Commuting During and after COVID-19: The Impact of COVID-19 on Shared Mobility and Extreme Commuting in the Bay Area - Central Valley

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract

This project looks at the mobility patterns and experience in using alternative modes of transportation for disadvantaged workers during COVID-19 in California's Bay Area and Central Valley. We use governmental survey data of commuters and traffic data from StreetLight to document mobility patterns of the two distinct regions throughout the pandemic. Our findings from SJCOG's dibs survey suggests that dibs service affects mode choice by increasing the share of commuters who use carpool / vanpool and decreasing the share of those who drive alone. These gains remained sticky during the Covid-19 pandemic. Survey results also point out that carpool / vanpool programs in this region are used by a rather narrow demographic. This group of workers were also more likely to be deemed "essential" and were less likely to work remotely during the pandemic. Evidence from our COVID-19 and commute analysis provides verification of existing income and occupation disparities in commute flexibility that likely contribute to making people more vulnerable to COVID-19. During the first one and a half years of COVID-19, lower-income, essential natural resource and production workers traveled more are more likely to face higher exposure to COVID-19 at their workplace, while higher-income, office workers were able to travel less and shield themselves.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Boarnet, Rodnyansky, Wang, and Comandon conducted this research titled, "Commuting During and after COVID-19: The Impact of COVID-19 on Shared Mobility and Extreme Commuting in the Bay Area - Central Valley" at the Department of Urban Planning and Spatial Analysis, Sol Price School of Public Policy, University of Southern California, with a sub-contract to the Department of Urban and Environmental Policy, Occidental College. The research took place from January 1, 2022 to December 31, 2022 and was funded by a grant from the California Department of Transportation in the amount of $78,837 with a subcontract from the U.S. Department of Transportation in the amount of $21,803. The

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Abstract

This project looks at the mobility patterns and experience in using alternative modes of transportation for disadvantaged workers during COVID-19 in California's Bay Area and Central Valley. We use governmental survey data of commuters and traffic data from StreetLight to document mobility patterns of the two distinct regions throughout the pandemic.

Our findings from SJCOG's dibs survey suggests that dibs service affects mode choice by increasing the share of commuters who use carpool / vanpool and decreasing the share of those who drive alone. These gains remained sticky during the Covid-19 pandemic. Survey results also point out that carpool / vanpool programs in this region are used by a rather narrow demographic. This group of workers were also more likely to be deemed "essential" and were less likely to work remotely during the pandemic.

Evidence from our COVID-19 and commute analysis provides verification of existing income and occupation disparities in commute flexibility that likely contribute to making people more vulnerable to COVID-19. During the first one and a half years of COVID-19, lower-income, essential natural resource and production workers traveled more are more likely to face higher exposure to COVID-19 at their workplace, while higher-income, office workers were able to travel less and shield themselves.

Research Report

Executive Summary

This project assesses the mobility trend of disadvantaged and minority workers and their experience of using alternative modes of transportation during the pandemic. The mega-region that spans the San Francisco Bay Area east to California's Central Valley and Sierra Nevada Foothills has an uneven distribution of people and economic centers. The Bay Area created many high paying jobs, and the associated increase in housing demand raised housing costs in the metropolitan area beyond what most residents can or are willing to pay. As a result, in the past 3 decades, the population in surrounding counties has increased much faster than in the Bay Area. However, the highest concentration of jobs remains in the Bay Area, leading to some of the country's highest rates of long-distance commutes.

The Central Valley was already experiencing increased pressure from migration from the Bay Area prior to the COVID-19 shock. The region's low density and long distance to job centers limit opportunities for traditional transit but enable viability of niche transportation modes such as vanpool and app-based rideshare, which are often used by lower income workers. However, riders sit in very close proximity in vanpools and ride share, making these modes riskier during COVID-19, particularly in the early stages of the pandemic when less was known about the disease's transmission or treatment.

We use three sources of data: (1) Survey data of vanpool and app-based rideshare users from the San Joaquin Council of Governments (SJCOG) Dibs program, (2) survey data of commuters from the National Association for Commuter Transportation (ACT), and (3) traffic data from StreetLight, Inc., a mobility analysis firm, to document mobility patterns between the Central Valley and the Bay Area throughout the pandemic.

