus. More simulation studies need to be done to validate this modified k-core test-isolation strategy.

Impact of Entrance Screening

During the COVID-19 outbreak, radiation thermometers were installed at the entrances to certain metro/bus stations. This is an example of an entrance screening. The goal of such a policy is to identify passengers with symptoms. Although entrance screening can help prevent the spread of disease, the operation cost is high, as we need to examine many passengers. Thus, we need to optimize the budget for each entrance, if we want to adopt such a policy. Qian and Ukkusuri [14] proposed an algorithm based on their Trans-SEIR model. With an optimized resource distribution, they showed that the reproduction rate can be significantly reduced. They showed that in New York City, if we can screen 48,000 travelers every day with a success rate of 70%, the reproduction rate can be reduced to 2.32, and the number of secondary infections can be reduced by 29.6%. This policy requires a budget to install screening at stations and may have side effects such as queuing at screening stations. Additional study is required to evaluate such side effects, and this policy is difficult to implement when budgets are already cut.

Impact of Social Distancing Rule

It is essential to evaluate and optimize the social distancing rule for the operation of a safe and efficient transit system. According to studies on intercity bus outbreaks [9, 10, 17], all passengers on an air-conditioned bus are at risk if they do not wear masks. One passenger even contracted COVID-19 at a distance of 4.5 m (15 ft) from an infectious passenger after a 1-h trip [17], even though public transportation agencies in the U.S. follow the instructions of the Centers for Disease Control and Prevention of 6-foot (< 2 m) social distancing rule [2]. However, it remains unclear if the 6-foot rule is safe when passengers are wearing masks. The data suggests that the current rule is sufficiently safe [15, 16]. A computational fluid dynamics analysis by Yang et al. [21] showed that having passengers sit in non-adjacent seats and using a backward air supply can effectively reduce infection risk. For now, we recommend sticking to the Centers for Disease Control and Prevention (CDC) (2020) newest rules.

Impact of Regular Cleaning

During the pandemic, public transportation employees have regularly cleaned their facilities. Does this help prevent COVID-19 transmission? An experiment performed by Yang et al. [21] showed that more than 85% of droplets are deposited on an object surface in a bus coach. Therefore, cleaning all the surfaces of a bus/train vehicle will be helpful. It is difficult, however, to do a quantitative study on the effectiveness of surface cleaning based on real-world data since all systems have adopted such policies, and we do not have a control group. For now, cleaning regularly is recommended.

### 4.2 *Insights from Studies Combining COVID-19 and Transportation Models*

Although the assumptions and the recommended strategies are different, there are some valuable common insights obtained from studies [4, 9, 10, 12, 14] as discussed below.

For one, if a city is almost homogeneous in its COVID-19 infection rate (i.e., the infection rates of different districts in the city are almost the same), the goal of minimizing COVID-19 infection in public transportation networks coincides with reducing the total travel time and crowd levels. If passengers spend more time in a more crowded system, the COVID-19 infection will be high. On the other hand, if a city is highly heterogeneous in terms of its COVID-19 infection rate, the goal of minimizing COVID-19 infection in public transportation networks coincides with reducing the weighted sum of the travel time and crowd levels, and passengers from high-risk regions should be given higher weight. Therefore, if the city is almost homogeneous in its COVID-19 infection rate, some techniques used in public transportation network design can also be applied to the COVID-19 risk minimization problem.

## 5 Conclusions

In 2020, researchers from different fields tried to evaluate COVID-19 policies in intracity public transportation systems using both model-based and non-model-based methods. Some researchers combined the transportation models with regional pandemic models to evaluate different policies. They used agent-based or flow-based transportation models to trace all possible contacts and used pandemic models, such as compartmental models, to predict the risks of COVID-19 contraction. Other researchers adopted a model-free approach and evaluated policies based on data collected in 2020, aiming to evaluate the currently implemented policies.

According to the models, one of the essential concepts for preventing COVID-19 contractions is to reduce the number of passengers served by the system, e.g., by reducing the capacity and closing lines. Closing one line that has high demand is more efficient than closing many low-demand lines, if the lost demand is the same. However, managers should closely monitor the demand after implementing such policies; if people are unwilling to switch to other transportation modes, this type of policy can be harmful, as it might lead to longer queues on platforms or bus stops. The risk of COVID-19 is higher when the budget is limited, and bus/train lines cannot be run with a sufficiently high frequency to serve queuing passengers on platforms.

From studies of COVID-19 in public transportation settings, we notice that minimizing the risk of COVID-19 coincides with minimizing the weighted travel time, where the weight is the infection rate. If a city is homogeneous in its infection rate, then all the weight is the same and the goal of stopping the pandemic coincides with minimizing the total delay.

Overall, the effectiveness of currently implemented preventive measures in the U.S., such as wearing masks, social distancing, and regular cleaning, has been supported by the evaluation results from models and data collected during the past year. Researchers have also proposed policies such as isolating passengers and entrance screening. If we can accurately trace contact or isolate susceptible passengers, a k-core isolation strategy would be more efficient than any capacity or line-closing policy when k is 4. We also propose a modified version of this policy, where we identify passengers in k-cores in the contact network as "high-risk." Instead of isolating these passengers, we can test them frequently and isolate infected ones as early as possible. Moreover, screening daily travelers at the entrance of stations can significantly reduce the reproduction rate according to models and practice in China. However, these policies have high operational costs and are not implemented in most U.S. systems.

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# Pandemic Transit: A National Look at the Shock, Adaptation, and Prospects for Recovery

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**Abstract** While the COVID-19 pandemic in some way affected every person and enterprise on the planet, the temporary hollowing out of concentrated economic, political, and cultural agglomerations in cities dealt a devastating and potentially enduring blow to the public transit systems that depend on them for so many of their customers. This chapter draws on a survey of 72 U.S. public transit systems and semi-structured interviews with 12 transit agency staff, both conducted in the late summer and early fall of 2020, to consider how the pandemic shocked the transit industry at the outset, and how the industry adapted to deliver transit services. We find that: transit agencies adapted quickly, and many of their changes are now standard operating procedure; the pandemic tended to affect large and small transit agencies differently; transit's role as a social service provider took on increased visibility and importance; and financial collapse has been averted, but funding shortfalls may become a pressing issue in the years ahead when federal emergency funding runs out. We conclude that while transit systems have adapted remarkably to dramatic change and that federal funding has largely forestalled fiscal crises, the longer term future of public transit in the U.S. remains very uncertain.

## 1 Introduction

While the COVID-19 pandemic has in some way affected every person and enterprise across the globe, the temporary hollowing out of concentrated economic, political, and cultural agglomerations in cities early on dealt a devastating and potentially

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enduring blow to the public transit systems that depend on them for so many of their customers. This chapter explores this shock to and adaptation by U.S. public transit systems large and small during the first year of the COVID-19 pandemic, with a focus on the extraordinarily challenging first 6 months of the public health crisis. For evidence, we draw on aggregate transit use data, a review of a rapidly developing literature on public transit in the pandemic, a national mid-pandemic survey of transit agency staff, and in-depth interviews with transit managers. We discuss our four principal findings from the survey and interviews, and close by considering their implications for post-pandemic public transit.

## 2 Public Transit Before and During the Pandemic

Public transit systems play widely varying roles depending on the environments within which they operate. In the central parts of large cities that developed prior to the widespread adoption of automobiles in the 1920s, public transit buses and trains are central to urban life. Large, dense agglomerations of economic, political, and cultural activities in these places could not effectively function without transit moving tens or hundreds of thousands of travelers into and out of them each day. Public transit, which excels at moving large numbers of people in the same direction at the same time, thrives in such environments. Driving, by contrast, is typically harder, as streets in the central parts of big cities are often congested and parking is expensive.

But in more outlying suburban and rural areas where the vast majority of trips are made in private vehicles, public transit systems play a decidedly peripheral role in mobility—though still an important one. Lower development densities and plenty of off-street parking in such places combine scatter trip origins and destinations and make them harder to serve effectively with fixed-route, fixed-schedule transit services. While some suburban workers ride express buses and commuter trains to jobs in the city, the overwhelming majority of suburban and rural person trips are by car. So in these areas, as well as in cities, public transit plays a second, important role as a critical social service providing mobility for those who, because of age, income, or ability, are not able to drive.

The COVID-19 pandemic that gripped the world in the early months of 2020 cast these two distinct roles of transit in the sharpest possible relief. Seemingly overnight large, dense concentrations of activities became dangerous threats to public health to be avoided as much as possible. The vast majority of those who formerly rode buses and trains to and from major employment centers abandoned public transit entirely; many began working from home, some began driving to avoid contact with others, while others lost their jobs altogether [1]. The few who remained on public transit in the early months of the pandemic were primarily frontline workers—nurses' aides, grocery store clerks, warehouse workers, and so on—who could not work from home or commute by car [20]. These workers were more likely to have limited mobility options, reside in low-income households, and be immigrants or people of color. As

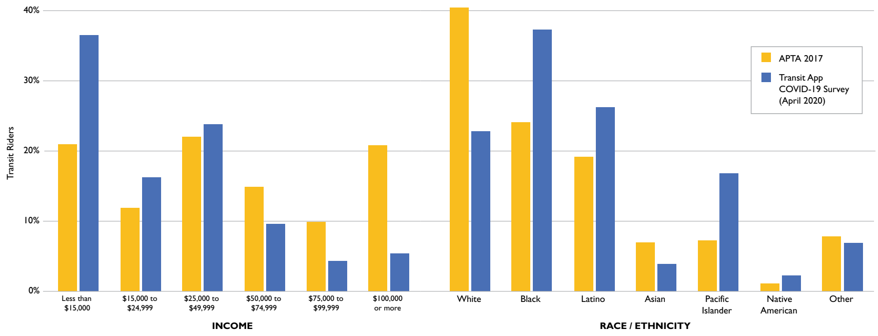


**Fig. 1** Transit riders' income and race/ethnicity distribution in 2017 and 2020. *Data source* [20]

seen in Fig. 1, transit riders at the start of the pandemic were considerably poorer and less white or Asian than pre-pandemic riders. In other words, the social service role for public transit became its *raison d'être* in the pandemic [18].

The circumstances faced by transit systems shifted dramatically over the course of the pandemic, from an initial *Shock*, followed by a period of *Adaptation*, and then a longer, more gradual period of *Recovery*. We define the *Shock* period as the 3 months of March through May of 2020, when lockdowns were widespread and public transit systems were scrambling to cope with a ridership free fall, how to protect the safety of their bus and transit operators[1] and patrons, and how to manage the sudden, dramatic losses in fare revenue (see Fig. 2). This was followed by about a 9-month period of *Adaptation*, from June 2020 through January 2021, when riders began to gradually return, pandemic operations became more regularized, and finances were somewhat stabilized, if still uncertain. Finally, with vaccines becoming widespread, activity restrictions easing, and the passage of the American Rescue Plan pandemic relief bill promising substantial support for public transit for up to 3 years, public transit systems entered a period of *Recovery* in February of 2021.

Given the swift, devastating initial effects of the COVID-19 pandemic on public transit, as well as the scale of the challenges faced by transit managers, early research on the issue advanced quickly. While all forms of travel fell precipitously during March and April of 2020, in response to safer-at-home orders and the temporary closure of many businesses, transit use fell more sharply than other means of travel and recovered more slowly [11]. Companies began implementing sweeping work-from-home policies, in-person grocery shopping became less frequent, and inter-regional and international travel was curtailed or stopped altogether [15, 16].

Given early uncertainty about transit's role in the spread of the virus and short-lived Centers for Disease Control recommendation that all travelers avoid public transit, most former transit riders who could travel by other means or avoid travel altogether did so in the spring of 2020 [6, 9]. While transit staff at systems sprang into action

[1] The workers who drive buses and operate trains in the public transit industry are commonly referred to as operators, and not drivers.

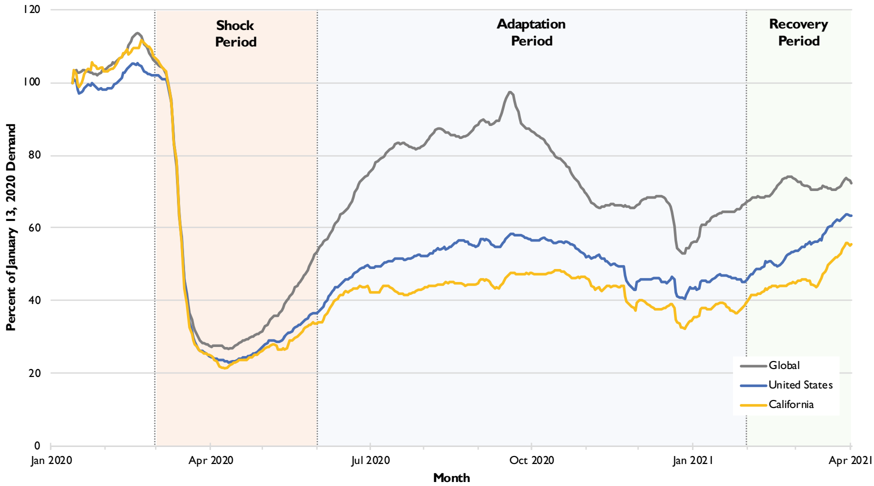


**Fig. 2** Public transit ridership trends globally, in the U.S., and in California between January 2020 and June 2021 (7-day moving average). *Data source* Estimated change in transit demand, measured by Apple Maps routing requests. Details at https://covid19.apple.com/mobility

to regularly deep clean their vehicles, minimize operator/customer interactions, and enforce mask wearing and social distancing, ridership on most systems fell precipitously to levels not previously seen [14]. As the number of those infected and hospitalized grew and the transmission vectors of the SARS-CoV-2 virus became clearer, public health advice shifted to emphasize protection from airborne over surface transmission, causing shortages in personal protective equipment for healthcare workers, grocery clerks, and transit operators, and facemasks for nearly everyone. However, by July 2020, preliminary studies in Paris and Japan found few or no infections attributed to public transit [12]. A related study of influenza published during the pandemic found no positive correlation between citywide transit ridership and viral spread, so by September 2020, general health advice described transit as relatively safe [10, 17].

With lost riders and widespread fare-payment-suspension policies combining to crater fare revenues and the pandemic-induced recession cutting many sources of state and local subsidies, many transit agencies across the country cut service, depended increasingly on federal bailout funding, or some combination of the two [4, 5]. The CARES Act, passed in March 2020, provided $25 billion for public transit claimants. This and subsequent emergency funding largely waived the usual state/local funding match requirements for federal transportation dollars, as well as the usual restrictions on which funding could be used for capital, operating, and maintenance expenditures [22]. This influx of funding prevented draconian cuts in service and personnel at most systems, but given the depth of early pandemic fare revenue and other state and local funding losses and the increased costs associated with equipping vehicles and personnel for pandemic operations, the "burn rate" of

CARES Act funds by New York's and many large cities' transit systems was high [9, 21].

While many state and local revenue sources for transit began to recover quickly over the second half of 2020, fare revenues remained low because patronage was cut roughly in half and many systems continued to offer fare-free service to reduce operator–customer interactions and as a service to riders. At the same time, costs for vehicle cleaning and improved air filtration systems remained high [2]. By the fall of 2020, many transit operators around the country began preparing plans for substantial cuts in service and personnel to avert financial collapse. But, in December 2020, the Coronavirus Response and Relief Supplemental Appropriations Act was passed, which earmarked another $14 billion in "reprieve and not [..]rescue" funding for transit [3].

Less than 3 months later, the new Biden administration pushed through the American Rescue Plan Act, with an additional $30.5 billion for transit [23]. So, in less than one year, the U.S. government provided public transit systems with nearly $70 billion in additional funding to cover pandemic-related revenue losses. While this aid is expected to help most transit agencies financially weather 2020 and 2021, long-term financial stability will depend on when and to what extent riders return [13, 19].

## 3 Survey of and Interviews with Transit Managers

During the early fall of 2020, we conducted a survey of transit professionals working in planning and operations regarding the problems posed by the pandemic and their responses to them. Concurrently, we also conducted a series of interviews to explore in-depth issues covered in the surveys. We sought to examine agencies from a variety of geographic areas with a variety of ridership levels that operated buses, rail, or both. We used Federal Transit Administration (FTA) regions to determine geography and the National Transit Database (NTD) to stratify agencies by unlinked passenger trips to develop a list of 200 agencies that represented all ten FTA regions and a variety of ridership levels. Then, in September 2020, we sent survey and interview invitations to two office staff at each agency, one in planning and one in operations.[2]

We collected 56 completed surveys from our national representative sample in September and October 2020. The response rate was 28 percent, with respondents coming from nine of the ten FTA regions and from a variety of agency ridership levels. To focus on major differences in agency size, we disaggregated between smaller agencies with fewer than 10 million annual reported boardings and larger agencies with 10 million or more annual reported boardings. In addition, we collected 16 additional responses through a collaboration with the California Transit Association (CTA). In this chapter, we report results from both our nationally representative sample

[2] At many smaller agencies, this proved to be one person. In some case, no one person had these job titles; in those instances, we chose the next closest match based on job title.

and our larger total sample, which includes these additional responses. Further, we augmented our collected survey data with ridership data from the National Transit Database (NTD) from before and during the pandemic.

We also concurrently conducted 12 semi-structured interviews of at least 30 min with transit professionals from around the U.S. Interviewees were solicited from both the 200-agency national sample and the additional 16 responses from CTA members; participants ultimately represented six FTA regions. Nine of the interviewees represented small agencies, and three larger ones. Topics for both the survey and interviews included (1) routes and service planning, (2) operations and labor, (3) public health guidance, (4) riders and equity, (5) performance measurements and crowding data, (6) communications with riders, and (7) long-range plans and effects. Survey respondents answered questions on all these topics, while interviewees selected three to four of the seven topics about which they could best discuss given their job responsibilities and time constraints.

## 4 Findings

We learned that:

1. *Transit agencies adapted quickly and in collaboration with public health officials to a crisis for which there were few prior plans*

While transit agency staff reported finding the COVID-19 crisis enormously challenging, both the pace and scale of responses to it were substantial. With one exception, every survey respondent told us that vehicle cleaning had become more extensive. Most also told us that they adopted rear-door boarding and/or suspended fare collection (either temporarily or on an ongoing basis) at least in part to protect bus operators; these measures helped ensure social distance between operators and passengers. Multiple interviewees mentioned (in September 2020) that front-door boarding would resume when new plastic shields for operators were installed. The public health response measures reported by our respondents and their frequencies are shown in Table 1.

Nearly all respondents told us that they relied on public health officials for guidance. Over 90 percent reported relying on published health guidance, and nearly 70 percent regularly held meetings and discussions with public health officials. In the nationally representative sample, most respondents told us they relied most on state and county governments for public health guidance and information. In addition, nearly one in six said that they expected to contribute to the ongoing regional/external pandemic response planning moving forward.

Heavily patronized public transit does not permit social distancing. Roughly 85 percent of survey respondents reported they had adopted some kind of social distancing policy during the pandemic. On 40-foot buses, for instance, surveyed agencies reported restricting the number of passengers permitted on board to between 8 and 30, with the majority reporting limits between 10 and 20—a significant decrease

**Table 1** Surveyed Public Health Interventions

| Intervention | National sample (%) | Total sample (%) |
|---|---|---|
| More extensive cleaning and disinfection | 98 | 99 |
| More frequent cleaning and disinfection | 87 | 90 |
| Boarding limitations/vehicle capacity restrictions | 87 | 87 |
| Newly installed dividers between operator and riders | 72 | 72 |
| Some seats restricted from use | 64 | 69 |
| Masks required but passengers are still able to board without masks | 53 | 49 |
| Rear-door only boarding | 53 | 49 |
| Masks required and passengers are unable to board without masks | 43 | 48 |
| Windows open during vehicle operation | 28 | 31 |
| New air filters and/or filter changing protocols | 21 | 25 |
| Masks recommended | 17 | 18 |
| **Total respondents (number)** | **53** | **67** |

*Data source* UCLA Transit's Response to COVID Survey
*Notes*
(1) "National Sample" refers to our nationally representative sample of transit systems (N = 56), while "Total Sample" refers to our National Sample plus our California add-on sample (N = 16, see methodology section for details)
(2) Some respondents indicated they did not know or were unsure for this survey question, so the number of respondents shown above is lower than the total for each sample

from pre-pandemic levels. Agencies also reported very different responses to "overcrowded" bus conditions. Some agencies gave their bus operators the discretion to simply bypass stops with waiting passengers if their bus were "full;" some had their operators report full buses to dispatch in order to request additional relief bus service.