The San Joaquin Valley has one of the highest rates of supercommuters, with many workers traveling long distances to Sacramento and Bay Area cities. In this fragmented region, alternative transportation options like carpool / vanpool fill a critical segment of the transportation needs of mobility disadvantaged workers. Our findings from the dibs survey suggest that SJCOG's dibs service influences the travel behavior of dibs registrants. It affects mode choice by increasing the share of commuters who use carpool / vanpool at least some of the time (>20 p.p. increase) and decreasing the share of those who drive alone (15 p.p. decrease). Moreover, these gains remained sticky during the Covid-19 pandemic.

At the same time, the dibs and ACT surveys point out that carpool / vanpool programs in this region are used by a rather narrow demographic. Namely, Government / Civil Service and Construction / Warehouse / Utilities workers, those who live far from work, those with access to vehicles, and those making below $150,000. It is possible that the nature of such services is more amenable to these types of work. During the pandemic, employees in these sectors were more likely to be deemed "essential" and were less likely to work remotely (nationally, and according to our survey data).

Evidence from our COVID-19 and commute analysis suggests that during the first one and a half years of COVID-19, lower-income essential workers traveled more, while higher-income workers were able to shield themselves. Similarly, essential natural resources and production workers traveled more and hence likely faced higher exposure to COVID-19 at their workplace, while service, sales and office, and business / science / arts workers had flexibility to travel less. Both patterns were the reverse of the pre-COVID-19 pattern that showed high-income ZCTAs and those with fewer natural resource and production workers generated more peak AM trips. Our results also provide verification of existing income and occupation disparities in commute flexibility that likely contribute to making people more vulnerable to COVID-19.

Our study contributes to the long-term understanding of travel behavior recovery during a prolonged shock such as a pandemic. We show that health interventions and safety perceptions (as proxied by vaccine take-up rates) were a necessary condition for AM peak and home-based-work trip recovery. Reopening policy, in turn, dictated which ZCTAs recovered trips quicker. We surmise that in future crises, addressing the core of the crisis (e.g., virus prevention) will lead to quicker traffic volume recovery than administering and repealing stay-at-home orders.

Chapter 1: Introduction

Background

This project looks at the mobility patterns and experience in using alternative modes of transportation for disadvantaged workers during COVID-19 in California's Bay Area and Central Valley. The mega-region that spans the San Francisco Bay Area east to California's Central Valley and Sierra Nevada Foothills has an uneven distribution of people and economic centers. The Bay Area is dense, with significant constraints on land supply. It has become one of the most expensive housing markets in the country, but also has high incomes and rapid job growth in high productivity growth sectors. The Central Valley has historically been a dominant agricultural region with urban centers serving as hubs for logistics and manufacturing (except for Sacramento). The region has significantly lower median incomes and housing costs, and higher unemployment.

Based on our previous research, Central Valley has several metropolitan areas within the top ten of the highest shares of supercommuters in the U.S. San Joaquin, Stanislaus, and Merced had 10.2%, 8.6%, and 8.6% share of super-commuters, as a fraction of commutes originating in those counties (ACS 2015-2019 5-year estimates). The region's low density and long distance to job centers limit opportunities for traditional transit, but enable viability of niche transportation modes such as vanpool and app-based rideshare, which are often used by lower income workers. However, riders sit in very proximity in vanpools and ride share, making these modes more risky during COVID-19.

We use three sources of data: (1) Survey data of vanpool and app-based rideshare users from the San Joaquin Council of Governments (SJCOG) dibs program, (2) survey data of commuter rail users from the Altamont Corridor Express (ACE), and (3) traffic data from StreetLight mobility analysis firm, to document mobility patterns between the Central Valley and the Bay Area throughout the pandemic.

Shared Mobility

The analysis focuses on understanding the three key research questions for this study, via the lens of rideshare users in the North San Joaquin Valley:

- Where do disadvantaged workers in mobility poor areas commute to and how?
- How do shared mobility options fill the void?
- How have these workers adapted to the pandemic?

COVID and Commute

The COVID-19 pandemic saw one of the most significant changes in work and commute patterns ever experienced. In this paper, we use daily data on trip volume for the San Francisco Bay Area and Central Valley mega-region in California to examine how morning peak period driving patterns changed based on income levels, occupation, and pre-COVID-19 travel volume characteristics.

The first confirmed case of COVID-19 in California was on January 26, 2020. The U.S. declared a National Emergency on March 13, 2020. State and local governments began to issue stay-at-home and social distancing orders by mid-March 2020 to constrain human movement and curb the spread of the disease. Although the various social distancing measures slowed disease transmission (1,2), they were also associated with large economic and social impacts (3,4).

The pandemic has exposed disparities built into commute patterns. Previous studies suggested that higher-income and higher-education populations followed stay-at-home orders more closely than lower-income populations who feared losing their income, were more likely to have jobs considered "essential", or whose work was unable to be performed remotely (5-7). While disparities across groups are clear, evidence is lacking in explaining the magnitude of disparities and uncovering the causal mechanism behind them (8). There is a lack of empirical studies on how workers in different industries reacted to the policy interventions, and how different interventions changed commuting patterns. While the pandemic is a unique event, it is likely that other health and climate-induced emergencies will lead to future disruptive policy interventions with similar tradeoffs. Understanding the factors associated with the change in commuting behavior is, therefore, critical in planning more equitable responses to future events (9).

This study analyzes the effects of evolving policy interventions in California, one of the states with the earliest and strictest set of orders. The analysis relates policy changes to Zip Code-level socioeconomic composition to better understand variation across income and industry categories. We focus on the Northern California Megaregion that spans the San Francisco Bay Area east to the Central Valley. The region is an ideal study area because it includes large concentrations of workers in industries that quickly shifted to remote work (e.g., tech) in the Silicon Valley and more rural areas in the San Joaquin Valley where agricultural and low-wage industries (e.g., logistics) dominate.

We use data on daily trip volume to answer the following questions:

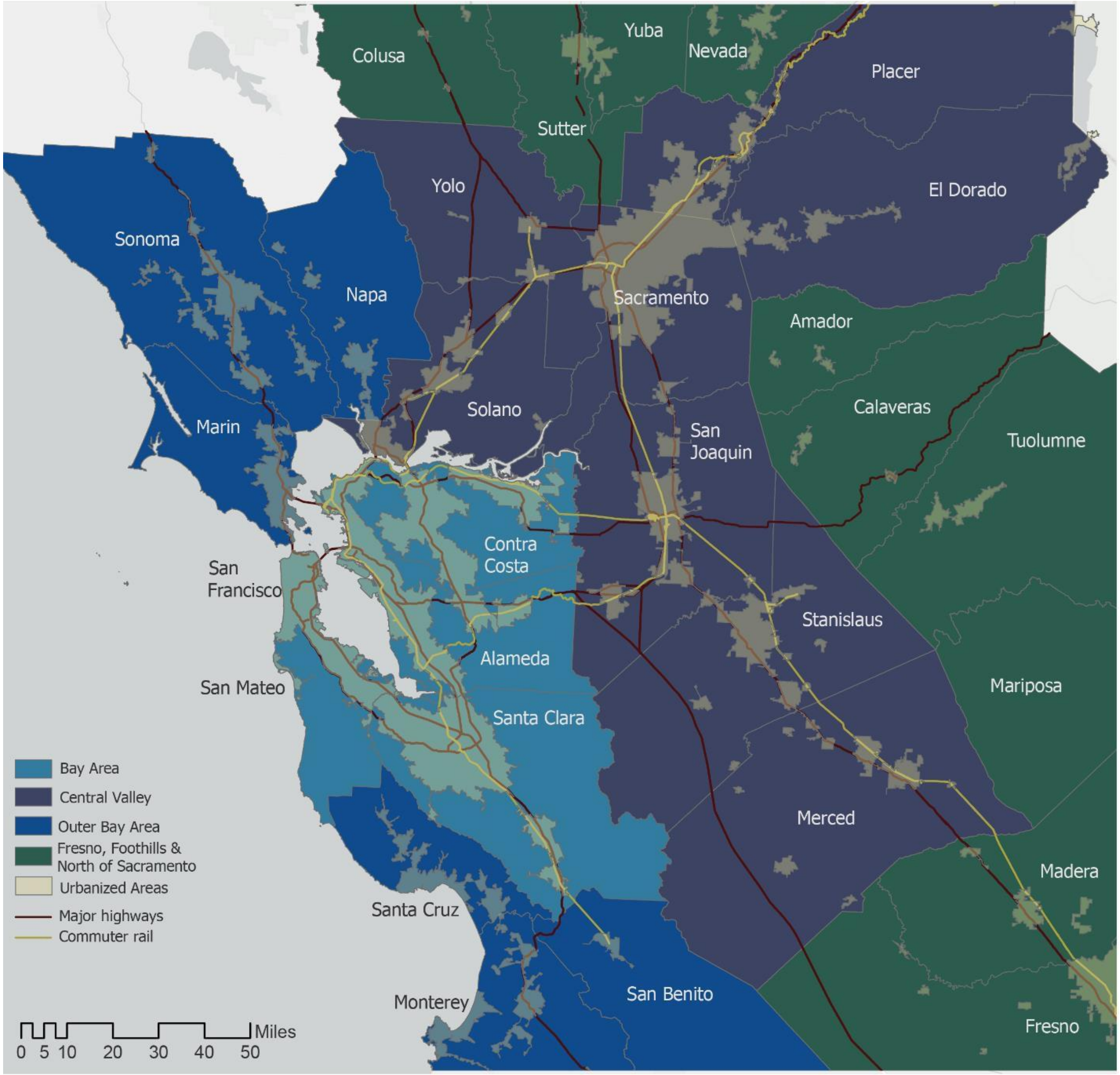
1. How do peak AM and home-based work trip volumes change in the early days of the pandemic, at peak transmission, and in the post-vaccination phase of COVID-19?
2. How did local industry composition impact peak AM and home-based work trips during COVID-19? Is there evidence of convergence between industries over time?
3. What other Zip Code demographic characteristics affect trip volume overall?