Mask requirements varied across the agencies surveyed, reflecting perhaps the widely varying, and at times conflicting, public health guidance across the U.S. About 28 percent of respondents reported having problems dealing with riders who refused to comply with public health directives. While we asked about public health directives broadly, the vast majority of those who added explanatory detail to their responses specifically mentioned mask mandates. Reported responses to maskless patrons seeking to board included offering masks to those without, denying boarding to the maskless, and calling law enforcement to deal with recalcitrant customers.

We asked if their agency's emergency preparedness plans had a component for pandemic response and got widely varying responses as well. Only 15 percent told us that they had existing epidemic/pandemic response plans. One interviewee noted that while a pandemic plan existed, it had not addressed social distancing, but simply better surface sanitization. Survey respondents also reported a need to improve existing plans based on the experiences of the pandemic. In addition, 22 percent said that they had added a pandemic response plan in 2020, another 22 percent told us that they now planned to add one, while 15 percent were planning to contribute to a regional or external pandemic response plan.

2. *Transit demand plummeted at all agencies, but their responses differed by agency size and mode*

Similar to the Apple Mobility data presented in Fig. 1, National Transit Database data show that both large and small agencies saw dramatic drops in boardings between March and April 2020 to about 30 percent of the January 2020 totals. Then, from May to October, agencies began showing a slight recovery in boardings, albeit at different paces: In September 2020 (during our survey window), the average smaller agency reported 53 percent of pre-pandemic boardings, while larger agencies reported only 44 percent, but ridership dipped down again with the pandemic's fall and winter wave [7].[3]

Responding to these dramatic changes in ridership required agencies to adjust service more frequently than prior to the pandemic. Most survey respondents told us that they adjusted service once every 3 to (most commonly) 6 months prior to the pandemic. But 6 months into the pandemic, a majority of respondents reported adjusting their service three or more times. This was true for both smaller and larger agencies, but larger agencies were more likely to have adjusted service five or more times, by a margin of two to one (41−21%).

While passenger demand fell more at large agencies (which tended to serve more downtown commuters before the pandemic), changes in transit service supplied actually tended to be greater at smaller agencies. Among agencies operating bus service in our sample, nearly half of the smaller agencies reported offering less than 75 percent of pre-pandemic service in September 2020. By contrast, only *one* of the surveyed larger agencies was offering less than 75 percent of their pre-pandemic service, 60 percent were offering between 75 and 90 percent of pre-pandemic service, and 40 percent were offering 90 percent or more of pre-pandemic service. That larger agencies tended to cut their service less than smaller ones, despite losing more passengers on average, could reflect that larger agencies typically had much higher passenger load factors (the ratio of passengers to seats) during the pandemic and/or it could reflect less flexibility to reassign or lay off workers at larger systems. While all of the large agencies' operators in our sample were unionized, nearly half (45%) of the smaller agencies' operators were not.

In the early months of the pandemic, surveyed agencies not only adjusted bus service more frequently than rail service, the bus adjustments also tended to cut service more as well. Table 2 shows the percentages of surveyed agencies that employed various types of service modifications, including changes to service hours, frequency, and geographic coverage. Our survey data suggest that larger bus agencies made the biggest and broadest changes to their bus service offerings, as compared to smaller bus agencies and rail agencies. Only one agency eliminated any rail line

[3] NTD data and Apple Mobility data capture different angles of the same trend. NTD data report the number of actual transit boardings for each agency that received federal funding, while Apple Mobility data report the number of transit directions queries in Apple Maps.

**Table 2** Type of service modifications by bus and rail operators

| Type of service modification | Small bus (≤10 million boardings) (%) | Large bus (>10 million boardings) (%) | Rail (%) |
|---|---|---|---|
| Changed service headways/frequency | 23 | 62 | 80 |
| Changed off-peak weekday service hours | 38 | 38 | 60 |
| Changed peak-hour weekday service hours | 21 | 38 | 50 |
| Changed peak-hour weekday service hours | 21 | 38 | 50 |
| Changed weekend service hours | 25 | 23 | 50 |
| Eliminated some lines/routes | 33 | 54 | 10 |
| Moved to Saturday or Sunday service on all days | 25 | 38 | 0 |
| Added capacity | 2 | 8 | 30 |
| Changed geographic service coverage | 10 | 8 | 0 |

*Data source* UCLA Transit's Response to COVID Survey
*Note* Respondents were able to choose multiple responses, so columns do not add to 100%

service entirely as part of pandemic service cuts, while *over half* of larger bus-operating agencies indicated they eliminated lines. Rail service changes were more likely to manifest as modifications to existing schedules, including changing service hours and frequencies. Bus agencies employed service hour and frequency modifications, too, but they were much more likely than rail agencies to move to an existing weekend schedule and to eliminate routes.

Respondents told us that they most often used ridership data to make decisions regarding service changes (80%), followed by public health guidance (50%); other responses included financial constraints, crowding data, and Title VI considerations.[4] A notable difference between bus and rail operations was the role of city and regional employment data in guiding service changes: 40 percent of agencies operating rail service indicated using employment data in their service adjustment decisions, but only 13 percent of bus-only agencies reported doing the same. This suggests that agencies viewed the purpose of these two modes differently during the pandemic, as

[4] Title VI prohibits agencies from discriminating on the basis of race, color, or national origin in their programs or activities [8].

bus agencies focused on providing service regardless of changing commute patterns, while rail agencies often continued to focus on how riders traveled to and from work.

We asked survey respondents to indicate how labor events like voluntary leaves, medical leaves, furloughs, and reductions in overtime affected operations between March and September 2020. Three-quarters of respondents told us that labor shortages, medical leaves, and operator safety concerns inhibited their ability to deliver service during the early *Shock* period of the pandemic, but many respondents and interviewees indicated that over time, their agencies were able to maintain needed workers, adjust service levels, and refine safety protocols. These adaptations allowed systems to attain a steadier state of scheduling, particularly as they gained a clearer understanding of COVID-19 virus's means of transmission. Two in five survey respondents reported needing to adjust service because of operator medical leaves; in open responses, participants indicated that childcare needs were a big part of operators' need to take leaves as well.

Finally, as ridership on most systems continued to lag significantly into the fall of 2020 at roughly half of pre-pandemic levels, several respondents reported working hard to avoid laying off staff, while others told us that they had shifted some positions, including operators, to assist with elevated vehicle cleaning protocols in an effort to avoid layoffs or furloughs.

3. *The pandemic highlighted transit's importance to disadvantaged travelers and forced agencies to find new ways of engaging with riders*

Transit's role as a critically important service in ferrying essential workers and providing mobility to essential destinations grew more pronounced during the pandemic. Many respondents reported asking riders to take only essential trips, particularly during the early *Shock* period of the pandemic. Two agencies shared internal data with us in survey responses: one showed that 60 percent of 2020 passengers were essential workers, and that most of those riders in turn had no other transportation options for that trip; the other showed that bus ridership had dropped to just under half its pre-pandemic levels and that the remaining riders were primarily making essential trips, mostly to work, food stores, pharmacies, or medical appointments. Many reported that most of the passenger trips on their systems during the early fall of 2020 were for essential purposes to get to work or health care, with very few discretionary trips. Many of our survey and interview respondents identified increased working from home as the major factor behind patronage losses, while a dozen identified decreased trips to and from primary and secondary schools and colleges and universities as major factors as well. Across our entire survey sample, a quarter of respondents reported analyzing ridership patterns in areas with known concentrations of transit-dependent riders, with slightly more respondents reporting making specific outreach to transit-dependent riders.

Beyond changes to ridership, we were interested in how transit operators were tracking and communicating with their riders. Accordingly, we included questions in our survey and interviews about shifts in riders and ridership patterns, and asked how agencies were engaging with their riders during the pandemic. Ninety percent of systems reported deploying rider surveys either in-person or online. Perhaps not surprisingly, customer engagement had shifted to be primarily virtual. Nationally, the number of agencies holding in-person community engagements dropped from 92 to 10 percent during the first 6 months of the pandemic, while systems using virtual engagement events rose from 22 to 58 percent. Large agencies, perhaps because they are better resourced or have staff readily available to facilitate outreach, were much more likely to adopt virtual engagement, with the percentage using virtual engagement jumping from 27 to 91 percent. Smaller agencies were about twice as likely to adopt virtual engagement than pre-pandemic, with adoption expanding from 21 to 49 percent. In-person surveys also saw a similar severe drop, with 80 percent of systems using in-person surveys pre-pandemic, compared with 10 percent during the pandemic. Perhaps surprisingly, there was a drop in online surveys during the pandemic as well; however, smaller systems accounted for all of this reduction. While roughly half these agencies used online surveys prior to the pandemic, only a third used them during. Conversely, nearly all (91%) agencies used online surveys prior to March 2020; 6 months into the pandemic, all of the surveyed larger agencies had done so. Part of our survey also asked about communicating information on vehicle crowding to riders in real time to facilitate social distancing on board. Overwhelmingly, respondents indicated that such data were collected and used internally, but only about a quarter of agencies in our national sample reported making such data publicly available.

Finally, a plurality of agency representatives (40%) reported that they had no intention of making the service cuts permanent, though roughly one in six (17%) did, while roughly two in five (43%) were not sure. These patterns did not meaningfully vary by agency size. Across both surveys and interviews, some agency representatives forecast lower levels of service well into 2021, while others told us that they had cut low-performing routes, perhaps permanently.

4. *Pandemic-specific federal funding prevented drastic financial cuts in the near term, but much longer term financial uncertainty remains*

Many agencies reported facing financial shortfalls during the pandemic, although in open responses and interviews many representatives in the early fall of 2020 (and prior to the two federal pandemic funding packages for transit passed in the winter of 2020–21) reported worrying that the problem could become dire without further federal intervention. Across the national sample, about half indicated experiencing financial shortfalls that had affected service offerings during the first 6 months of the pandemic. Figure 3 details how these responses broke down across transit mode types and among varying levels of budgetary effect. When parsing the data by agency size, smaller agencies were relatively evenly split among large, moderate, and no effects on finances, while large agencies reported a more dichotomous divide, in that fiscal shortfalls were substantially affecting service (30%) or not at all (58%).

An important corollary here is that many respondents in both survey responses and interviews told us that their agency's financial standing had been substantially buoyed by the March 2020 federal CARES Act. Nearly two-thirds of the surveyed larger agencies in the national sample indicated that the pandemic affected their long-term planning, while only 42 percent of smaller agencies said the same. When

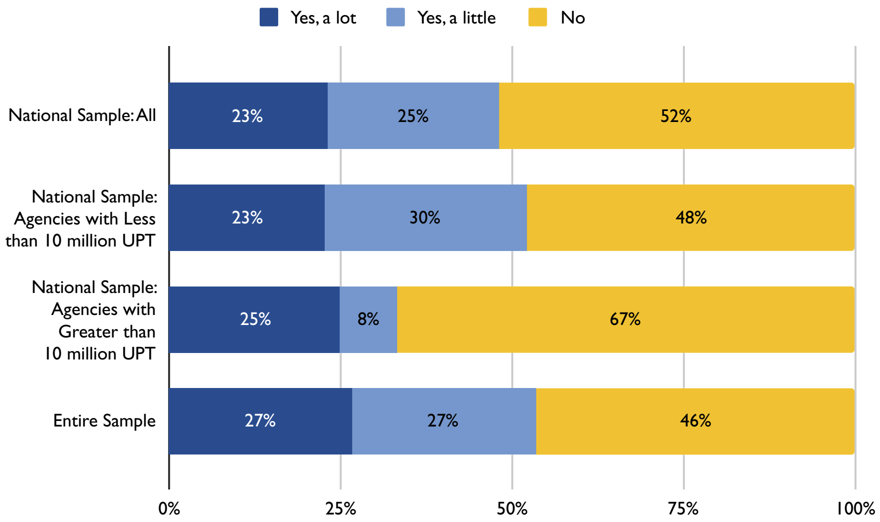


**Fig. 3** Financial shortfall effects on service offerings as of September 2020. *Data source* UCLA Transit's Response to COVID Survey

asked to explain specifically how their plans had changed, several respondents told us that uncertainty about future ridership demand was affecting their vehicle fleet planning.

The relatively generous federal financial bailouts discussed earlier notwithstanding, many respondents expressed concerns over the possible diminution of state, regional, and local sources of funding for transit over the longer term. While many reported that non-federal funding sources were holding relatively stable in the early fall of 2020, many also reported being uneasy about not knowing what next year's revenues would look like given the pandemic-induced recession of 2020, (the then) uncertainty of additional Federal emergency funding, and depressed fare revenues. As a result, according to many respondents and interviewees, longer term financial planning was nearly impossible.

Perhaps due to the substantial federal emergency funding, respondents at only a few bus agencies and no rail agencies indicated that reduced fare revenues were affecting their service planning. This hints that transit agencies, whether explicitly or implicitly, were prioritizing their roles as essential social service providers over their revenue-generating obligations for as long as they were able to do so.

## 5 Conclusion

The first year of the COVID-19 pandemic profoundly affected nearly every household and firm. More than any other means of metropolitan travel, public transit systems—the lifeblood of large urban agglomerations and an important source of mobility for those without access to motor vehicles—weathered extraordinary periods of *Shock* and *Adaptation* in the 12 months after March of 2020 that will likely affect them for years to come. This chapter drew on a nationally representative survey of transit systems and in-depth interviews of managers of those systems to learn about how they coped with extraordinary patronage losses, uncertain and often-changing public health guidance, shifting to pandemic operations, and managing considerable fiscal uncertainty.

First, we learned that systems had to make substantial shifts in operations, policies, and practices seemingly overnight, and that some of these new practices—such as the newly installed plastic barriers between operators and passengers, improved air filtration, and public health crisis contingency plans—are likely to endure. Many of those interviewed reported being more flexible and adaptive to new conditions than they could have imagined prior to the global public health crisis.

Second, while the pandemic affected every transit agency surveyed, the effects and changes varied by the size of the transit system and the service modes operated. Larger agencies cut service less than smaller ones, perhaps to maintain pandemic crowding standards given their higher average passenger loads. Smaller agencies, by contrast, tended to lose fewer riders, likely because they hosted proportionally more transit-dependent riders before the pandemic.

Third, public transit's role as a social service transportation provider for those unable to travel by cars or trucks took on increased visibility and importance during the pandemic, and many operators surveyed reported focusing their policies, outreach, and service delivery to meet the needs of their often economically disadvantaged riders. Further, many of the agency staff surveyed or interviewed reported pivoting to other ways to learn from and communicate with their pandemic riders, including trying new ways to virtually reach riders who may have limited or no digital access.

Fourth, three federal pandemic relief bills in 2020 and 2021 steered nearly $70 billion in additional funding to transit systems across the U.S. For the most part, fears of imminent fiscal collapse of many systems had been forestalled by the time of our September 2020 survey, and since then. But the longer term financial prospects for U.S. public transit remain highly uncertain. How long ridership and fare revenues will stay depressed remains an open question more than a year into the pandemic. Long-term capital planning is particularly vexing, both because future funding remains uncertain, but also because capital needs may change if the demand for transit service evolves substantially post-pandemic.

Overall, the transit agency staff and managers we interviewed and surveyed collectively reported that the uncertainty of future rider demand was perhaps their most pressing concern. Many reported worrying that attracting pre-pandemic levels of ridership back onto their buses and trains might take years to realize, if ever. Depressed ridership post-pandemic could be due to at least three reasons: (1) many workers choosing to work from home full—or at least part time, (2) former transit riders who switched to driving not coming back to transit, and/or (3) lingering public health concerns making travelers reluctant to crowd back onto buses and trains—all of which are beyond the control of transit system managers.

But while the future is surely fraught, post-pandemic public transit is to a large extent lashed to the future of cities. There is considerable evidence that large metropolitan areas will remain the engines of economic and cultural life in the U.S., and that public transit systems will still be needed to provide critical mobility for people throughout metropolitan areas who are unable or unwilling to drive.

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# Monitoring of Bus Transit in Bay Area During COVID-19

**Alex Kurzhanskiy and Servet Lapardhaja**

**Abstract** During the pandemic, from March 2020 through March 2021, we monitored three San Francisco Bay Area transit agencies: two large—AC Transit and VTA; and one small—Tri Delta Transit. As the lockdown was imposed, white-collar commuters, students and older adults stopped using public transit. Initially, the ridership fell by 90%, and then for a year slowly climbed up to less than 50% for AC Transit and VTA, and to around 60% of the pre-pandemic numbers for Tri Delta Transit. This ridership recovery was not consistent. Local drops occurred during protests in June 2020, during fare reinstatements, and during the second COVID wave in Winter 2021. We found that the agencies' response to the pandemic consisted of three parts: (1) maintaining health and safety of their employees; (2) minimizing transmission risk for riders by keeping buses clean and enabling social distancing through capping the number of bus passengers; and (3) changing their service. During the pandemic, we also observed a direct relationship between the socioeconomic level of population and transit ridership. More specifically, we observed higher ridership in low-income areas with a high percentage of Latino, Black and Asian population. These communities are populated by people, who generally rent their homes, do not have a car, but need to go to work, either because they belong to an essential workforce and/ or are undocumented immigrants who cannot afford staying jobless. On the other hand, in the wealthy neighborhoods of the Bay Area, transit activity all but disappeared.

## 1 Introduction

The pandemic and its associated restrictions, set at local and state levels, have radically changed people's behavior, and affected public transit. Most commuters abandoned public transit entirely. Many began working from home; some began driving

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to avoid contact with other people, while others lost their jobs [1]. It is believed that those who remained loyal to public transit during the pandemic were primarily frontline workers—nurses, grocery store clerks, warehouse workers, and so on—who could not work from home or commute by car [6].

Several studies (including studies presented in this book) investigated the impact of the pandemic on public transit. A study from Wilbur et al. [11] found that there was a drop of ridership by 66.9% at its peak in Nashville, Tennessee but by July 1, 2020, ridership had stabilized at a 48.4% reduction compared to the 2019 baselines. They also found that the most significant decline occurred during the morning and evening commute times, and that high-income areas of Nashville saw a decreased ridership of more than 19% compared to low-income areas. Another study conducted by Fissinger [5] in Chicago found that higher levels of ridership were maintained in lower-income parts of the city. On top of that, while there was more percentage growth in the high-income areas between the early stages of the pandemic and the summer, when looking at ridership loss since the pre-pandemic levels, the low-income areas remained much closer to pre-pandemic levels than the high-income areas. These findings are supported by other studies [3–4, 8], which found that lower-income, less-educated, and colored workforce experienced the least amount of change in travel behavior.

A study by Ahangari et al. [2] created a model to evaluate the factors affecting the ridership during the pandemic in ten cities, concluding that poverty and education levels, citizenship, vehicle ownership and employment status were the major influencing factors. Not surprisingly, communities with lower poverty and higher education levels, predominant U.S. citizenship, higher vehicle ownership and lower unemployment yielded higher reductions in bus ridership.