While we cannot measure commute trips directly or individually, we analyze the change in peak AM and home-based work trips to indirectly inform commute patterns and answer these questions. The data are gathered from the StreetLight Inc platform, which aggregates mobile phone data to generate information on trip volumes. The data were aggregated at the Zip Code level, which balances a fine enough geography that industry composition varies systematically and reliable sample size on mobility patterns. The data were collected every day between March 4, 2019, and September 25, 2021, giving the analysis the full span of policy stages up to the most complete relaxation of restrictions.

The Geographic Extent of the Study

This research focuses on studying the combined San Francisco Bay Area region and the Central Valley region. The Bay Area is the home to some of the country's least affordable housing markets, highest incomes, and fastest high-tech job growth. The Central Valley, separated from the Bay Area by a mountain range and river valleys, faces higher unemployment, and has a large agricultural and manufacturing base, with lower median incomes and housing costs. For this study, we analyze the commute pattern between core Bay Area counties (Alameda, Contra Costa, San Francisco, San Mateo, and Santa Clara County) and nearby counties in the Central Valley (El Dorado, Merced, Placer, Sacramento, San Joaquin, Solano, Stanislaus, and Yolo County) (see Figure 1). For the purposes of this study, we refer to these 8 counties as the Central Valley. Although this research focuses on studying the combined Bay Area and the Central Valley region, the models and methods are generally applicable to other regions since supercommute has become a growing trend nationally and globally.

Figure 1. Map of the geographic extent of the study



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Chapter 2: Literature Review

Shared Rides and Share Mobility

Shared mobility or ridesharing are umbrella terms that include carpool, vanpool, app-based rideshare, minibusses, and demand-responsive transit. Shared mobility solutions have been considered as strategies to reduce air pollution, CO2 emissions, and traffic congestion. In the San Francisco Bay Area alone, shared mobility is estimated to reduce 450,000 to 900,000 gallons of gas per year (10). Carpooling has long been the largest of the shared mobility segment. In 1970, 20.4% of U.S. workers commuted by carpooling, though carpooling's modal share declined to 9.3% in 2016 due to drops in gasoline price and shifting social trends (11,12). More recently, vanpools, app-based rideshare, and other niche modes have seen increased use in certain regions.

The different types of shared mobility are built upon similar concepts, but vary between vehicle types, ownership structures, operational systems, and financial models (13). Ridesharing facilitates formal or informal shared rides between a group of people with similar origins and/or destinations. Vanpooling is defined as a group of 7 to 15 people commuting together in one van for medium to long distance (5-20 miles) reoccurring trips. Carpooling is defined as a group of fewer than 7 people traveling together for trips over 5 miles in one car (13). App-based rideshare combines traditional carpool with an ability match demand to supply (often using mobile apps or websites), similar to transportation network companies (TNCs), but without paying for a fare.

Vanpools vary by who owns the vehicle, most commonly one of four types: "owner-operated, agency-provided, contracted service, or privately-provided" (14). Vanpooling tends to attract the lower-income population because it is often subsidized by employers or public agencies to lower commuting costs (15). Commuters living in the Bay Area tend to use more casual carpooling to get from East Bay to downtown San Francisco (16). In contrast, commuters living in the San Joaquin Valley often use government-operated vanpooling services to commute to the Bay Area (17). Large portions of the San Joaquin Valley region face pollution and environmental justice concerns (18). Improvements in transportation technology and increased utilization of shared mobility have the potential to improve this region's environmental standing (18,19).

The Central Valley Shared Mobility Context

The high proportion of low income populations make the Central Valley a potentially attractive place for public transit. However, the lower densities and interspersed rural and urban areas make traditional transit systems challenging to sustain (19). As a result, agencies in the Central Valley have been innovative and more willing to experiment with different and less traditional forms of transit, including vanpool and app-based rideshare (17). For example, transportation planning agencies in San Joaquin, Stanislaus, and Merced Counties launched a Commute Connection program in 1978 to encourage residents to travel around and commute to work. This program later became the dibs Smart Travel program, which is operated by the San Joaquin Council of Governments (SJCOG) to serve residents in the three counties. This program was established to promote smart travel through alternative modes of transportation including app-based rideshare, vanpooling, riding transit, walking, and biking.

SJCOG partners with private entities (CalVans and Commute with Enterprise) to provide dibs vanpooling services for the region and with RideAmigos for advanced ride-matching and carpooling services. RideAmigos is a private company that provides innovative technology and a platform that helps improve trip planning, direct communication with rideshare matches, and transit integration for commuters for residents in the San Joaquin area. Unlike rideshares, the dibs vanpools are eligible for subsidies; subsidies range from $250 to $600 per month depending on the county. Some public transit agency vanpool programs also keep their costs down by subcontracting operations and maintenance to carsharing companies.

Shared mobility services are important for residents in more rural regions to access housing, jobs, education, and other services. It is most useful to connect areas that are not well served by public transit and has been considered as a complement to the under-resourced public transit system in the U.S (20-22). While investing in public transit could be expensive and time-consuming, ridesharing is considered a cheaper and more flexible option to help bridge the gaps for rural neighborhoods to reach existing public transit networks (17).

Research on Shared Mobility

Recent data from the National Household Travel Survey and American Community Survey indicate that lower-income populations and minority groups tend to use ridesharing more than the general population. Several studies also found that ridesharing could be important for improving mobility for low-income, immigrant, and non-white households (23-25). The low-income population often experiences longer commute times and higher fares than the middle- and upper-income population (26). Research has also found a spatial mismatch between where low-income people live and where jobs at their skill level are located within a 90-minute commute time (27), though this varies region-by-region (13). Ridesharing can increase access and improve mobility for these disadvantaged groups.

The impact of ridesharing is unclear due to limited research in the field. Carpooling and vanpooling have been referred to as the “invisible mode” because they are difficult to observe and study (13). The lack of quantitative data, records, and counts results in little systematic documentation for ridesharing history (Minett, 2010; Winters, 2010). The actual usage of shared mobility systems by low-income populations remains lower than the usage by the general population (1,19). More research is required to understand the actual access needs faced by disadvantaged groups.

COVID and Commute

The spread of COVID-19 to California in early 2020 led to a series of policies aiming to curb the spread of the disease. The restrictions on mobility and social interactions had an immediate and dramatic effect on the economy and, by extension, people’s travel behavior (29,30). Within two weeks, workplace activity in the Northern California megaregion plunged by about 55% on average with significant variation. Bay Area counties surrounding San Francisco, San Jose, and Oakland decreased by 64% but in Central Valley counties like Sacramento, its suburbs, and the Stockton area, the decrease was 44%, according to the analysis of Google Community Mobility Reports (31).