Another study, which examined 113 transit systems across the US [7] found that the average value for the ridership reduction was about 73%. However, there were clear geographic differences, with cities in the Deep South and Midwest presenting a smaller decline in public transit demand, while high tech locations, such as the San Francisco Bay Area, and university cities, such as Ithaca, Ann Arbor, and Madison, generally experiencing a larger decline in public transit demand. The study showed that greater decreases in transit demand were associated with a higher percentage of people in non-physical occupations. Additionally, higher percentages of older people and African Americans in communities contributed to higher levels of continued transit use during the pandemic [7].

But how transit providers reacted to the new conditions brought about by the pandemic? This chapter describes the results of monitoring three transit providers in the San Francisco Bay Area—AC Transit, VTA and Tri Delta Transit—for one year, starting in March 2020 through March 2021. At the beginning of our project, the general hope and expectation was that in the Summer and Fall of 2020 the pandemic would be over, and the economy would reopen. So, the original idea was to monitor transit during the reopening, estimate the transit factor in the economic recovery, and discover non-traditional approaches in transit planning and operation. However, man proposes, but God disposes: Table 1 summarizes our original expectations at the start of the pandemic and what actually happened.

**Table 1** Expectations and reality

| What we expected | Reality we faced |
|---|---|
| Removal of COVID-19 restrictions by June 2020 | Removal of restrictions happened partially; theaters, concert halls and churches remained closed |
| Reopening of small businesses during the Summer and early Fall 2020 | Small business reopening happened to a rather small extent; some small businesses, such as hair salons, reopened briefly, but then closed again in anticipation of the second COVID wave |
| School and university students return to classes in the Fall | Schools and universities decided to stay in the online mode |
| Organizations resume business as usual during the Fall 2020, and by the end of the year society returns to its pre-COVID normal | Some non-essential workers returned to their offices following safety guidelines that prevented crowding. But at the end of 2020, a new lockdown was imposed due to the second COVID wave |
| As the economy and society returns to the pre-COVID mode, city streets and highways start experiencing higher than usual vehicular and bicycle demand at the expense of public transit ridership due to "coronaphobia." | Transit ridership remained low; vehicular traffic in Fall 2020 returned almost to pre-COVID levels, but did not exceed them |
| Plethora of opportunities for bus transit agencies to try out on-demand dynamic services to attract more travelers | Transit agencies dismissed the whole idea of on-demand dynamic routes as nonviable |

*Data source* Authors' survey

The rest of the chapter is organized as follows: First, we introduce the monitored transit agencies; second, we describe the agencies' response to COVID-19—based on our interviews with their staff; and third, we discuss the geography and demographics of the areas serviced by the three agencies.

## 2 The Monitored Transit Agencies

The three agencies are different in size, structure and, to a large extent, types of travelers they serve. *AC Transit* (Alameda-Contra Costa Transit District) is an Oakland-based public transit agency constituted as a special district under California law, which is not a part of or under the control of Alameda or Contra Costa counties or any local jurisdictions. It is a large agency governed by a board directly elected by constituents. The agency serves the western portions of Alameda and Contra Costa counties. Its area of operation is divided into five wards and encompasses a number of cities and unincorporated areas.[1] AC Transit serves many colleges and universities.[2] The agency serves a diverse population in terms of income, employment status, race and citizenship. Much of its ridership is skewed towards a few heavily trafficked local routes connecting colleges and shopping malls with regional train services, primarily BART (Bay Area Rapid Transit), in addition to ACE and Amtrak.

The Santa Clara *Valley Transportation Authority (VTA)* is a Santa Clara County Transportation Agency responsible for public transit services, congestion management, specific highway improvement projects, and countywide transportation planning. VTA is a large agency governed by a board appointed from selected public officials—city council members and County supervisors. Operating three light rail lines and 50 bus lines, it serves the core city of San Jose (where VTA is based and headquartered), with service to other municipalities.[3] It provides express bus service to nearby Fremont where it connects with BART, and also partners with Highway 17 Express to provide service to Santa Cruz, and with Dumbarton Express to provide service between Union City and Stanford University. Many VTA bus routes connect to its light rail service, and Caltrain stations. In addition, VTA operates a special service for Levi's Stadium events, school trip services, and free shuttle routes connecting to ACE commuter rail services. Most of VTA ridership are employees in the Technology, Healthcare, Government, Education and Construction/Utilities sectors [9].

*Tri Delta Transit* is a joint powers agency of the governments of Pittsburg, Antioch, Oakley, Brentwood, and Contra Costa County, governed by a board appointed by city and county representatives. it provides bus service for the eastern area of Contra Costa County. Its bus routes connect to BART at Pittsburg/Bay Point and Concord. They also connect with County Connection, WestCAT and Delta Breeze bus services, as well as Amtrak at shared bus stops. Tri Delta is a small suburban agency with just over 60 buses operating on 15 routes on weekdays and on 5 routes on weekends. A large portion of the Tri Delta ridership are blue-collar workers.

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[1] These are: *Ward 1:* Berkeley, Albany, Richmond, San Pablo, El Cerrito, Kensington, El Sobrante and East Richmond Heights; *Ward 2:* Southern part of Berkeley, Emeryville, Oakland and Piedmont; *Ward 3:* Alameda, Southern part of Oakland, San Leandro; *Ward 4:* Hayward, Southeastern part of San Leandro, Ashland, Castro Valley, Cherryland, Fairview and San Lorenzo; *Ward 5:* Western part of Hayward, Newark and Fremont. In addition, the District's bus lines serve parts of other East Bay communities, including Milpitas, Pinole, and Union City. The District also operates Transbay routes across San Francisco Bay to San Francisco and selected areas in San Mateo and Santa Clara counties.

[2] These include: University of California, Berkeley; Stanford University; California State University, East Bay; Chabot College; Holy Names University; Peralta Colleges (Laney College, College of Alameda, Berkeley City College, and Merritt College), Contra Costa College; Ohlone College; Northwestern Polytechnic University; and Mills College.

[3] These include Campbell, Cupertino, Gilroy, Los Altos, Los Altos Hills, Los Gatos, Milpitas, Monte Sereno, Morgan Hill, Mountain View, Palo Alto, Santa Clara, Saratoga and Sunnyvale. Only Campbell, Milpitas, Mountain View, San Jose, Santa Clara and Sunnyvale are served by light rail.

## 3 Geography and Population

In our study, we looked at the geography and demographics of transit users during the pandemic. Figure 1 illustrates the dramatic impact of the pandemic through the lenses of the three agencies—it displays the change of geography and transit usage intensity from April 2019, a year prior to the spread of COVID-19, to April 2020, when the whole Bay Area was in lockdown, to March 2021, which was the last month of our observations. These maps do not show the full geographic coverage of the three transit agencies, but rather the areas with significant transit ridership—areas where transit trips originate or terminate. Here, the unit of analysis is the census tract.

We examined the following parameters: housing (ownership vs. renting); property value and cost of rent; household income; unemployment and poverty rates; and race. We also looked at crime rates, but did not infer any particular dependency between various types of crimes and transit ridership during the observation period.

In the regions served by AC Transit and VTA, the areas with most active transit usage are those where over 75% of the population rent their homes. In the suburban region covered by Tri Delta Transit, the ratio of renters to owners is roughly 50/50. The median house value where Tri Delta Transit operates is 50% less than where AC Transit operates, and 65% less than in the VTA-served regions. However, even within the Tri Delta region, areas with more affordable houses and larger renter population have more transit users than those where house owners dominate.

For all three agencies, their ridership is in reverse proportion to household income. The lower the income, the higher the ridership has been a ubiquitous rule during the pandemic. Indeed, during this time, transit has been mostly used by people who have

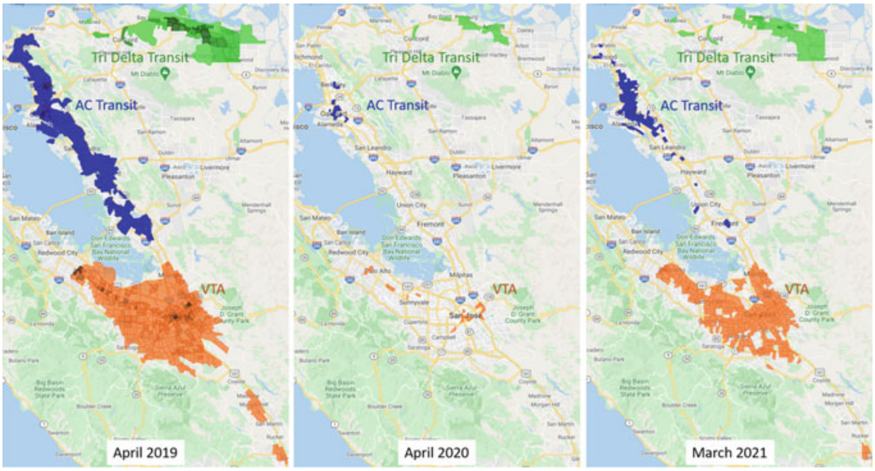


**Fig. 1** Areas with Most Active AC Transit, VTA and Tri Delta Transit Ridership. *Data sources* Passenger count data provided by AC Transit, VTA, and Tri Delta respectively; *secondary data source* OpenStreeMap.com. *Note* Shade intensity corresponds to the intensity of transit usage

**Table 2** Sociodemographic and Travel Characteristics of Areas Served by the Three Agencies

| | AC Transit operation area | VTA operation area | Tri Delta operation area |
|---|---|---|---|
| Average Number of Trips/Sq. Mile | 646 | 159 | 135 |
| Average Median Rent | $ 1,872 | $ 2,343 | $ 1,773 |
| Average Median Household Income | $ 110,346 | $ 143,386 | $ 83,617 |
| Average Poverty Rate | 11.41% | 7.61% | 12.96% |
| Average Unemployment Rate | 5.07% | 4.23% | 8.35% |

to go to work, but have no other means to get there than public transit. These are essential workers and/or undocumented immigrants who cannot afford losing their jobs. In the AC Transit and Tri Delta regions, these were predominantly Latino and Black riders. In the VTA region—Latino and Asian riders. The same people also use transit to go grocery shopping. To infer the dependency between the socioeconomic level of the population and its usage of public transit, we selected five variables:

1. Average number of transit trips per square mile per weekday initiated or ended in a given census tract during the monitoring period;
2. Median rent;
3. Median household income;
4. Poverty rate; and
5. Unemployment rate.

Values for variables 2–5 were obtained per census tract from the Census statistics for 2019. Table 2 gives information about the five variables for the three geographic areas served by AC Transit, VTA and Tri Delta Transit. The variables are presented as averages over the census tracts covered by each transit agency and weighted by the tract's population.

Since each census tract within the area of operation of the three agencies was represented by the five variables (features) listed in Table 2, we performed a cluster analysis on the set of feature vectors. The optimal number of clusters for this dataset was three.[4] In Fig. 2, the three clusters are presented in terms of their geographic coverage, parameter characterization and population breakdown. The three clusters—specified by red, blue, and green—have distinct characteristics (see the star plot): Census tracts with the highest unemployment and poverty rates and the lowest housing rent and household income have also the highest transit ridership and form the red cluster (24.5% of the population); tracts where the values of all parameters fall in the middle form are represented by the the blue cluster (47.8% of the population); and tracts with the lowest transit ridership also have the lowest unemployment and poverty rates and the highest housing rent and household income—they end up in the green cluster (27.7% of the population).

[4] We used K-means clustering, and the elbow method to find the optimal number of clusters.

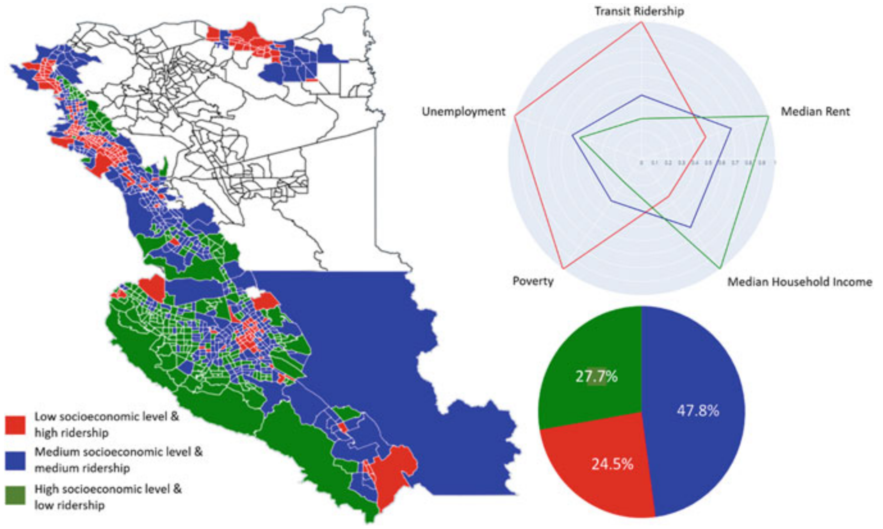


**Fig. 2** Results of a cluster analysis of Census tracts based on the five parameters. *Data source* U.S. Census Bureau

Prior to the pandemic, in 2019, such divisions were less articulated. For example, a lot of commuters were using transit for convenience—to avoid driving in heavy traffic and parking issues. This was especially true for those who worked in San Francisco, while living in the East Bay. Similarly in Santa Clara County, there was a large white-collar commuter activity, especially near light rail and regional train stations.

Other categories of transit users before the pandemic included older adults, students, and university employees and tourists. Older adults who do not drive themselves any longer, generally view public transit as an enabler of their independence. They use it to run errands without hurry, or to return home from appointments. Students and university visitors generally do not own cars and rely on public transit. Some university employees, especially those commuting from afar, also use public transit. Hence, there is high transit ridership around university campuses. All these categories—commuters to work, elderly riders, students, and miscellaneous university affiliates—stopped using public transit during the pandemic almost completely.

As the San Francisco Bay Area went into lockdown, transit activity died near university campuses, community colleges and high schools, and went down considerably near medical centers and shopping malls. Transit activity practically stopped in wealthy neighborhoods. All this is evident from the two maps—for April 2020 and March 2021—in Fig. 2.

It is interesting to note that low-income areas of Oakland and Richmond, with similar socioeconomic and demographic characteristics, used to have high transit ridership in 2019, before the pandemic. During the pandemic, however, transit activity in Richmond dropped almost to zero, while it remained relatively high in Oakland. Our interpretation of this phenomenon is that Oakland, as opposed to Richmond, is a sanctuary city [10]. As such, it hosts large number of undocumented immigrants, who cannot rely on unemployment benefits but need to work to make their living. Public transit is their means of getting to work.

AC Transit and VTA reported that in the period of fare-free service (April–October for AC Transit, April-July for VTA), their buses were used by unhoused people as shelters. According to AC Transit, at that time unhoused riders constituted almost 15% of their ridership. As a result, a notable portion of these agencies' ridership did not contribute to their economic recovery during the fare-free periods. Even though Tri Delta Transit had the longest fare-free period among the three agencies, it did not experience the phenomenon of using buses as shelters for unhoused individuals.

Our monitoring went through March 2021. Although some public transit recovery was evident, it was still very slow. Thus, AC Transit and VTA ridership were still below 50%, and Tri-Delta Transit ridership was around 60% of their pre-pandemic levels. On the other hand, activity resumed around regional train stations, shopping malls and medical facilities. As California came out of COVID-related restrictions in mid-June of 2021, and universities and colleges opened their classrooms in Fall 2021, transit usage is expected to jump up.

## 4 Transit's Response to the Pandemic

As in other regions across the nation, the COVID-19 lockdown declared by the Bay Area counties on March 16, 2020, spelled turmoil for mass transit. AC Transit and VTA ridership had fallen almost by 90% by early April 2020, while Tri Delta Transit had suffered a ridership loss of almost 80%. The subsequent recovery was slow, and as of this writing (a year later), ridership is still well below the pre-COVID levels. For reference, Fig. 3 presents a timeline of ridership, spending, COVID spread, vehicle traffic on Bay Area bridges, and events from March 2020 to March 2021 compared with the same data from a year before.

Next, we present the findings that emerged from our interviews with staff at the three monitored transit agencies. In the period from March to June 2020, these agencies reviewed their ongoing and planned projects, and put on hold those projects not directly helping to address the COVID-19 crisis. To respond to the crisis, the agencies identified similar priorities, as follows:

1. Preventing the spread of the decease among agency employees. The agencies discussed the distribution of regular COVID tests for their employees and installation of contactless thermometers to prevent employees with fever from entering crowded areas.
2. Protecting bus drivers from virus spreading passengers. To achieve this, a rear-door boarding was suggested as well as installation of plastic shields separating the driver from passengers.

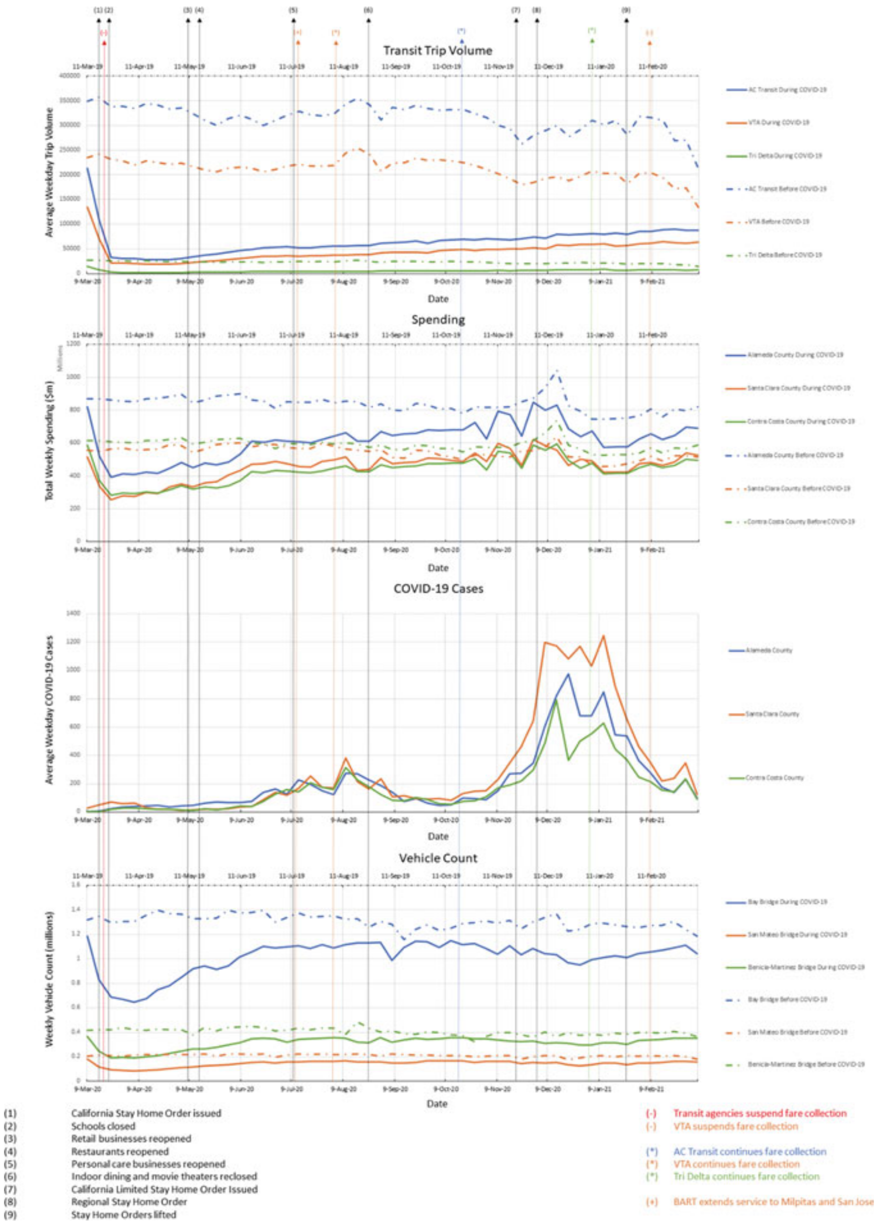


**Fig. 3** Timeline of Ridership, Spending, COVID cases, Vehicle Traffic on Bay Area Bridges and Events (from March 2020 to March 2021 compared with the same data from a year before). *Data source* Ridership data provided by AC Transit, VTA and Tri Delta Transit; spending and COVID statistics provided by Replica (https://replicahq.com); traffic volumes on bridges provided by Caltrans PeMS (https://pems.dot.ca.gov)

3. Keeping passengers safe through the following means:
   a Reducing (by the end of the summer 2020) the passenger capacity limit to 12 for single-car buses to enable 6-feet social distancing. Masks for passengers became mandatory later.
   b Keeping buses clean through frequent disinfection. The discussion was centered around hiring more janitorial services and exploring the use of ultraviolet lamps.
   c Implementation of contactless payments. This issue did not become pressing, as all three agencies went into a fare-free mode in the second half of March 2020.
4. Keeping up the funding and maintaining the workforce. None of the three monitored agencies downsized their employees, although they reduced their services considerably.