The variation in policy impact on commuting patterns is tied to the heterogeneity of people and economic structure. Higher-income and higher-educated populations, younger people, and people working in information and technology sectors were the most likely to shift to working at home and were relatively unaffected in their employment stability (5-7,32). People who were able to shift to a work-from-home model decreased their travel dramatically in the early days of the pandemic as work, school, and non-essential shopping-related trips were eliminated. They were also slower to return to pre-pandemic travel habits as many workplaces allowed full or part-time remote working (33).

In contrast, many lower-income workers faced compounded crises. Lower-wage workers in industries like hospitality and retail faced a much higher incidence of unemployment (34). The overrepresentation of people of color, especially Latinos, in these industries meant that the burden of the stay-at-home policies fell disproportionately on these populations (34-35). The unemployment racial gap was lower for African Americans who tended to work in industries more sheltered from the economic downturn (36).

Employment stability for low-wage workers, however, often did not come with the protection of remote work. Workers deemed essential were often at greater risk of exposure to the virus and continued to commute to work much like before the pandemic (37). Essential workers who did not own a car had little choice but to rely on transit. Transit service was often reduced, limiting the options for transit-reliant people, many of whom switched to car transportation (38). Despite the reduction in transit and higher unemployment, declines in traveling were significantly smaller for lower-income people in the Seattle region (39).

The pandemic led to a shifting perception of occupation and a rapid re-organization of jobs that were considered critical and required constant in-person engagement (e.g., health care and grocery stores) and those that were primed for termination. These changes not only had immediate effects on people, but are also likely to have long-term effects on job perception and people's willingness to travel (40). The ability to work remotely, in particular, is likely to create permanent differences in travel behavior (39)

While economic structure had the most direct link to policy interventions, other factors were likely to affect travel behavior. COVID-19 itself affected willingness to travel. People developed an early awareness of risk and adjusted accordingly, but with limitations, based on available information. County-to-county travel decreased significantly in response to higher case rate (41). Yet, changes in travel frequency were less clear for new cases in contrast to new deaths, with some variation based on the distance traveled (42). Perceived risk also varied depending on the built environment. The early peaks in infection and death in large, dense cities shaped people's perceptions. People living in counties with more compact development reduced their trips to grocery stores and transit significantly more than people in less compact counties (43). While vaccination rates plainly showed the partisan nature of the pandemic, the role of political ideology was visible early on. People in states where Donald Trump received greater support were less likely to respect stay-at-home orders and reduced traveling significantly less (44).

Research on the impact of COVID-19 and commuting aligns well with a larger narrative surrounding the pandemic in the United States. The pandemic exacerbated health disparities and economic precarity. People of color and low-wage workers shouldered a disproportionate share of the burden of stay-at-home and social distancing policies imposed. There is, however, limited research to support these narratives with the kind of specificity that can inform more equitable policy decisions in the future. Most published research focuses on the early days of the pandemic at large geographic scales (state and county), and much of it relies on data for countries other than the United States. Research on mobility specifically has used small survey data that is only representative at large scales or data that are not meant to measure travel behavior directly (e.g., SafeGraph). This study is the first to analyze travel behavior at a small scale, using data designed to measure trip volume for the entire period during which policies were actively implemented.

COVID and Shared Mobility

Mobility changes are not equally distributed across the population. Researchers found that people with disadvantaged social conditions tend to experience a more significant impact and reduction in travel mobility than those with advantaged social conditions (45,46). During the COVID-19 pandemic, mobility disadvantaged populations such as the elderly (aged 60 and above), children and students, low-income population, migrant workers, prisoners, disabilities, sex workers, and domestic violence victims are more likely to face higher risks of worsening socioeconomic and living conditions due to disease infection and restrictions from the various social distancing orders (47).

Mobility changes are not equally distributed across transportation modes either. Public transit, which the disadvantaged population relies the most on, suffers the most (48). During the lockdown, the limited access to public transit could generate higher barriers for disadvantaged groups to reach health care services, grocery stores, and job opportunities (49). In contrast, the mobility advantaged group, those who have access to a private vehicle, have a higher ability to access services, and, at the same time, can better protect themselves from being exposed to the disease.