After the initial shock, the transit agencies found some new equilibria concerning service, fleet management, performance evaluation and paratransit. We discuss below the agencies' operations relating to these topics.

## *4.1 COVID-19 Service Adjustment*

AC Transit canceled all transbay, school-bus and flex (otherwise known as dynamic) routes, and adopted a weekend schedule for weekdays. In general, all processes for route adjustments remained the same as before the pandemic. The agency makes route adjustments four times a year—in December, March, June, and August; it makes minor schedule adjustments, small route changes, and bus stop fixes on a monthly basis. As mentioned above, the AC Transit bus network is divided into five wards, and the service is managed by ward.

As opposed to AC Transit, the VTA transit network is managed as one single unit. In pre-pandemic times, annual service changes were scheduled at the beginning of each year. As the pandemic started, initially the service was adjusted on a weekly basis. Notably, all school-bus, express and rapid routes were suspended. Light rail service was also initially canceled, but reinstated in April 2020. Some routes were shortened, such as areas around Santa Clara University and State University of San Jose, since these schools went into lockdown. The Sunday schedule was taken as a basis for daily operation. Weekday additions to this basis included routes going to hospitals.

Tri Delta Transit did not change the structure of its routes. Changes were limited to reducing weekday schedules (intervals between buses became twice as long as before the pandemic) and replacing Saturday and Sunday schedules with just one Sunday schedule. Following its mission of connecting people to BART, Tri Delta Transit tailors its schedules to those of BART.

To reduce COVID spread among their employees, all three agencies stopped fare collection, beginning in April 2020. VTA resumed fare collection and front-door boarding on August 1, AC Transit—on October 19 of 2020, and Tri Delta—in January 2021. VTA, however, went back into the fare-free and rear-door boarding mode on February 8, 2021, a month after new COVID cases peaked again in Santa Clara County.

All three agencies admitted that available funding defined their service adjustments. They all are funded with a mix of federal, state, and local government subsidies, as well as passenger fares. Passenger fares in this list were not decisive during the pandemic. Thus, although AC Transit and VTA were losing over a million dollars per week in uncollected fares, they were not too concerned about this. A bulk of funding for them came from the CARES Act distributed by the Metropolitan Transportation Commission.

### *4.2 Fleet Management*

AC Transit uses different kinds of buses for different services—local, transbay, express, school. About 75% of its buses are equipped with automatic passenger counters (APC), which are used to assess ridership. Within a given service, the agency rotates its fleet to maximize ridership coverage in its service area. During the pandemic, about 80% of the fleet has been used, bringing the APC coverage up to 95%.

About 85% of VTA buses and all its trains are equipped with APC. Its fleet rotation before the pandemic was conditioned on maximizing the APC coverage and the requirement of having long (double-car) buses on certain routes with high ridership. Given a 56% service reduction during the pandemic, all buses are now equipped with APC, so the rotation is governed only by the bus size requirement.

Tri Delta Transit buses are also equipped with APC. Except for two routes, where electric buses operate, everywhere else the fleet is assigned randomly. The two routes with electric buses are determined by the Low Carbon Emissions Funding Program to connect certain underprivileged communities to BART services. About 70% of the Tri Delta fleet has been active during the pandemic.

None of the three agencies to date processes APC data in real time. Passenger counts are downloaded from buses at the end of the day as they return to the garage. Then, it takes 3–5 days for data to be processed, cleaned and entered into each agency's system.

### *4.3 Performance Evaluation*

Transit agencies use various performance metrics to evaluate their services. One such metric is the numbers of "pass-ups." When a bus is full, and nobody wants to exit, a bus driver keeps going without stopping, even if passengers are waiting at a stop. This situation is called a "pass-up" and is reported by a bus driver. Since the breakout of COVID-19, all three agencies have experienced pass-ups, and the number of pass-ups became an additional performance metric for AC Transit and VTA.

The main performance metrics for AC Transit include transit vehicles being on time and ridership numbers on most routes. Ironically, being on time during the pandemic often implied that bus drivers had to stop mid-route and wait to avoid arriving too early at their destination. This was because the streets were largely empty. Route productivity is estimated based on the number of boardings per revenue hour. The guiding principle for service adjustment is to keep up or improve high-productivity routes (generally, running along major arterials); and reduce, modify or cancel underperforming routes (generally, peripheral routes). These metrics are examined monthly, and decisions are made about service adjustments. It is not always easy to cancel an underperforming route. AC Transit has constituents, who pressure the agency's Board to keep certain routes, even when there are very few passengers.

As mentioned, prior to the pandemic, AC Transit operated two flex routes.[5] The route that these flex routes replaced carried on average 8–10 passengers per revenue hour, and the flex routes' ridership was only 3–4 passengers per revenue hour, which constituted an unsuccessful experiment. These flex routes were canceled during the pandemic and are unlikely to resume.

Once a week, AC Transit evaluates the number and geography of pass-ups. For routes experiencing frequent pass-ups, the agency assigns standby buses, which are ready to start operation as needed and pick up those passengers left unserved. These standby buses are managed from the Operations Control Center, which provides a real time response.

VTA uses boardings per hour as a primary performance metric for route adjustment. During the pandemic, the number of pass-ups was used to adjust the schedule. In general, VTA tries to concentrate on trunk routes and maintain high-frequency service there, whereas peripheral routes with low ridership are being canceled. Ridership performance is not a sole criterion for route modification though. For example, in Morgan Hill there is a single route, which always had a low performance, but VTA does not cancel it to keep the community connected. Metrics such as equity do not play a role in VTA decisions about their service.

Tri Delta Transit monitors ridership (boardings per revenue hour) and being on time as its performance metrics. However, these metrics are not used as triggers for service adjustments. Routes are set and do not change very often. Schedules can be modified, but those modifications are dictated by BART schedule changes. Pass-ups are expected only on selected routes during certain hours of the day. During these hours, the agency is ready to dispatch extra buses as needed. Tri Delta and VTA do not consider flex routes; given their ridership patterns and operational structure, they believe that flex routes do not add value.

[5] A flex route allows for deviations without creating excessive delays for other riders on the bus.

All three agencies expressed a desire to have APC data available in real time, possibly through a transit app, for the purpose of reporting bus overcrowding to end users. Presently, when this information is displayed in a trip planner, it comes from a ridership estimation based on historical passenger counts.

Protests and riots that took place in early June 2020 had a negative impact on AC Transit ridership and operation in the Oakland area, and the agency had to establish detours in Downtown Oakland. A lot of pass-ups were recorded because buses would not stop when it was not considered safe. Ridership during the first half of June dropped across the board, but especially on the Oakland - San Leandro route. VTA observed a mild drop in ridership during the period of protests, but this did not affect its operation. The Tri Delta operation was not disrupted by protests either.

### *4.4 Paratransit*

In pre-COVID days the demand for paratransit services was higher than the agencies were able to provide, and the service was handled on a first-come-first-serve basis. During the pandemic, however, demand was dramatically reduced. AC Transit partners with BART to provide paratransit service. AC Transit's paratransit is the largest operation in the San Francisco Bay Area. It is demand-based and operated through contracted services. Normally, they run 2500 trips per day, which during the pandemic dropped to 450 trips per day. Since it is a contracted service, its reduction does not affect AC Transit operations. VTA acknowledged that its paratransit service was suffering during the pandemic due to low demand; however, it did not indicate any service disruptions or workforce downsizing. Tri Delta Transit started as a paratransit provider, only later becoming a general-purpose transit agency. During the pandemic, the agency's paratransit demand went down, but on par with the rest of the service. So, no extraordinary measures were required.

## 5 Takeaway Summary

During the year particularly hit by the COVID-19 pandemic, from March 2020 through March 2021, we monitored two large and one small transit agency in the Bay Area. As the lockdown was imposed, white-collar commuters, students and older adults stopped using public transit. Initially, the ridership fell by 90%, and then for a year slowly climbed up to less than 50% for AC Transit and VTA, and up to around 60% for Tri Delta Transit. This recovery was not consistent. Local drops occurred during protests in June 2020, during fare reinstatements, and during the second COVID wave in Winter 2020–21.

People who stayed loyal to public transit came mostly from low-income areas with a high percentage of Latino, Black and Asian population. These are people, who generally rent their homes, do not have a car, but have to go to work either because they belong to an essential workforce or are undocumented immigrants and cannot afford staying jobless. AC Transit and VTA also reported that during fare-free service periods, they observed numerous unhoused individuals, who used their buses as shelters. This portion of the agencies' ridership did not contribute to their economic recovery.

Agencies' response to the pandemic consisted of three parts: (1) maintaining the health and safety of their employees; (2) minimizing COVID risk for their riders by keeping buses clean and enabling social distancing through capping the number of passengers on buses; (3) reducing their service. By fall 2020, all three agencies started providing hand sanitizers and masks to passengers as well as cleaning their buses more than once a day. AC Transit and VTA had to perform structural service change—cancel or modify certain routes in addition to bus frequency reduction. Tri Delta Transit had only reduced their bus frequency tailoring their schedules to those of BART, and that was enough. AC Transit adjusted its service on a monthly basis; VTA—week by week; and Tri Delta Transit—quarterly.

All three agencies reported a pass-up problem when bus drivers passed stops with awaiting passengers because their buses were already full. This happens on certain routes during certain times of day. AC Transit and Tri Delta solve this problem in real time by dispatching extra buses on routes with pass-ups as needed. VTA revises its schedule weekly accounting for the reported pass-ups.

All three agencies are skeptical about the flex route concept in mass transit. AC Transit was the only one experimenting with it. Prior to the pandemic, it had proved to be ineffective, and during the pandemic it ended up not being used at all and was canceled.

Despite the dramatic ridership loss, public transit proved to be an indispensable means of transportation for those categories of people who could not afford private alternatives and who had to get to work, providing essential services for the rest of us. Thus, public transit is a necessary buttress for our economy both in times of crisis as well as in good times. Yet, the service now fully depends on subsidies. To become a significant source of revenue, ridership needs to grow much faster than the current experience indicates. But ridership growth depends on the availability of reliable and well-maintained service, as well as general business activity. It is imperative to keep public transit running.

Transit recovery is underway, but as of Spring 2021, it goes very slowly. Nevertheless, California's reopening in mid-June 2021 and the subsequent back-to-the-classroom mode of education in the Fall 2021 gives us some grounds for optimism.

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# COVID-19 and Transportation Revenue: Using Scenario Analysis to Project a Range of Plausible Futures

**Asha Weinstein Agrawal, Hannah King, and Martin Wachs**

**Abstract** The sharp reduction in travel caused by the COVID-19 pandemic quickly created a financial emergency in the transportation sector, as fees paid by travelers provide much of the revenue for transportation. This chapter reports on research that began late in the summer of 2020, a time when there was widespread recognition among transportation experts that falling travel was decreasing fuel tax revenue, but great uncertainty about *how much* transportation revenue would be lost in both the short and longer term. The project developed six scenarios projecting California's state-generated transportation revenue through 2040. The scenarios vary by factors such as the length of the economic fallout from the pandemic and changes in the number of electric vehicles in the light-duty fleet. Although the specific findings presented in this chapter come from California, the results illustrate different ways that scenario analysis helps policymakers make decisions in the face of immense uncertainty.

## 1 Introduction

Throughout the United States, the COVID-19 crisis resulted in dramatic reductions in economic activity and, consequently, in travel. Immediately after most states implemented shelter-in-place orders in the spring of 2020, there was a precipitous decline in vehicle miles traveled (VMT), particularly for personal travel. For example, in California, VMT dropped to a low of 41% below the normal in mid-April 2020, and was still down by 14% in June 2020 [4].

The sharp reduction in personal travel quickly generated both positive and negative impacts. On the one hand, communities realized unexpected benefits such as much cleaner air, the disappearance of traffic congestion, and the opportunity to designate some streets in urban centers for active transportation. At the same time, states also saw their state-generated transportation revenue plummet. Most notably, the drop in

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travel led to a corresponding drop in revenue from the state excise tax on fuel, one of the major sources of state transportation revenue.[1]

This chapter reports on research that began late in the summer of 2020, a time when there was widespread recognition among transportation experts that falling travel was decreasing fuel tax revenue, but great uncertainty about *how much* transportation revenue would be lost in both the short and longer term. The project, which we completed for the State of California, developed six scenarios projecting transportation revenue through 2040. The scenarios vary by factors such as the length of the economic fallout from the pandemic and changes in the number of electric vehicles in the light-duty fleet. Although the specific findings presented in this chapter come from California, the results illustrate how scenario analysis can help policymakers make decisions in the face of immense uncertainty.

Our study builds on a long tradition of using scenario analyses to support decision-making within the military, public policy, and business [6]. Within the transportation sector, scenario analysis is commonly used to explore how different policies may impact emissions of greenhouse gases or air quality pollutants, as well as to project how different transportation improvement programs may impact travel behavior and accessibility [1–2, 5].

With scenario building, it is critical to keep in mind that the objective is very different from the objective of forecasting efforts. While forecasting studies aim to accurately predict future outcomes, studies like ours that project the future under a variety of scenarios do *not* try to make such predictions. Instead, as one planning scholar put it, "Projections are conditional 'if, then' statements about the future. They are calculations of the numerical consequences (the 'then') of the underlying assumptions (the 'if')" [8]. Scenario analysis thus permits policymakers to assess how well different policies would achieve desired outcomes under a wide range of different plausible futures.[2] It is for this reason that we do not compare our projections with reported revenues over the past year, the analysis is designed to examine the inherent uncertainty underlying the prediction process rather than attempting to predict the future accurately.

Because it is notoriously difficult to project any travel-related activity farther than a few years out, the scenario approach demonstrated in this study could be adapted to help policymakers think through the long-term impacts of possible changes in many factors, including population size, vehicle technology, or fuel prices.

The remainder of the chapter first describes the study methodology, then presents findings from the California analysis, and concludes with reflections on how transportation policymakers can use this scenario approach to make wise decisions in the face of great uncertainty.

[1] This study looks only at state-generated revenue. However, the COVID-19 pandemic also impacted local and federal sources of transportation revenue for the state, including sales tax revenue.

[2] Because our study did not aim to forecast future revenue, we do not discuss how actual revenue raised to date compares with the study scenarios.

**Table 1** Transportation tax and fee rates established by California's senate bill 1 (2017)

| Tax/fee | Rate as of January 1, 2020[a] |
|---|---|
| *Fuel taxes* | |
| Gasoline excise tax | Base excise (30¢ per gallon) + swap[b] excise tax (currently 17.3¢ per gallon) |
| Diesel excise tax | 36¢ per gallon |
| Diesel swap[b] sales tax | 5.75% on purchase price |
| *Vehicle fees (annual)* | |
| Transportation Improvement Fee | \$25 to \$175 per vehicle annually, with rate depending on the vehicle's value |
| Road Improvement Fee | \$100 per ZEV with model year 2020 or later, annually (effective 7/1/2020*)* |

*Data source* Adapted from California legislative analyst's office, overview of 2017 transportation funding package (2017), http://www.lao.ca.gov/Publications/Report/3688

[a] The rates are to be adjusted for inflation starting July 1, 2020, for the gasoline and diesel excise taxes, January 1, 2020, for the transportation improvement fee, and January 1, 2021, for the road improvement fee on ZEVs. The diesel sales tax rate remains fixed

[b] For details about the "gas tax swap," including tax and fee rates prior to the swap, see Anne Brown, Mark Garrett, and Martin Wachs, (2017). "Assessing the California fuel tax swap of 2010," Transportation Research Record: The journal of the Transportation Research Board, no. 2670, pp. 16–23

## 2 Methodology

The projections made for this study consider the transportation revenue collected directly by the State of California through a set of taxes and fees governed by California Senate Bill 1: The Road Repair and Accountability Act of 2017. Senate Bill 1 revenue is a critical component of transportation program funding in California, even if it only represents one portion of the total funding spent in the state for transportation purposes. As of 2017, just before the bill started taking effect, state sources provided about a third of transportation revenue spent in California by all levels of government [11].

The state taxes and fees for which we projected revenue are (1) collected from vehicle owners and users and (2) have their proceeds dedicated to transportation programs. These are the state's gasoline excise taxes, diesel excise taxes, diesel sales taxes, the annual Transportation Improvement Fee assessed on all vehicles, and the Road Improvement Fee assessed annually on zero-emissions vehicles (ZEVs).[3] Table 1 shows the rate for each tax or fee at the start of the calendar year 2020, as established by Senate Bill 1.

Given the enormous uncertainty inherent in projecting 20 years into the future, we explored a variety of different scenarios and projected revenue for each. We do not, however, assess the *likelihood* that any particular scenario will occur. As

[3] Revenue from the state's base vehicle registration fee and vehicle license fee was not projected because the proceeds are not dedicated to transportation programs.

discussed previously, the primary purpose of the projections is to examine how different combinations of inputs might impact revenue streams over time rather than to predict a specific future outcome. Second, the data do not allow us to assign specific probabilities to the likelihood of any particular future.

## 2.1 The Projection Models

We constructed the projections using spreadsheet models that estimate annual transportation revenue collected by the State of California. The models are adapted from work the authors developed in three earlier research studies, the most recent of which projected revenue through 2030 under different COVID-19 economic recovery scenarios [14–16]. Complete methodologic details for the current study, including specific values for all model inputs and outputs, can be found in the published project report [17].

The models calculate revenue by applying the scheduled tax and fee rates set under Senate Bill 1 to projected sales of motor fuel for transportation purposes and the projected fleet size for both internal combustion engine (ICE) and ZEV light-duty vehicles. Key inputs to the models include projected vehicle miles traveled, fuel efficiency rates for ICE vehicles, diesel fuel prices, the number of registered vehicles, ZEV adoption rates, and the sales price and depreciated value of light-duty vehicles.[4]

The projections used data from authoritative sources, such as revenue data from the State of California and widely used fuel price projections prepared by the Energy Information Administration (EIA) of the US. Department of Energy [12]. Complete details about the data sources and assumptions employed to operationalize the projections are available in the project report [17].

## 2.2 The Recovery Scenarios

We constructed six recovery scenarios by positing a set of three possible trajectories for each of several transportation-specific model inputs that met two criteria: they significantly impact revenue and are likely to be affected over time by the social and economic impacts of the COVID-19 pandemic. The selected variable inputs are annual state vehicle miles traveled, light-duty vehicle fleet size, light-duty ZEV fleet size, light-duty ZEV vehicle values, and heavy-duty diesel fleet size. The numerous other model inputs were kept constant across all six scenarios (e.g., inflation rate,

[4] The formulas used to project the revenues can be found in the Technical Appendix A of Agrawal et al. [17].

share of annual state VMT driven by light-duty versus heavy-duty vehicles, and fuel prices).[5]

Annual state VMT was the one variable input that we assumed could be directly and strongly affected by the pandemic. VMT increases during a growing economy because employment-related travel will be higher when a higher percentage of the workforce is employed. In addition, in a strong economy both individuals and firms are more able and willing to spend on goods and services. Increased consumer and business spending generates additional travel both as *people* travel to reach goods and services, and as *goods* travel from suppliers to purchasers. Conversely, VMT typically falls during periods of economic weakness, so both short-term COVID-19-related lockdowns and any long-term depression of economic activity would reduce VMT.

The other five variable inputs are assumed to vary according to overall fleet size and the rate at which Californians adopt ZEVs. We assumed that all else being equal, revenues will be higher with larger fleet sizes. Also, a larger number of ZEVs will increase revenue associated with ZEV adoption (e.g., the Road Improvement Fee) and decrease revenue linked to the consumption of fossil fuels (e.g., the gasoline excise tax).

Finally, although the impetus for the research was to explore how strongly the pandemic might impact revenue into the future, the scenarios were also designed to explore variations in annual state VMT and the rate at which ZEVs replace light-duty ICE vehicles. Both are changes that have been discussed in California as possible strategies to reduce carbon emissions, with the latter recently receiving considerable attention. During the time this study was underway, California Governor Gavin Newsom issued Executive Order N-79-20, which directs state departments and agencies to adopt regulations and programs that would lead to no sales of new light-duty ICE vehicles as of 2035 [9].

To estimate specific values for the high, medium, and low trajectories of each model input, we relied on conversations with subject matter experts and the literature on past trends for the inputs of interest. In addition, we developed two principles to guide our choices:

- *Consider evidence of how COVID-19 has affected travel volumes and fuel sales.* There is clear evidence that VMT fell dramatically as soon as states imposed shelter-in-place rules in March. Some communities saw VMT fall by 40%, 50%, and even 60%, although the dramatic declines of the early months mostly eased with the passage of time [3]. To account for change in VMT over time, we estimated specific values for the high, medium, and low revenue trajectories for each of the model inputs. Our analysis considers data dating back to 2008 (i.e., the start of the Great Recession and its impact on employment and travel demand), when available.

[5] These were all inputs for which we predicted either that the COVID-19 pandemic was unlikely to have a major impact on the trajectory or that the variable has minimal impact on the total state revenue collected in any year. The complete list is presented in "Technical Appendix 2" of Agrawal, et al. [17].

- *Explore the impact of extreme changes in VMT, the light-duty fleet size, and/or the ZEV fleet size.* It is conceivable that a very slow recovery from the COVID-19 crisis, increasing commitment to reducing greenhouse gas emissions, or other major disruptions in the state could produce trends in travel and vehicle ownership over the coming two decades that are radically different from the trends since 2008.

Table 2 presents the high, medium, and low trajectories for each of the five key variable inputs used to build the recovery scenarios. The trajectories are described in simple terms that can be easily understood by non-experts and also can be modeled in widely available spreadsheets.

Table 3 shows how the six recovery scenarios draw on the high, medium, and low trajectories for the variable inputs described in Table 2.

The six scenarios differ along two major dimensions: travel behavior and changes in the fleet by motive power (ICE vs. ZEV). We varied travel behavior by varying the amount of travel (VMT) and vehicle ownership levels (light-duty fleet size). We varied changes in the fleet by power source by examining changes in the number of ZEVs in the fleet (both light duty and heavy duty vehicles) and by examining changes in the values of light-duty ZEVs relative to the value of light-duty ICE vehicles. Our six scenarios thus represent different combinations of future patterns in travel behavior and fleet composition.

## 3 Findings

This section discusses key findings from two components of the analysis: projected total annual revenue for each scenario through 2040 and the proportion of revenue raised annually from each tax and fee under each scenario through 2040.

Figure 1 presents the total revenue that California would collect from 2020 to 2040 under the six COVID-19 recovery scenarios. All projections are presented in inflation-adjusted 2020 dollars. The annual revenue steadily diverges among the scenarios as the years pass. By 2040, annual revenue ranges from a high of $10.9 billion for the high-carbon scenario (#1) to a low of $6.5 billion for the low-carbon scenario (#6). The *cumulative* revenue raised from 2020 to 2040 varies by more than $40 billion across the scenarios. At one extreme, the high-carbon scenario (#1) generates a total of $195 billion by 2040. At the other extreme, the low-carbon scenario (#6) generates $153 billion by 2040.

Figure 2 shows for each scenario how the proportion of total California state revenue raised from each tax and fee evolves over time.

Key findings include:

- Revenue from the two taxes on diesel fuel provides a small portion of total annual revenue for the moment, and the value may dwindle considerably more. These taxes generate less than a quarter of revenue today (23%). By 2040, the revenue will fall to at most 13% (the high-carbon scenario), and will be less than 1% in four other scenarios.

**Table 2** High, medium, and low trajectories used to construct the scenarios for the variable inputs

| Variable inputs | High trajectory | Medium trajectory | Low trajectory |
|---|---|---|---|
| Annual state VMT | Increases linearly to 90% of predicted pre-COVID-19 levels by January 2021, increases linearly to predicted pre-COVID-19 levels by January 2022, and increases linearly to 120% of predicted pre-COVID-19 levels by 2040. | Remains at August 2020 levels until April 2021, then increases linearly to the predicted pre-COVID-19 level by April 2023, and remains at predicted pre-COVID-19 VMT through 2040. | Remains at August 2020 levels until March 2025, increases linearly to reach 90% of pre-COVID-19 levels December 31, 2030, and remains at 90% of predicted pre-COVID-19 VMT through 2040. |
| Light-duty vehicle fleet size | Increases by 1.9% annually (median year-to-year growth rate from 2008 to 2017). | Increases by 0.8% annually (year-to-year growth rate from 2018 to 2019). | Declines linearly to 0.66 vehicles per person by 2040. |
| Light-duty ZEV fleet size | The number of light-duty ZEVs increases at an exponential rate so that they constitute 75% of light-duty registered vehicles by 2040. | Light-duty ZEV fleet size increases exponentially such that the state of California reaches its goals of 1.5 million ZEVs by 2025 and 5 million ZEVs by 2030. After 2030, the ZEV fleet grows by 1 million every year. | Light-duty ZEV fleet size increases by 94,112 vehicles per year (the annual rate of growth from 2018 to 2019). |
| Light-duty ZEV vehicle values | Start at EIA projections in 2020 and converge linearly to EIA projections for light-duty ICE vehicles by 2040. | Start at EIA projections in 2020 and converge linearly to EIA projections for light-duty ICE vehicles by 2035. After 2035, ZEV values follow EIA projections for light duty vehicles. | Start at the EIA projections in 2020, converge linearly to EIA projections for light-duty ICE vehicles by 2030, and follow EIA projections to 2040. |
| Diesel share of the heavy-duty fleet | Follows EIA projections, falling to 73% in 2040. | Declines logarithmically to 55% by 2030 and 50% by 2040. | Declines logarithmically to 40% by 2030 and 0% by 2034. After 2034, the heavy-duty fleet remains 0% diesel. |

*Notes*

- The exact values for each input variable trajectory are shown in "Technical Appendix C" of Asha Weinstein Agrawal, Hannah King, Martin Wachs, and Jeremy Marks, (2020). *The Impact of the COVID-19 Recovery on California Transportation Revenue: A Scenario Analysis through 2040.* San Jose: Mineta Transportation Institute
- Acronyms: EIA = Energy Information Administration; ICE = internal combustion vehicles; VMT = vehicle miles traveled; and ZEV = zero-emission vehicle

**Table 3** Trajectories chosen for each variable model input in the scenarios

| Scenarios | Annual state VMT | Light-duty fleet size | Light-duty ZEV fleet size | Light-duty ZEV vehicle values | Diesel share of heavy-duty fleet |
|---|---|---|---|---|---|
| 1. High carbon: high VMT + large fleet + low ZEV | High | High | Low | High | High |
| 2.High VMT + large fleet + high ZEV | High | High | High | Low | Low |
| 3. All medium | Medium | Medium | Medium | Medium | Medium |
| 4. High VMT + medium fleet + high ZEV | High | Medium | High | Low | Low |
| 5. Medium VMT + medium fleet + high ZEV | Medium | Medium | High | Low | Low |
| 6. Low carbon: low VMT + small fleet + high ZEV | Low | Low | High | Low | Low |

*Note* Although scenarios one and six are labeled "High carbon" and "Low carbon," respectively, the intervening scenarios are *not* intended to rank carbon consumption outcomes

- Over time, revenue from fuel taxes will decline as a proportion of state transportation tax revenue even as the tax rates are increased annually to reflect inflation. Fuel tax revenue will drop from roughly three-quarters of all revenue in 2020 to as little as 23% of total revenue under the low-carbon scenario. Even under the high-carbon scenario (#1), revenue from taxes on fuel drops only to 57% of total revenue by 2040. The fuel taxes lose their dominance because the scenarios assume some combination of two trends. First, revenue from fuel taxes drops as more and more vehicles are ZEVs or extremely fuel-efficient ICE vehicles. Second, revenue from the two annual fees assessed on light-duty vehicles (the Transportation Improvement Fee and Road Improvement Fee) will grow considerably because new ZEVs are assumed to start out as more expensive than new ICE vehicles. We also assume that ZEVs and ICE vehicles do not achieve price parity before 2030 at the earliest, and that new ZEV prices never dip below new ICE vehicle prices.
- The relative contribution of the fuel taxes and vehicle fees (RIF and TIF) reverses over time under all but the high-carbon scenario. In every other scenario, the growth of ZEVs and increasing fuel efficiency of ICE vehicles reduce revenue from fuel taxes in proportion to revenue from the annual vehicle fees. In 2020, the

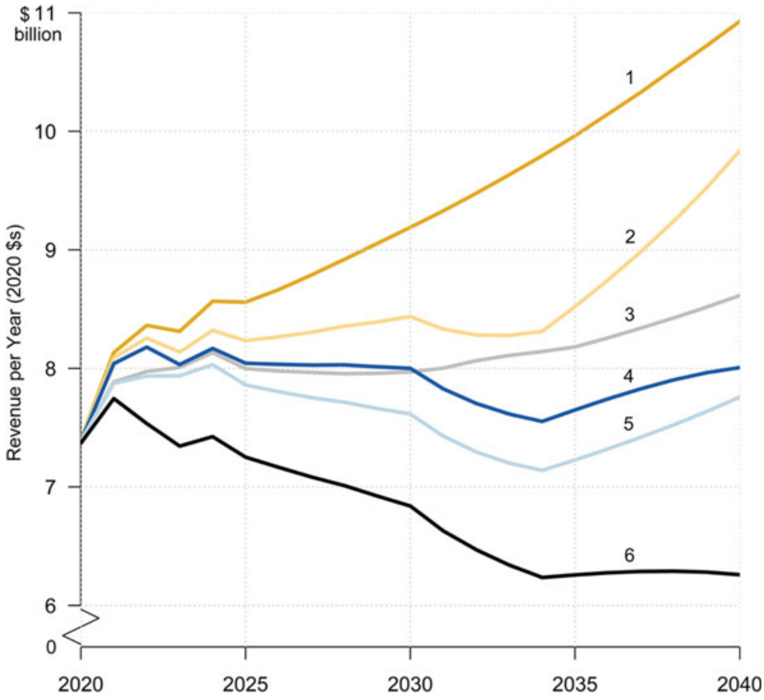


**Fig. 1** Total annual state revenue by scenario, 2020–2024 (2020 Dollars). *Data source* Authors.

fuel taxes contribute three-quarters of revenue, but by 2040 fuel taxes contribute no more than a quarter of revenues in four of the scenarios.

In summary, the models predict that even if the COVID-19 pandemic disrupts travel behavior (and thus transportation revenue) in the short and medium terms, over the long term other structural factors will have far greater impacts on revenue. For example, the ability of the cents-per-gallon motor fuel excise tax proceeds to fund transportation needs will continue to decline in the face of increasing fuel efficiency for ICE vehicles and rising numbers of vehicles that consume no fossil fuels at all.

## 4 Conclusion

We conclude by discussing eight lessons learned from the study that may be useful to transportation policymakers and analysts preparing to act in the face of uncertainties, whether those relate to technology adoption, natural disasters, or radical policy change. The first four points discuss the ways that scenario analysis can be useful to policymakers, and the remaining four offer strategies for conducting effective scenario analyses.

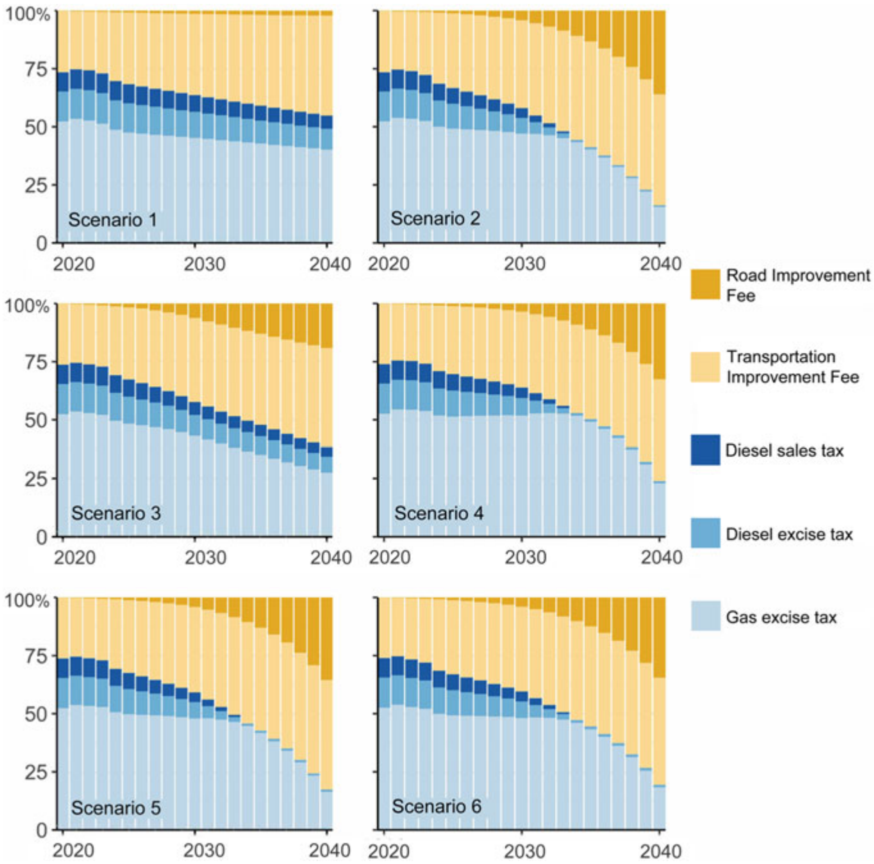


**Fig. 2** The proportion of total revenue raised annually from each tax and few, by scenario. *Data source* Authors.

### *4.1 The Value of Scenario Analysis for Policymakers*

For one, scenario analysis reveals the wide variety of plausible futures for which policymakers should plan. The study results show just how much uncertainty there is about future travel and vehicle patterns, vividly reminding stakeholders that a policy which seems ideal in the short run might prove disastrous in the medium or longer term. For example, the annual revenue raised under our different scenarios diverges steadily over time such that by 2040, annual revenue ranges from a high of $10.9 billion for the high-carbon scenario (#1) to a low of $6.5 billion for the low-carbon scenario (#6). Even if one excludes the two most extreme scenarios (the high-carbon and low-carbon ones), total revenue raised annually in 2040 varies across the remaining four scenarios by more than $2 billion.

While the COVID-19 pandemic introduced an entirely unexpected series of events, even in less turbulent periods, transportation policymakers face huge uncertainty about the future given unknowns such as future demographic changes, technology innovations, and economic performance. Indeed, the models for this study demonstrate that changes in revenue due to the impacts of the pandemic are dwarfed over time by other factors, such as changing rates of ZEV adoption and statewide VMT trends.

Second, scenario analysis can help policymakers identify resilient policy options. Comparing the projections across a wide range of scenarios, as we did in this study, allows policymakers to identify "resilient" policy options that are likely to perform well across a range of possible futures. For example, the models compare how fast ZEV adoption would impact vehicle registration fees, finding that by 2040 ZEV registration fees may generate annual revenue as high as $3.5 billion, or as low as $250 million.

Third, scenario analysis reveals the relative impacts of different model inputs. For example, when we began the present study, there was a sense among some experts that revenue lost to COVID-19 would be a primary challenge that policymakers would need to address. However, the study results suggest that while COVID-19 may have a substantial impact on revenue that impact is dwarfed by the impacts from possible changes in vehicle technology or overall levels of VMT.

Fourth, the models can be used to compare projected future revenue from existing taxes and fees to revenue that would be generated by alternative ones. In the case of this study, we were able to use the models to show that the gap in revenue between the scenarios that generate the most and the least fuel tax revenue in 2040 could be raised by supplementing the existing tax structure with a new road-user charge of one cent per mile. If California were to experience the low VMT growth projected in the low-carbon scenario (#6), but policymakers wished to raise as much revenue as is generated by the high-carbon scenario (#1), then that difference could be made up with a charge of 3.3 cents per mile on travel by light-duty vehicles. That mileage fee would generate as much revenue in 2040 as the high-carbon scenario would raise through both the fuel taxes and annual fees assessed on light-duty vehicles.

## *4.2 Strategies for Conducting Effective Scenario Analysis*

Our work on the four different scenario analysis studies that culminated in the current study revealed several strategies for designing effective analyses.

For one it is important to include scenarios that push the boundaries of conventional wisdom in both directions. This tactic allows policymakers to look for options that perform well in a wide range of futures. While there may be pressure to focus the projections on a "most likely" future, the real value of the exercise comes from using a wide range of possibilities, so that stakeholders understand what the future might hold if the unexpected occurs. If most stakeholders consider the boundary scenarios reasonable, then the range of scenarios is likely too conservative.

Second, engaging stakeholders in the analysis process can foster shared understanding and collaboration. With scenario studies, it can be valuable to directly involve stakeholders in the process of defining the scenarios. An extensive literature on public participation has shown that engaging stakeholders in the process of generating data and information leads to more collaborative long-term outcomes [7, 10, 13]. In the content of scenario planning, such participation would include having stakeholders help to select the assumed trajectories for the model inputs. Not only will this approach ensure that the models consider scenarios of importance to different stakeholders, but participants will likely come to a better understanding of each other's general understanding of the issues at hand.

Third, scenario projection studies will be most useful in public discussion when they rely on relatively simple and transparent models. The value of any scenario projection exercise is to test the relationships between different combinations of inputs and the model outcomes. If analysts design models with simple enough inputs and formulas, then the models allow a wide variety of interested stakeholders to understand *why* changes in inputs influence the results. Further, if the models are reasonably simple to explain and use, stakeholders can run additional analyses using different sets of inputs. In our case, the original set of projections for Senate Bill 1 revenue ultimately led first to a request from policymakers to explore how different rates of ZEV adoption in the state would impact revenue, and later to requests for two different projects exploring COVID's potential impact on state transportation revenue.

Fourth, it is important to be mindful of the particular challenges posed when conducting scenario analysis in the midst of an unfolding crisis. This study highlighted some challenges unique to designing scenarios and choosing input data during an ongoing crisis. First, in the heat of an emergency, analysts may face considerable pressure to complete the study quickly, yet we found that it takes time and care to choose a useful set of scenarios. Analysts must be allowed sufficient time and resources to complete their work even when timeliness is a high priority. Second, critical input data changed during the process of designing the models, and then changed even more by the time the final project report was published. The most dramatic example is VMT, forecasts of which were almost continually revisited during the pandemic. We addressed this challenge by analyzing data from before as well as after the onslaught of the COVID-19 pandemic. This approach increased the number of data points for us to consider, thus improving our understanding of how variables operate under "normal" conditions.

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# The Future of Public Transit and Shared Mobility: Policy Actions and Research Options for COVID-19 Recovery

**Susan Shaheen and Stephen Wong**

**Abstract** The global tragedy of the COVID-19 pandemic devastated communities and societies. The pandemic also upended public transit and shared mobility, causing declines in ridership, losses in revenue sources, and challenges in ensuring social equity. Despite ongoing uncertainty, guidance can instruct recovery and build a more resilient, socially equitable, and environmentally friendly transportation future. This chapter summarizes a recent scenario planning exercise conducted by the University of California Institute of Transportation Studies in collaboration with the Transportation Research Board (TRB) Executive Committee in Spring to Fall 2020. The exercise convened 36 transportation experts in the United States who developed policy actions and research options crafted to guide near- and long-term public transit and shared mobility. Clear themes emerged from the study regarding key actions for public transit operators in the areas of: (1) innovation and technology, (2) planning and operations, (3) customer focus, and (4) workforce development. A second grouping of broader policy strategies for both public transit and shared mobility included: (1) immediate policy and actions across actors, (2) alignment of societal objectives, (3) federal transportation spending authorization, and (4) finance and subsidies. While the exercise reiterated the need for rapid actions, thoughtful planning and decision-making can prepare both sectors for a more cooperative, multimodal ecosystem.

[1] In this chapter, we define shared mobility as the shared use of a vehicle, motorcycle, scooter, bicycle, or other travel mode that provides users with short-term access to a transportation mode on an as-needed basis. While public transit is a form of shared mobility, we define public transit as a more traditional public transport system that is owned and/or operated by public agencies, transporting individuals predominately via bus, rail, and ferry.

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## 1 Introduction

The COVID-19 global pandemic upended travel and triggered a crisis for public transit and shared mobility services.[1] Plunging ridership and unstable funding across public transit and many shared mobility modes led to many uncertainties. Starting mid-March 2020 for much of 2020, public transit ridership for many agencies in the U.S. fell by over 60 percent compared to 2019 [1]. In New York City, the Metropolitan Transportation Authority reported that ridership dropped in mid-March 2020 by about 50 percent on buses, 60 percent on subways, and up to 90 percent on commuter rail, compared to the same time period in 2019 [15]. Meanwhile, the Bay Area Rapid Transit (BART) District in the San Francisco Bay Area experienced ridership drops over 90 percent compared to similar time periods in 2019 [5]. These impacts were not isolated to urban areas. Many small public transit agencies in rural areas also experienced major declines in ridership in 2020 [2]. Even into 2021, public transit only experienced moderate ridership recovery, hovering between an average of 40 to 60 percent of baseline ridership from 2019 depending on the operator size [4]. It is important to note that public transit ridership was already experiencing small declines prior to the pandemic (for example, in California, see [18]. However, the shock of the pandemic led to substantial ridership drops far below the estimated declines.

Transportation network companies (TNCs), such as Lyft and Uber, also reported ridership drops in Summer 2020, ranging from 54 to 75 percent compared to the prior year [22]. Other forms of shared mobility, such as carsharing, bikesharing, and scooter sharing, saw mixed ridership changes, depending on the geography and trip purpose [6, 26]. Unlike other transportation sectors, delivery services driven by e-commerce growth [14] became profitable for the first time [12]. Moving into 2021, TNCs experienced substantial recovery, reflecting post-pandemic levels [17, 23]. In contrast, the longer term effects of the pandemic on other mobility forms, for example, bike sharing and scooter sharing, were largely negative into 2021 [8].

The COVID-19 crisis tragically struck many communities, leading to terrible loss of life, long-term health challenges, and substantial emotional toll and grief. This pain was exacerbated by the collapse of basic life necessities such as transportation, exposing underlying issues in how mobility was provided to society. Short-term fixes, while critical, will not solve pervasive transportation issues related to access, high-quality service, and social equity. Policy- and decision-makers at all levels of government, especially at public transit agencies, need strategies and actions to recover from COVID-19 and build long-term sustainability and resilience into communities and transportation systems. At first glance, untangling the complex web and creating guidance would require years of dedicated research. However, what can policy- and decision-makers do now? Our strategy was to use a well-known tool to address both uncertainty and the need to make immediate decisions. This tool—scenario planning—can help organizations prepare, plan, and develop robust alternatives to manage risk and produce positive outcomes.

This chapter summarizes a multi-phase scenario planning exercise conducted by the University of California Institute of Transportation Studies (UC ITS) in partnerships with the Transportation Research Board's (TRB) Executive Committee from June to September 2020. Convening 36 transportation experts in the United States (U.S.), the exercise developed a focal question, possible driving and external forces, future scenario (or worlds) based on these forces, and future policy options/actions. The exercise explored different pathways and potential outcomes for public transit and shared mobility across three timeframes: within 12 months, 1 to 3 years, and 4 to 6 years. The developed scenarios helped to inform the creation of policies and strategies to aid in recovery.

This chapter is organized into six sections. First, we present the methodology employed for the scenario planning workshops. Next, the scenario worlds are described, followed by actions to take within each timeframe. In Section 5, we present integrated policy options and actions across all three timeframes, which are categorized as key actions for public transit operators and broader policy strategies across a larger ecosystem of transportation stakeholders. Next, we present future research needs and offer concluding remarks in the final section.

## 2 Methodology

This research employed a Delphi to develop a series of sustainable policies for public transit and shared mobility services. The Delphi approach is a group process that develops collective judgments over several rounds of investigation [11]. This process also allows group participants across a wide range of disciplines to explore all possible alternatives and assumptions and build consensus [16]. In this study, we followed a similar procedure employed in Shaheen et al. [24] to conduct online workshops (due to COVID-19 in-person restrictions) with 36 transportation experts from a diversity of sectors, organizations, and geographic areas. The workshops were divided into four phases involving three different sets of committees: steering, scenario planning, and policy (see Table 1 for summary).

### *2.1 Scenario Planning Workshops*

The multi-day workshops were designed to develop recommendations to assist in the short-term recovery of public transit and shared mobility services, while promoting future sustainable and equitable mobility. The 36 experts represented multiple geographies in the U.S. and various transportation and related sectors including: (1) public transit agencies and operators of various sizes and modal mixes; (2) non-governmental organizations (NGOs); (3) academia and research institutes; (4) transportation consulting and futurists; (5) local, state, and federal governmental

**Table 1** Summary of workshop phases

| | Phase One | Phase Two | Phase Three | Phase Four |
|---|---|---|---|---|
| Timeframe | June/July 2020 | July/August 2020 | September 2020 | September 2020 |
| Committee | Steering | Scenario Planning | Policy | Steering |
| Number of Experts | Seven | 18 | 10 | Eight* |
| # of Sessions | Four | Four | Two | One |
| # of Hours Total | Seven | Eight | Six | Two |
| Goals | • Develop a focal question<br>• Define scenario timeframes<br>• Identify driving forces<br>• Identify the two most critical driving forces per timeframe | • Refine focal question and timeframes<br>• Identify and build two scenario worlds for each timeframe<br>• Develop preliminary policies, research needs, and signposts | • Refine scenario world descriptions<br>• Refine policies, research needs, and signposts | • Review all material and finalize the exercise |

* One member joined only for the second steering committee phase

agencies; and (6) private transportation, sustainable design, and shared mobility companies.

In the first phase, the eight-person steering committee developed the framework for the scenario planning exercise. The participants first defined the study's focal question as follows:

> What are sustainable and equitable, short- and longer term public transit and shared mobility policies for different types of communities (e.g., urban, suburban, and rural) under different scenarios in the context of the global pandemic and recovery?

This focal question was reviewed by each committee and remained largely unchanged. The steering committee then developed a list of 30 driving forces that could impact the scenarios. Driving forces were generated by employing the **S**ocial, **P**olitical, **E**conomic, **L**egal/Policy, **T**echnology (SPELT) framework. Each steering committee member selected the six most important driving forces for each timeframe. Results were aggregated and used to select the top two driving forces per timeframe.

In the second phase, the 18-person scenario planning committee was divided into three groups to each focus on a specific timeframe. In each breakout discussion, experts explored and altered the two key driving forces accordingly. Two scenario worlds (out of four possible worlds) were selected for in-depth evaluation. Scenario planning committee members crafted characteristics of each scenario world along with initial policy options and research directions. It is important to note that the drivers were selected independent of each other for each timeframe, as key drivers were likely to change over time.

In the third phase, the ten-person policy committee reviewed and refined the work of the second phase and began identifying policies/actions across the three timeframes. Two plenary sessions offered holistic thinking across the three timeframes. Finally, the steering committee was reconvened to further refine the results through a holistic plenary session. The key data from the workshops—policies and strategies for public transit and shared mobility recovery—are presented at the end of this chapter.

This research has several limitations. First, the Delphi approach does not capture all viewpoints and can also encourage groupthink. Second, due to time constraints, we developed only six worlds, two for each timeframe (rather than the 12 possible worlds) that represented the most probable and highly consequential scenarios. Third, the timespan of the scenario workshops (June to September 2020) may have altered opinions due to changes related to the pandemic. Fourth, policy actions and research needs were not inherently new or innovative. However, many actions and needs are framed within the context of the pandemic, which offers a more targeted approach in policy development. Finally, this research focuses on key drivers selected by the committees for public transit and shared mobility not necessarily all driving forces. Entrenched land-use patterns, private automobile use, and systemic inequalities are a few drivers that will impact public transit and shared mobility recovery in the short and longer terms. Additional research is needed to better integrate these challenges into policies and actions.

## 3 Scenario Worlds

For each timeframe, experts created and explored two selected scenario worlds in depth. The two chosen worlds per timeframe were considered the most probable from the four quadrant worlds created by the two intersecting driving forces. Table 2 presents the six final worlds.

### *3.1 Within 12 Months*

For the first scenario timeframe (within 12 months), the policy experts explored two driving forces: (1) new funding sources versus no additional funding sources and (2) public transit demand remains depressed versus return to pre-pandemic levels. Policy options for this timeframe focused on stabilizing public transit and shared mobility service immediately, while building a foundation for future timeframes as a secondary goal. Figure 1 shows the final vectors and worlds, highlighting selected worlds in yellow.

**Table 2** Final driving forces and scenario worlds

| Timeframe | Level of optimism | Final scenario worlds | Framing assumptions |
|---|---|---|---|
| With 12 months | Less optimistic | Shrink to essential services | • Public transit demand remains depressed<br>• New funding sources are secured |
| | More optimistic | Restore services | • Return to pre-COVID-19 public transit demand<br>• New funding sources are secured |
| 1 to 3 years | Less optimistic | Downward spiral | • Lack of political will to fund and support change<br>• Slow economic recovery |
| | More optimistic | Change the conversation | • Political will to fund and support change<br>• Slow economic recovery |
| 4 to 6 years | Less optimistic | Unguided incremental change | • Limited focus on sustainability<br>• Gradual evolution in business models* |
| | More optimistic | Business and policy evolution | • Greater focus on sustainability<br>• Innovative new business models** |

* Gradual evolution in business models refers to incremental developments, such as public–private partnerships among public transit, local/regional governments, and shared mobility operators (e.g., the US Department of Transportation's Mobility on Demand (MOD) Sandbox initiative)
**New business models reflect innovative (previously untested) approaches to public transport provision through partnerships between the public and private sectors. These new models: (1) embody a synergistic relationship among public transit, local/regional governments, and shared mobility operators; (2) reflect federal funding flexibility; and (3) prioritize social equity and accessibility for underserved communities

The more optimistic world, named *Restore Services*, assumes that public transit demand will be recovering to pre-COVID-19 ridership levels. Through this recovery, public transit and shared mobility operators will need to explore new funding sources to overcome deep budget deficits. This world also focuses on a pathway to multiyear federal transportation spending reauthorization legislation and distributes resources to retain public transit riders and recapture some core riders. In contrast, the more negative world, *Shrink to Essential Services*, assumes that public transit demand remains depressed over the next 12 months, leading to drastic service cuts. While exploration of new funding sources also occurs, all available resources are directed to only essential services.

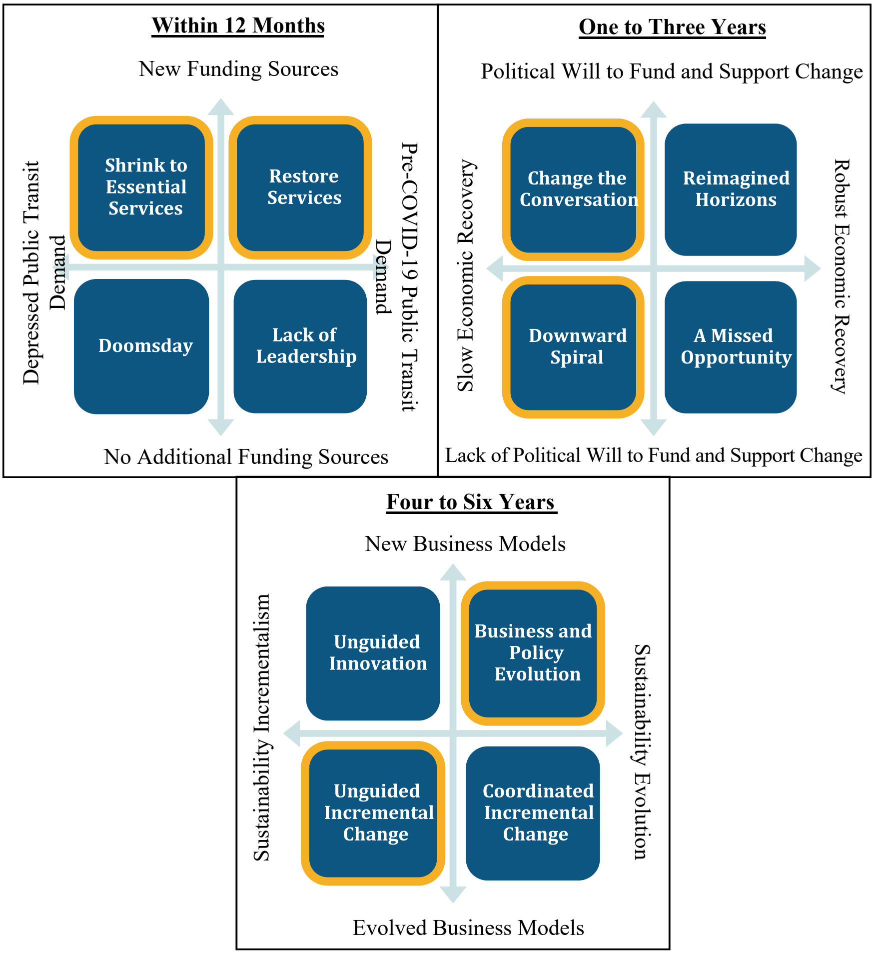


**Fig. 1** Final scenario worlds and driving forces

## 3.2 *One to Three Years*

Over the next 1 to 3 years, more focus should be dedicated to laying the foundation for *systemic change* through state and local policies and the federal transportation spending reauthorization process. The two scenario worlds for this time period were based on the presence or absence of political will to fund and support change; both scenarios assume slow economic recovery (see Fig. 1). The more optimistic world, *Change the Conversation*, reflects high political will and funding to support change. This scenario world assumes that public transit ridership will begin to return due to successful COVID-19 vaccines. Congressional reauthorization is focused on a multi-modal approach with a clear pathway to systemic change that embraces transportation as a fundamental right and increased funding. The less optimistic *Downward Spiral* world is characterized by a lack of political will and funding. This world reflects a federal "Bare Bones Bill" and more incremental infrastructure funding that merely attempts to keep public transit stable with basic funding for operating subsidies and services.

### *3.3 Four to Six Years*

Four to six years from now, in an optimal scenario, policy action and research would set the stage for innovation in public transportation with corresponding national sustainability action (particularly related to climate). Similar to the prior timeframes, two worlds were assessed, based on two driving factors: (1) business models (new versus evolved) and (2) sustainability (evolution versus incrementalism) (see Fig. 1). The more optimistic world is *Business and Policy Evolution*, which is characterized by further refinement of new technologies and operations. In this world, the experts assume that a complementary ecosystem (i.e., an integrated system across modes and trip purposes with public transit as its backbone) would start to emerge, embracing new and sustainable business models. For the less optimistic case, the *Unguided Incremental Change* world assumes more slowly evolving business models, inaction on climate change, growing socio-economic inequality, incrementalism, political gridlock, and a lack of innovation.

## 4 Actions to Take Within Each Timeframe

Policy options and needs were first developed by all three expert committees within each timeframe. These options and needs reflect the unique characteristics of the scenario worlds, and they guide actions for a specific temporal point for both public transit and shared mobility.

### *4.1 Within 12 Months (Timeframe One)*

While some additional short-term funding is assumed for this timeframe, public transit demand may or may not return to pre-pandemic levels within 12 months. In light of this, public transit operators should take immediate and rapid actions to ensure essential travel and longer term public transit sustainability. Policy- and decision-makers (e.g., public transit officials, shared mobility leaders, regulators, legislators) should consider declaring a "state of emergency" (similar to actions taken in New York City following the September 11 terrorist attacks) to: (1) integrate public health goals into transportation; (2) refocus attention on customer experience; (3)

restore trust in the public transit system; (4) build public–private partnerships (PPPs)[2] (e.g., between private shared mobility operators and public transit agencies) and new funding structures; (5) address barriers to flexible use of public transit assets and offer innovative services (see Box 1); (6) start initiating systemic social change in transportation; and (7) construct coalitions and convene key organizations to combat the crisis.

**Box 1**

Effective public transit and shared mobility recovery should address barriers to providing innovative public transit service, including inflexible funding formulas, procurement issues, and limits on what public transit can do (e.g., goods movement use case restrictions). For example, current automated vehicle (AV) pilots have been expanded during the pandemic to offer contactless delivery [7], including a unique partnership with Jacksonville Transportation Authority (JTA), the Mayo Clinic, and Beep (a private AV company) to shuttle COVID-19 tests to laboratories. JTA also offered innovative and equitable COVID-19 vaccine access by using modified buses as mobile vaccine clinics [8].

### *4.2 Actions to Take in 1 to 3 Years (Timeframe Two)*

Over the next 1 to 3 years, the most important factor is whether a political consensus can be developed to significantly increase public transit funding during an expected slow economic recovery. The experts assumed that COVID-19 would be increasingly controlled over this timeframe. Once public transit and shared mobility services are stabilized, policy- and decision-makers should: (1) enact new funding and pricing mechanisms; (2) employ a customer-centric approach to transportation (see Box 2); (3) create new public transit business structures; (4) engage with employers during recovery; (5) incorporate environmental and social equity in all future plans, actions, and policies; and (6) integrate transportation policies into non-transportation legislation.

[2] Experts indicated that PPPs could enable public transit to better meet shifting mobility demand following the pandemic and reduce operational costs. However, experts also indicated that more research is needed to develop fair agreements and outcome-based evaluations. Guardrails, such as: (1) mechanisms to prevent the pass through of fees and taxes to consumers or (2) permitting processes, which also require development.

**Box 2**

A customer-centric approach for transportation modes across all levels of governance should be a primary focus of this timeframe, including providing real-time information about traveler services, increased service reliability, customer-friendly operators, and seamless and contactless payment systems. For example, the California Integrated Traveler Program will help improve the interoperability of payment platforms and mobility data standards among public transit agencies [9], making public transit more convenient and easier to navigate.

### *4.3 Actions to Take in 4 to 6 Years (Timeframe Three)*

In the longer term, the future of public transit and shared mobility will depend on whether the sectors can develop new business models that reflect a significant commitment to sustainable practices. COVID-19 is largely assumed to be controlled worldwide, but recovery efforts remain. If the groundwork is in place from the previous timeframes, an innovative mobility ecosystem that meshes public transit and shared mobility services can begin to provide transportation for all, especially underserved communities. Combining public transit and mobility services, either through PPPs or a public agency mobility program, will offer expanded and flexible services for more people in more geographies and times of day. Public- and private-sector operators will have the opportunity to: (1) create a connected shared mobility ecosystem that complements public transit (see Box 3); (2) deploy fare payment technology and mobility on demand (MOD)[3] and mobility as a service (MaaS)[4] platforms; (3) emphasize electric vehicle (EV) technology and social equity-based programs to reduce greenhouse gas emissions (GHGs) and localized pollution; (4) address labor concerns with automated transit and shared mobility vehicles; and (5) augment resources to retain and restructure the public transit and shared mobility workforce to become more multimodal and mobility focused. In addition, communities must undertake the challenging task of changing land-use patterns to better facilitate public transit and shared mobility and considering mechanisms to reduce auto ownership and vehicle miles traveled (VMT) [7, 13].

[3] A system that enables consumers to access mobility, goods, and services on-demand by dispatching or using shared mobility, delivery services, and public transportation strategies through an integrated and connected multimodal network.

[4] A mobility marketplace in which a traveler can access multiple transportation services over a single digital interface.

**Box 3**

A customer-centric approach for transportation modes across all levels of governance should be a primary focus of this timeframe, including providing real-time information about traveler services, increased service reliability, customer-friendly operators, and seamless and contactless payment systems. For example, the California Integrated Traveler Program will help improve the interoperability of payment platforms and mobility data standards among public transit agencies [9], making public transit more convenient and easier to navigate.

## 5 Integrated Policy Options/Actions

To supplement the policy options for each timeframe, we developed an integrated set of policy options and actions that span all three timeframes. While specific policy options and details can be found in [25], this section provides a brief overview of: (1) key public transit operators and (2) broader policy strategies for the mobility ecosystem. Combined, these two groups of policy options and actions offer a policy strategy pathway for the future of public transit and shared mobility (Fig. 2). It is important to note that while shared mobility strategies are concentrated in the broader policies section, shared services operated by public transit agencies could benefit by implementing key public transit actions as well. The framing of these options/actions was developed by the research team using general themes from the

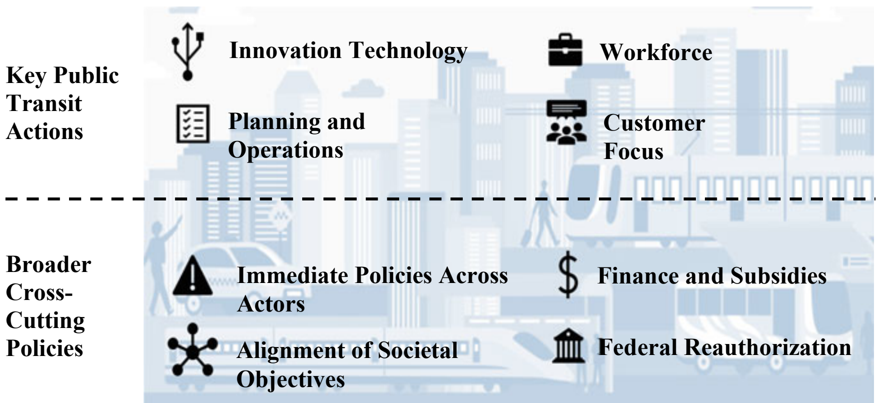


**Fig. 2** Policy Strategy Pathway with Two Integrating Areas

scenario and policy committees, followed by refinement and verification from the steering committee.

## *5.1 Key Actions for Public Transit Operators*

Public transit operator actions are categorized into four key areas: (1) innovation and technology, (2) planning and operations, (3) customer focus, and (4) workforce development.

### 5.1.1 Innovation and Technology

Public transit operators should employ innovative technology to offer complementary services among public and private operators. This could be accomplished through pilot projects and partnerships with shared mobility operators. For example, recent microtransit partnerships through the U.S. DOT's MOD Sandbox could be expanded or elevated to a more permanent status (see Cordahi et al. [10] for more details). Turnkey contracts with technology and/or transportation providers that employ pre-built and ready-to-use settings and platforms, typically for on-demand mobility services, could leverage technological advances more quickly.

Expanding on these projects and partnerships, MOD/MaaS platforms could fill service gaps, increase mobility options, integrate fare payment across modes and agencies, and provide real-time information via signs/applications. These platforms could also build social equity in the availability and frequency of service for public transit-dependent and underserved populations. Regulatory flexibility in enabling pilot projects, partnerships, new business models, and technology is needed to guide and spur innovation. For more long-term considerations, public transit agencies need to move forward with the implementation of EVs in fleets and consider how to employ AVs, especially in the context of workforce changes and retraining needs.

### 5.1.2 Planning and Operations

Public transit agencies should focus on planning and operational reforms to better serve underserved populations and build social equity into transportation services. One important early action is to stabilize funding sources. Options could include property taxes, carbon market mechanisms, road-user charges, and revenue bonds, in addition to traditional funding via gas taxes, vehicle registration fees, and sales taxes. Even though agencies are struggling to find revenue, they must first prioritize providing service to underserved and transit-dependent populations. This service must be safe and frequent, while also employing best practices to reduce the transmission spread of COVID-19 (see Matherly et al. [21], for example).

Once service is restored for transit-dependent populations, public transit operators can begin to consider how to attract core and choice riders again. Public transit agencies should also prioritize bringing vehicles and infrastructure up to good repair. In parallel, agencies can focus on expanding infrastructure changes for multimodal access and consider adopting a multimodal approach toward transportation infrastructure and services. In the long-term, agencies should advocate for/implement land-use policies to increase affordable and dense housing. Across all timeframes, actions conducted by public transit agencies must ensure social, environmental, and racial equity in services and operations.

### 5.1.3 Customer Focus

Public transit agencies should adopt a customer-centric business approach that ensures safe, healthy, and high-quality service focused on connecting and moving people, which increases social equity and addresses the needs of public transit-dependent and underserved communities. More immediately, agencies should identify public transit-dependent communities and workers and provide frequent service. Operators should work on expanding open-air micromobility options to and from stations. Customers also offer lived-experience and should be contacted for feedback on services, operations, public health protocols, and safety. For example, public transit operators could develop a rating system that crowdsources trip quality. Customer engagement also extends to fare collection. Discussions are needed with the community to determine reasons for fare avoidance, identify equitable fare structures, and test free public transit. Social and racial justice must guide any discussions, campaigns, and strategies.

Longer term policy options should be developed to improve customer service and public transit quality more holistically. For example, a focus on the entire end-to-end trip, not just its in-transit portion, could provide better service to connect and move people (not just vehicles). Agencies will also need to promote the essential role that public transit plays in the economy and accessibility. This new thinking could help guide the redistribution of funding to public transit-dependent and underserved communities. Consequently, this focus on customers will enable public transit to move beyond just survival mode and reprioritize resources in a sustainable way.

### 5.1.4 Workforce Development

The transportation workforce has been severely impacted by the pandemic. Early actions should identify and meet critical needs for public transit workers and independent contractors to ensure their safety in precarious working conditions. Strategies developed by the APTA [3], such as supplying personal protective equipment and moving riders away from drivers, should become essential and consistent across public transit agencies. An ongoing concern is the depletion of bus/rail/vehicle operators, who have become sick from COVID-19, retired early, or changed careers due to the high risk of infection. While specific policies and recruitment campaigns will differ by agency, a concerted effort will help reduce the loss of institutional knowledge and skills.

Over the upcoming years, public transit agencies will need to work with unions, workers, and independent contractors to address a range of concerns, such as growing automation. Retraining may be needed to ensure that workers still retain employment and can interface with automation. To increase long-term resilience and sustainability, agencies should consider implementing internal reorganizations, shifting funds to transportation projects, plans, and staff that focus on climate change. Agencies should also consider restructuring to become more multimodal, which could bring a mobility-for-all pathway to fruition and increase agencies' adaptive ability to tackle future disruptions.

## *5.2 Broader Policy Strategies Across Timeframes*

In addition to the specific policy options and actions for public transit operators, broader policy strategies across timeframes were constructed for both the public transit and the shared mobility sectors. These strategies are split across four areas: (1) immediate policy and actions across actors, (2) alignment of society objectives, (3) federal transportation spending reauthorization, and (4) finances and subsidies.

### 5.2.1 Immediate Policy and Actions Across Actors

Despite efforts to curb the spread of COVID-19, both public transit and shared mobility could benefit from a declaration of a state of emergency, setting the stage for structural changes with funding and PPPs. Any new partnerships must ensure that stakeholders are supporting sustainable transportation goals, which will require buy-in from all partners. Procurement waivers could also be issued to increase the flexibility of governments and public transit agencies. Over the next 3 years, both public transit and shared mobility should consider repurposing existing vehicles (or partial fleets) for new services. These services could include goods delivery, medical transportation, or mobile clinics for health care and vaccinations. Across all these actions, an integration of social equity should be immediate and sustained. The two sectors provide transportation assistance to essential workers, improve access for underserved communities, and prioritize resources for those most disadvantaged.

### 5.2.2 Alignment of Societal Objectives

Significant steps are needed to ensure that policy actions and strategies across the two sectors align with sustainability and resilience objectives, while still ensuring safety and efficiency. Public transit and shared mobility should first adopt new metrics and measures for their performance that place more focus on social equity, safety, and environmental outcomes. For example, metrics related to ridership could be replaced by measures of accessibility for transit-dependent populations or travel times to jobs and essential services. Public and private operators could then create more targeted and scaled services that are on-demand and higher frequency for people who need transportation the most. These services could be developed more quickly through environmental streamlining policies that increase the speed of environmental reviews without compromising environmental needs, mitigation, and goals. Over future timeframes, operators should also implement policies to ensure the coordination of services. A complementary system of shared mobility and public transit that improves access to jobs and services can help reduce the reliance on autos as a single mode, thus moving away from an auto-centric built environment.

### 5.2.3 Federal Transportation Spending Reauthorization

Federal surface transportation is funded through multiyear omnibus spending legislation. The Fixing America's Surface Transportation (FAST) Act of 2015 was the most recent bill passed and was set to expire on September 30, 2021. Each reauthorization of funding presents opportunities to shift funding priorities and societal objectives in transportation. For example, the new legislation could begin leveling the playing field across modes through more funding for public transit and shared mobility and increased spending flexibility on local needs, particularly during the COVID-19 recovery. This switch to spending funds on mobility (as opposed to infrastructure, especially automobile infrastructure) could help emphasize public transit as the backbone for transportation. To achieve a sustained and holistic focus on mobility, an exploration could be launched to reorient the US Department of Transportation (DOT) as the Federal Mobility Administration. Finally, a coalition of transportation advocates could help embed transportation funding and policies into non-transportation bills related to climate, housing, and public health. It important to note that the FAST Act was extended and replaced by the Bipartisan Infrastructure Law, which was signed by President Biden on November 15, 2021. This historic legislation was enacted over a year after the scenario planning exercise was completed. This law includes nearly $39 billion in funding for public transit systems.

### 5.2.4 Finances and Subsidies

With growing inequalities exacerbated by the pandemic, public transit and shared mobility have become more essential for equitable travel and access to jobs and services. A key first step is to stabilize funding streams for essential transportation, which includes rides for health services, education, and work. Alternative sources through property taxes, value capture, goods delivery, and other options could be leveraged. An opportunity also exists to better price transportation externalities through carbon taxes, road-user charges such as tolling, and congestion pricing. Both public and private operators will then need to direct funding and human resources to support sustainable transit modes and mobility in historically underserved communities. In addition, funding and attention must be focused on how transportation currently fills (and could fill) notable social service gaps. Operators should test and implement new technology, such as mobility wallets that link shared mobility and multiple public transit services together, to enable seamless transportation.

## 6 Future Research Needs

Moving forward, the public transit and shared mobility sectors will require substantial research to develop equitable, environmentally friendly, and resilient policies and strategies. With a significant amount of research already conducted on the immediate impacts of the pandemic, future research should shift to the pandemic's long-term impacts. Table 3 begins to answer these long-term impacts by presenting several highlighted research needs developed by experts. Additional attention and policy development are needed to address land use, auto ownership, and VMT patterns that diminish the recovery (and long-term feasibility) of public transit and shared mobility. Strategies should be created and refined by local, regional, state, federal, and tribal governments and agencies in collaboration with public transit and shared mobility operators.

**Table 3** Highlighted future research needs identified by experts

| Topic area | Identified research topics |
|---|---|
| Changes in travel, goods movement, and residence | • Determine short- and long-term implications of work-from-home policies<br>• Assess behavioral changes in e-commerce and its impact on goods movement, curb management, congestion, GHGs, and VMT<br>• Analyze how changes in land use and density due to COVID-19 will impact trip patterns and public transit ridership |
| Funding | • Determine viable and equitable funding and allocation mechanisms for public transit and shared mobility<br>• Reform federal mechanisms that finance transportation and distribute funds to local, regional, and state governments<br>• Analyze the harms of fare enforcement, especially on Black communities, and how to allocate funding from policing to transportation |

(continued)

**Table 3** (continued)

| Topic area | Identified research topics |
|---|---|
| Regulations and metrics | • Identify and remove barriers to funding requirements that hinder public transit agencies from being responsive<br>• Develop and expand General Transit Feed Specification (or GTFS) guidance<br>• Study and test equitable and efficient performance metrics (e.g., cost to the passenger, number of people to jobs, travel times) |
| Innovations | • Initiate pilot projects to jump-start technological innovation in public transit<br>• Conduct empirically driven evaluations to ensure pilots are sustainable and resilient<br>• Explore microtransit services and alternative transportation services |
| Social and cultural change | • Assess current barriers to reframing transportation as a right and creating an integrated and multimodal mobility ecosystem<br>• Determine mechanisms, funding, and operations to better serve low-income and underserved communities<br>• Identify opportunities to address social inequity and environmental injustices through transportation |

## 7 Conclusions

This chapter provides a pathway for the longer term recovery of public transit and shared mobility services following the tragic toll of the pandemic on societies, communities, and individual lives. First, while public transit and shared mobility face a dire future in the short run, steps can be taken immediately to reduce the effects of the current crisis, while laying the groundwork for more sustainable transportation in the future. Second, as disruptive as the pandemic has been, long-term external forces beyond COVID-19 will significantly drive the future direction of public transit and shared mobility services and determine the effectiveness and feasibility of policy strategies. Consequently, operators should look beyond the COVID-19 pandemic at policies and actions that can achieve future environmental, social equity, and resilience goals. Actions taken to only address the current crisis will not prepare the public transit and shared mobility industries for the future. Finally, future policies and actions will not be effective without in-depth analysis and development. Research and lessons learned from demonstration and pilot projects will be critical to crafting policies, identifying all positive and negative outcomes, and shaping actions toward greater mobility.

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# Conclusion: Reflections and Lessons from the Pandemic

**Alexandre M. Bayen, R. Jayakrishnan, Giovanni Circella, and Anastasia Loukaitou-Sideris**

**Abstract** This concluding chapter presents a summary of the research findings in the previous chapters, along with some reflections for each of the five themes of the book and a discussion of necessary future responses (post-pandemic or in the event of a new pandemic) and topics that require further exploration. The pandemic brought into sharp relief pre-existing social disparities and affected vulnerable populations the most. The economic impacts of the pandemic were diverse and varied by geography, but again certain geographies and economic sectors were more buffered from negative outcomes than others. A lesson and a challenge for policymakers is to find ways to understand and reduce these disparities, instead of pushing them under the rug. The impacts on mobility and travel were dramatic as total trips decreased, transit usage fell dramatically, and telecommuting and active modes of transportation increased. Some positive impacts included an improved air quality, a reduced number of traffic crashes, and a proliferation of walking and biking in some neighbourhoods. As cities are slowly recovering from the pandemic, the challenge is to keep the positive impacts but also find ways to help the transit industry rebound from its plunge. Long-term impacts of the pandemic in terms of changing patterns of work and work

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arrangements, shopping, recreation, and other human activities that will affect travel need additional time and more research to discern.

Throughout history, the world has faced crises, which humbled humanity, making the Earth's inhabitants rethink their understanding of nature, and forcing them to change course. Pandemics such as the one triggered by COVID-19 or the Spanish Flu a century earlier are certainly among the worst crises in modern times. Mobility—the epitome of modernity, as we stated in the introduction—is one of the key aspects of life that got severely impacted by the COVID-19 crisis. Naturally, the researchers in the mobility domain, who were themselves constrained to their homes and online interactions with other researchers, were quick to focus their attention on these impacts. The intent was to reset our understanding of nature and the puzzle it can throw at humanity, and to solve at least some pieces of it, as pertains to the mobility of human beings and the goods they need transported. This book is the result of the efforts of researchers at the University of California campuses, who delved into a variety of topics that address the effects of the COVID-19 pandemic on urban mobility and transportation.

The common themes across the chapters of this book were split into five primary threads, which focused on

- impacts on vulnerable populations;
- impacts on the economy;
- impacts on mobility and travel;
- impacts on the environment and safety; and
- responses to these impacts.

In this concluding chapter, we offer a summary synthesis of the research findings that were presented in this book, along with additional reflections on how successful the exploration into the unknown was, what topics require further exploration, and what kind of responses are necessary.

## 1 Vulnerable Populations

It is clear from the research reported in this collection, as well as from multiple other studies from around the world, that the pandemic has affected certain groups of individuals, and low-income households, in particular, the worst. On the one hand, lower income communities witnessed a higher spread of infection, particularly during the early period of the pandemic when many workers (often coined "essential workers") from such communities had to remain active, physically commuting to work and interacting in person with others, as opposed to more affluent workers who were more often able to shift to forms of remote work. Low-income workers were also highly affected by the economy's downturn, the reduction in employment, and small business closures. Indeed, documented evidence shows that low-wage workers lost jobs at about five times the rate of middle-wage workers [1]. Pay-cuts also disproportionately affected lower income workers. Automobile burden rose in low-income, Latino and Black households, as indicated in Chap. 2, at a time that members of these households needed their cars either because they were unable to telework or did not wish to use public transit out of a fear of infection. Some other low-income workers had to rely on private automobiles to reach their work, as many transit systems reduced their service levels.

The pandemic also exacerbated homelessness in transit environments, as discussed in Chap. 3. Even before the pandemic, transportation environments were frequently used for shelter by the unhoused. As many shelters reduced their capacity to comply with social distancing mandates, unhoused denizens had fewer shelter options. As a captive transit population with no alternative travel options, they naturally became more visible on transit during the shelter-at-home periods of the pandemic, when the ridership of the non-captive riders plummeted. While some transit agencies proactively took measures to improve the plight of these unhoused riders, others tried punitive measures. The pandemic showed the urgency of addressing the fundamental reasons for transit environments becoming magnets for the unhoused. Societal systems and enforcement mechanisms with proper funding need to be put in place, but with a humane approach. The unhoused population should not be viewed as an undesirable population segment to be ruthlessly eradicated from public transit spaces, but as humans who also have mobility and shelter needs for which society ought to offer help. Thus, a positive outcome from the higher visibility of homelessness during the pandemic may be a better focus and more efforts from federal, state, and local policymakers to improve the situation.

The disparities across urban populations in the spread of infection coupled with even higher disparities in economic impacts through wage losses and pay-cuts naturally led to a higher focus on equity and social justice issues. The research in this volume demonstrates disparities between large and small businesses, with the pandemic affecting small businesses and certain types of workers (for example, those in ride-hailing services) more adversely, as discussed in Chap. 4. From an urban and regional transportation planning standpoint, clearer quantitative and qualitative frameworks are necessary to analyze and understand how to reduce such disparities in the future. The analysis and policy frameworks of mobility improvement plans must explicitly evaluate potentially disparate outcomes on population segments. Such evaluations should examine equity impacts spatially as well as across selected other metrics such as size and type of businesses, income levels, gender, age, and racial composition of population segments. Once again, a hopeful outcome may be that the pandemic brought to the fore inequities that always lurked in the background, compelling society to address them rather than push them back under the rug.

## 2 Economy

The reduction of travel brought about by the pandemic was a phenomenon experienced worldwide, and one that had adverse economic effects on several economic sectors. Relating to the transportation sector, estimates of people worldwide subject to travel restrictions during the pandemic's first surge were around 4 billion, according to Deloitte (in [3]). The reduction in mobility and in-person interactions led to large changes in the organization of certain economic activities and had important impacts on the way individuals work, shop, travel and socialize. Among the largest impacts in the transportation sector caused by the pandemic, the reduction in the use of public transportation was particularly remarkable, and this led to huge impacts on public transit operators worldwide. As of September 2020, the fall in revenues for public transportation operators worldwide was estimated to be around 40 billion Euros [3]. The situation was particularly severe in the U.S., where the transit industry, already in trouble prior to the pandemic, saw its revenues plummeting due to the decreased ridership and travel behavior changes from the part of the public. A variety of factors explain the woos of public transit in the U.S., and the pandemic-induced fear of contamination added to them. The Federal Stimulus was key to cover the losses of the transit industry (see Chap. 17); nevertheless, the underlying struggles of public transportation and the corresponding infrastructure may create long-term challenges for the future of the transit industry in the U.S.

Other major pandemic impacts with direct or indirect economic and mobility effects included the major increase in telecommuting and forms of remote work during the pandemic's peak (discussed in Chaps. 13 and 14); changes in shopping/consumer behavior with a noted increase in e-commerce and preference for certain types of goods (discussed in Chaps. 6 and 7), and the related increase in last-mile truck deliveries (discussed in Chap. 8). While automobile sales plummeted during the early phases of the pandemic, sales solidly rebounded in later stages—despite the rise in the prices of new and used automobiles and the disruption associated with the supply chains. These are causing confounding effects on the vehicle sales market, which are still not completely understood, to date.

Economic impacts varied by geographies. For one, remote working affected various worker categories in different ways. Similar to what was discussed in Chap. 6 about social disparities in telecommuting in the U.S., a remarkable 74% of employees with higher education worked from home in Europe, but only 34% of those without higher education were able to do the same [3]. Several sources suggest that this disparity was experienced worldwide, highlighting some of the differential impacts brought by the pandemic on different socio-economic groups, with local variations depending on the nature of the industrial landscape and urban setting.

Disparities were also witnessed in the way cities and regions were prepared to respond and adapt to challenges brought about by the pandemic. Here we will dwell a bit more on the state of California, as this state represents the geographic context for many of the chapters presented in this book and is the home of the University of California Institute of Transportation Studies and of most of the book's authors.

Similar to other places around the world, California experienced a drastic drop in the routine journeys of its residents, starting with the first shelter-at-home order in March 2020. The state's economy was also shaken during this period, similar to many other geographies in the world. Nevertheless, California was able to defy some of the forecasted economic doom from the pandemic and even expand its GDP [6], thanks to some major sectors of its economy, including its high-tech industry, which was one of the sectors leading responses to the economic disruption and reorganization. Additionally, the relatively high vaccination rates of California residents and a combination of state and local response policies (e.g., physical distancing and vaccination mandates, measures adopted by schools, universities and other places where human contact was necessary, etc.) allowed the state to eventually work out a relatively successful management of the crisis that supported economic activities better than in other locations in the U.S. Additionally, the support of a military logistics for vaccine delivery placed the U.S. in a good position globally, and helped California specifically, for example, the U.S. Department of Defense worked directly with the California Department of Transportation to manage routes for vaccine-carrying trucks at a time when it was not clear if social unrest would perturb the distribution of vaccines. Another example of such joint work between federal and state authorities was in the development of routes for trucks carrying liquid nitrogen required for vaccine refrigeration, which was also masterfully managed by military logistics. All of this placed California ahead of many other places in the world, where the distribution process and resulting disorder led to further destabilization of local economies and slower recovery after the beginning of the vaccination campaign.

However, even within California, we observed disparities in how different regions and cities in the state were able to respond to the pandemic. The affluent and tech-savvy Bay Area—and in particular its white-collar employees—were able to wither the pandemic better than blue-collar workers in the Bay Area and in other parts of the state. Most of the industries in the Silicon Valley already had an embedded remote work framework in place to which most of their workforce was already used to, so it was not difficult to switch into a remote work schedule.[1] Further, many schools had excess laptops for their students and moved instantaneously to digital teaching. Similarly, several public agencies provided support to their employees to set up their home offices and work remotely. In parallel, as the need for digital venues rose, the market capitalization of many Silicon Valley companies went through the roof, and some industries (e.g., delivery services, gaming, etc.) (re)-entered a hypergrowth phase. As a result, the usual levels of "underemployment" of skilled workforce in Silicon Valley recovered to levels similar to the region's growth years. While some tech companies (such as Uber, Lyft, etc.) were initially adversely affected by the pandemic, some pivoted to growing their delivery services, as a way to counterbalance the decline in the use of their passenger services.

While many sectors of the economy of the Bay Area, thanks to its digital infrastructure, high-tech industries, and overall affluence, were not terribly disturbed and

[1] For example, Google had high-quality "Zoom-like" rooms to work between Mountain View and Zürich as early as 2007.

even benefited from the pandemic, other California regions with significant pockets of poverty—in the rural north, the Central Valley, and Los Angeles—did not fare as well. California is a huge state with rural, suburban, and urban areas, and diverse industries. The pandemic made preexisting disparities between regions and between groups of people within the same region clearer. While the high-tech industries of Silicon Valley (their stakeholders and white-collar employees) fared well, some other segments of the California economy and their blue-collar employees were severely affected: restaurants, movie theaters, hotels, and many small businesses. Numerous companies went bankrupt, relocated, or left the State. The longer term pandemic impacts and disparities on some of these industries remain uncertain.

## 3 Mobility and Travel

The mobility impacts of the pandemic were along expected lines. As discussed in Chap. 10, U.S. states witnessed significant traffic volume reduction during the first stages of the pandemic, along with an associated drop in vehicle miles traveled (VMT). At the time of this writing, traffic volumes have already rebounded in terms of total travel, even if the spatial and temporal distribution of trips, and the distribution by travel modes remain somewhat different from the pre-pandemic travel patterns. Overall, the impacts during the highest surge of the pandemic provide us with pointers on how sensitive our metropolises are to unexpected conditions.

The stark reality that strikes us first is, once again, the disparate nature of the impacts. The more disadvantaged a community was, the less the traffic reduction it experienced, as discussed in Chap. 9. Even the rebound of the traffic flows was faster in disadvantaged communities, pointing to the higher reliance in such communities on private automobiles. Good public transit systems can offer a lower cost and a better environmental option than private automobiles, but because of the fear of contagion and the reduced transit services during the pandemic, public transit was not a good option for many. Instead, a higher reliance on private automobiles was observed, despite all their costs and negative externalities. As discussed in a number of chapters, average traffic speeds increased, and air pollution from GHG emissions was lower during the early stages of the pandemic, due to lower systemwide VMT, the reduced total amount of travel, and modified travel patterns.

Systemwide, trip frequencies decreased across all modes, as expected, but this effect was less for certain required activities such as grocery shopping (Chap. 7). On the other hand, we noticed more effects on work trips, which could be more easily substituted by telework. This is not surprising, and it is conceptually clear that certain activities have more flexibility in duration and frequency, both of which directly affect the number of trips originating from these activities. Unfortunately, the current transportation planning models do not explicitly consider such aspects. The activity that follows the trip itself is often overlooked, and even in activity-based models, the flexibility of the activity is barely addressed. To that extent, we can say that what ensued as traffic in our cities is largely what our planning systems were designed to yield.

Another observation is that travel got reshuffled toward more individual transportation modes, as discussed in Chap. 12. Fear of infection during travel was certainly a big reason for this shift. It was understandably less attractive to travel in shared mobility modes, both in transit systems, ride-hailing services, as well as in any burgeoning private services offering pooled travel around the world, the latter being not prevalent yet in the U.S. The travelers' income was also an important variable in this reshuffling, as overall higher income households undertook fewer commuting trips.

Reduction in transit ridership had started prior to the pandemic but certainly intensified during the crisis period. Transit system ridership showed improvement and a partial rebound during the later stages of the pandemic, but has not reached the earlier ridership levels yet, in particular, for rail-based transit services. Thus, an urgent need of our times is to improve the public perception of public transit and encourage a back-shift from individual travel modes such as the automobile. One positive outcome is that not all the shift to individual modes were to automobiles. Higher trip frequencies were observed for active modes of transportation, such as bicycling and walking, in particular, for non-commuting purposes (see Chap. 12). This was fueled by many policies and immediate reactions from many cities, which quickly moved to expand the bicycling infrastructure and make active travel options more attractive for urban mobility. The hope is that active transportation modes will maintain some of their gains, even after the pandemic is over. However, investments in the pedestrian and bicycling infrastructure (and the consideration of temporary road closures, traffic calming strategies, and improved bicycling infrastructure into more permanent features of cities) are important to encourage this trend.

## 4 Environment and Safety

Ironically, many of the typical environmental key performance indicators (KPIs) of cities and states improved during the pandemic, at least during its early stage. With drastically reduced vehicle miles traveled (VMT), total travel time (TTT), and traffic congestion immediately improved due to shelter-in-place orders. As a direct corollary, GHG emissions and air quality improved drastically (see Chap. 10), a trend observed worldwide. Wildlife was given a break, and in certain areas expanded. These trends had as a result that many cities in California also rose in mobility rankings[2] (whereas cities like Los Angeles had been plagued by traffic congestion prior to the pandemic). The impact on safety was more complicated. As discussed in Chap. 11,

[2] For example, San Francisco's mobility indices, as measured by the *Urban Mobility Readiness Index* (a comparative index that measures mobility in 60 different cities around the world through the use of key performance indicators focused on mobility and developed around five pillars: social impact, infrastructure, market attractiveness, system efficiency, and innovation) were higher compared to other cities during the pandemic.

reduced traffic volumes led to lower numbers of total crashes but higher rates of serious injuries in some geographies because of the unusual driving behavior of high speeds in mostly empty freeways. Social equity problems were once again revealed for the part of the population that had to travel to work. While these trends were reversed, at least partially, after the introduction of vaccines, other longer term patterns started to emerge.

For example, some early changes in land use and mobility patterns are already visible. Some companies like Shopify and Airbnb declared themselves "virtual forever" (everybody works from home). Many of the Silicon Valley companies are evolving toward a 3-days-per-week model, which many other companies around the world have adopted as well. This in turn has created a mini urban exodus phenomenon in some localities, and/or the acquisition by a wealthy part of the population of secondary residences, which will be now used "over the long weekend." While this only affects the wealthy part of the population, affluent cities in California (some parts of the Bay Area, Los Angeles, San Diego) are likely to experience subsequent shifts in their mobility patterns, as many wealthy households adjust their commuting patterns to 3-days-per-week in the longer term, thereby changing overall demand on the transportation system. Outside of California, extreme cases of this phenomenon were even observed in the middle of the pandemic, where helicopter traffic increased drastically between the Hamptons and Manhattan, for the super wealthy, commuting by air to work.

Overall, while many newspaper headlines have predicted the exodus from expensive cities of California, the price of real estate in many of these locations has continued to rise through the pandemic, indicating an increased housing demand, fueled by a local vibrant economy as well as scarce housing supply and monetary policies that have maintained mortgage rates very attractive. So, in these cases, the pandemic did not (at least in the short term) significantly affect the real estate market. It just changed the nature of demand, by adding a new model of living—far from work—for part of the week, and causing some relocation among those segments of the population that can more easily move (e.g., office workers, who are renters and live in households with no children). The impact of this new (longer term) trend on the environment is still uncertain.

Several larger scale effects of the pandemic with respect to mobility are also still poorly understood at this stage and would necessitate a deeper life-cycle analysis. For example, the heavy use of the digital economy for work certainly has important energy impacts, which remain to be quantified. These changes include the increased use of Zoom and other digital platforms, cloud computing to support services at scale, and multiplication of devices to work from home, among others. Similarly, the increased use of delivery vehicles is still an active topic of investigation at the U.S. Department of Energy. In the middle of the pandemic, thousands of jobs were created in the cardboard industry. The impact of this by-product of transportation services on the environment still remains to be quantified. Many other indirect externalities of these new services, and their impacts on highways and local streets remain to be studied to understand their impact, in particular, on cities, where these services are predominant.

Finally, the reliance on global supply chains revealed the weaknesses of several nations. Among some of the most extreme examples, during the early stages of the pandemic, entrepreneurial investors showed up on tarmacs to re-buy huge supplies of masks for double their original prices to get them to their countries. Control of production of specific drugs became a geostrategic interest. Disruption in the supply of wood, components, and many other goods became a wake-up call for political powers, who decided to "re-localize" production in their own countries for national safety reasons, after decades of increased globalization and relocation of production activities overseas. In the months leading to the 2020 national elections in the U.S., while the political debate was dominated by the pandemic, its impact, and responses to it, the U.S. had already put in place military logistics (inherited from experiences going back to WWII) to handle the pandemic and post-pandemic era. This served many other countries as a lesson in re-considering globalization. As supply chains change in the future to match new geopolitical power struggles, one expected effect is that corresponding mobility patterns will also change, some with potential positive effects for the environment: producing locally and avoiding long-haul transportation, when possible, at least in certain strategic sectors.

## 5 Response and Need for Further Research

An array of responses emerged from policymakers in their efforts to address the spread of the virus. As already discussed, these involved shelter-in-place orders, business lockdowns, and later vaccination mandates. On their part, public transportation agencies, right from the early days of the crisis, undertook a number of responses (see Chaps. 16 and 18), even though the COVID-19 virus and its dynamic spreading characteristics were not understood well for several months since the pandemic started. These responses, mostly meant to counter the effect of the pandemic on human and freight mobility, can only be called "walking in the dark." It is, however, fair to say that these responses generally were not counter-productive. Actions such as enforcement of physical distancing, mask usage, and cleaning of surfaces in transit systems were certainly necessary. Over time, these actions helped reduce the fear of transit systems to be causing infection clusters, as evidenced by a slow return of some of the lost ridership. Several actions were also taken to help control and manage the crisis. These included responses by certain transit agencies to accommodate visible homelessness in transit environments by suspending fares and offering a helping hand to the most unfortunate riders, as discussed in Chap. 3. Such outreach responses uphold transit's social role and must be complimented, while the punitive measures undertaken by other agencies must be discouraged.

A pressing issue felt by transit agencies is ridership loss. While federal aid largely counteracted the revenue loss, as discussed in Chap. 17, it is imperative that transit agencies take steps to reverse the decline of their industry—through innovation and technology, customer focus, planning and operations, and workforce development. Such actions are perhaps the only way to increase ridership (and compensate for the ridership that was lost during the pandemic and may not return completely to pre-pandemic levels). The industry's current challenges should be viewed as an opportunity for innovation and change. One option could be to re-design transit network operations, re-assigning vehicle and driver resources to increase the service levels in the productive sectors. This will also require developing schemes of same or similar transit accessibility in the unproductive sectors (typically in the lower density neighborhoods) via microtransit and shared mobility options that use smaller and less expensive vehicles.

We should note that the pandemic again dealt us a tough hand, as the public became fearful of such efficient shared mobility options. Now that vaccination programs have been largely effective and the fear of infection has been somewhat reduced—in the hope that new variants will not compromise the path to recovery from the pandemic—transportation agencies must take steps to improve public perceptions about transit; develop innovative plans to increase their revenues (see Chap. 19); and also utilize and integrate new mobility alternatives such as car-sharing, ride-sharing, and microtransit along with individual active transportation modes like shared bikes (see Chap. 20). Using such innovations in a coordinated manner with public transit, as cooperating feeder services rather than competing modes of travel, may prove to be the only way to bring public transit ridership back and reduce individual automobile usage.

Our research in this book has left questions unanswered on how permanent some of the pandemic's impacts, such as its impacts on traffic congestion, VMT, and GHG emissions, will be. E-commerce has received a boost, and telework has increased significantly for certain segments of the working population, but the extent to which these shifts would last post-pandemic is not known. Nevertheless, clear policies and strategies are needed if we want to retain some of the transportation and environmental benefits observed during the pandemic, such as the increased reliance on active travel and less vehicular trips and associated air pollution. Further, the boost in e-commerce cannot be at the expense of poor neighborhoods. As pointed out in Chap. 7, zoning changes may allow e-stores to locate in residential inner-city neighborhoods and ensure that expansion of e-commerce activities does not further penalize low-income communities. Strategies should be developed for work-from-home options and telecommuting programs to include low-income employees as well. Firms should provide logistics, training, and coordination of remote workforces in poor neighborhoods as well, and the state may need to develop incentive plans to encourage this.

Examining the direct inter-relationship mechanisms between the spread of COVID-19 and transportation systems is another area that has left us with some unanswered questions. The ongoing research from around the world attempting to identify if or by how much different transportation systems exacerbate the spread of the virus is still inconclusive (see also Chap. 15), due to the chicken-and-egg problem of establishing causal links and their directions. At the same time, there is evidence of the effectiveness of lockdowns of transportation systems and travel restrictions in slowing down the viral spread. An example of this was in India, which undertook one of the most stringent lockdowns among democratic countries, completely shutting down its 70,000 km of national railways. Restrictions on air travel and cross-state and cross-provincial travel may have also helped slow down the spread of the virus in the U.S. and around the world.

Research is also still scant on quantifying the effect of transportation systems on transporting the virus from region to region in larger countries such as the U.S. Well-established mathematical models based on system-dynamic differential equations used by epidemiologists to predict disease spread were relatively ineffective in predicting the COVID-19 spread, as [2] indicates. To be prepared to tackle future pandemics, modeling schemes must be incorporated into mathematical and epidemiologic models which examine the larger network of transport systems. Examples of attempts in these directions can be found in [4, 5]. However, this is an area where transportation researchers have not been very active.

There are also actions needed in matters that may indirectly affect transportation systems, as travel patterns change, and mobility is disrupted because of a pandemic. For instance, King et al. in Chap. 5 recommend incorporating an element of uncertainty in developing implementation plans for projects that rely on transportation tax revenues, since pandemic-induced reductions in travel can drastically undercut such revenues. Distinguishing projects in different tiers from more urgent to less urgent can prove useful in the face of such financial uncertainties.

There is also the critical question of how different the post-pandemic workplaces will be. Different types of work arrangements could lead to different types of travel needs, and activities at certain workplaces could be more amenable to telework. How can we bring about an efficient allocation of on-site and at-home work tasks based on the travel required for any task? And how essential that travel is? Should two trips be considered of equal value or equal cost, just because they are of equal distance/time and cause equal congestion/emission externality costs? Currently, transportation planning and analysis follow an "all trips are equal" approach, but this may not be the right approach in a pandemic situation. Should we then consider for elimination the travel for an activity that may cause disease spread (say, a company meeting), which can be more easily substituted by teleconferencing, before we eliminate a similar trip from the part of a low-wage worker who may be going to do gardening—an activity that may cause no disease spread?

If we deem that all trips may not be of equal priority, we then need strategies to prioritize trips on the basis of the activity that ensues after the trip. But there is currently no research that provides input to policymaking on strategies for pricing or incentivizing that leads to efficient travel patterns during the buildup phase of a pandemic, during lockdowns, or during the relaxation phases. While activity-based modeling in transportation has developed during the last three decades, such prioritizing of activities for systemwide travel management purposes has not been an area of research. This is but one example of how the pandemic may have opened our eyes to view trip-making in our transportation systems under a new light.

In conclusion, the COVID-19 pandemic brought shock to cities and towns around the world, upending millions of lives, disrupting local and national economies, and altering patterns of mobility. What we learn from studying this global disaster and its impacts, as this book tried to do, and how we use this knowledge to prepare for the future will define the outcome of the next global disaster, and possibly the fate of humanity.

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