COVID-19 poses particular challenges for both vanpools and app-based rideshare. Both of these modes require sharing space with individuals, often outside of one's household, potentially increasing infection risk. Since low-income workers tend to have fewer telework options (17), each use of vanpool and rideshare involves a risk calculation between health and continued employment and income. Research also points out the deep near-term challenges faced by public transit, TNCs, and shared mobility systems during the pandemic. Based on interviews with transportation experts, they suggest that in order to successfully recover, these services will need to innovate and invest in technology, focus on planning and operational reforms to serve marginalized and disadvantaged groups, provide customer-centric service, and invest in workforce safety (48). However, no studies to date specifically evaluate vanpool and rideshare services during the pandemic, highlighting a gap that is highly relevant to research and policy making (50).

Chapter 3: Vanpool and App-based Rideshare Survey

Research Design and Data

The analysis focuses on understanding the three key research questions for this study, via the lens of rideshare users in the North San Joaquin Valley:

- Where do disadvantaged workers in mobility poor areas commute to and how?
- How do shared mobility options fill the void?
- How have these workers adapted to the pandemic?

To do so, we have partnered with the San Joaquin Council of Governments (SJCOG) who run the "dibs" vanpool and app-based rideshare programs. These programs serve over 10,000 people in San Joaquin, Stanislaus, and Merced counties. Together with SJCOG Assistant Program Specialist Stephanie Maynard and with input from SJCOG Senior Program Specialist Yvette Davis and other key agency partners, the USC / Occidental team developed a user-friendly questionnaire via the MetroQuest survey tool. The questions focused on the joint goals of understanding dibs members' travel behaviors and dibs resource access and marketing. Regarding the research questions above, the survey queried the following topics:

1. User demographics
2. Trip origin, destination, and frequency
3. Sector of employment
4. Access to alternative mode of transportation (e.g., # of cars per working adult in household)
5. Reason for using vanpool or carpool (cost, lack of alternatives, convenience, etc.)
6. Impact of COVID-19
    a. Usage frequency
    b. Concerns about using service
    c. Satisfactory protective measures
7. Post-COVID-19 use expectations

A demo version of the survey is available here: https://demo.metroquestsurvey.com/?u=bm4p4l#!/?p=web&pm=dynamic&s=1&popup=WTD. See Appendix A for a set of questionnaire screen shots.

The email-based survey was sent out in September 2021 to about 10,000 dibs members with active accounts, located in San Joaquin, Stanislaus, and Merced counties. We received 157 completed survey responses over about a month-long period, representing a 1.6% response rate. The next section provides descriptive statistics on several key questions, cross-tabbed by respondent demographics.

Given the relatively low response rate, we also supplemented our sample with a survey conducted by the National Association for Commuter Transportation (ACT) in 2020. This national survey queried commuters' responses to Covid-19 (SJCOG 2020). The ACT survey had reasonable overlap in the types of questions asked with the dibs survey described above. See Appendix B for ACT survey questions. SJCOG provided survey responses from dibs users in San Joaquin, Stanislaus, and Merced counties. We note where data comes from ACT vs dibs surveys in the highlights section below.

Comparing dibs and ACT surveys

To ensure a broader sample and external validity of the dibs survey, we compared it to ACT's 2020 survey of a similar population group, in the same study area, and along similar questions. The surveys were broadly comparable on age, but ACT survey respondents were more likely to indicate carpool/vanpool as their primary transportation mode than dibs respondents (Table 3.1). Methodologically, the ACT survey specifically asked respondents to denote their primary mode of transportation, however, the dibs survey asked respondents to declare the number of days they used each method. Therefore, in order to compare the two surveys, researchers reclassified responses in the dibs survey based on the mode of transportation they used the greatest number of days to determine their "primary pre-covid mode of transportation." The ACT survey had less difference across modes by age compared to the dibs survey. Note that the sample sizes for the youngest and oldest respondent categories as well as the Telecommute mode are were very low.

Table 3.1: dibs v. ACT: Primary Mode of Transportation by Age

ACT survey

Pre-Covid Mode	18 to 24	25 to 34	35 to 44	45 to 54	55 to 64	65 to 74	All Ages
Drive Alone	57%	48%	43%	47%	43%	50%	45% (126)
Carpool/Vanpool	14%	30%	33%	38%	35%	17%	33% (92)
Bike/Walk	0%	5%	14%	6%	12%	25%	10% (29)
Public Transit	29%	18%	7%	9%	9%	8%	10% (28)
Telecommute	0%	0%	1%	0%	1%	0%	1% (2)
Total Respondents	***7***	***40***	***69***	***68***	***81***	***12***	***277***

dibs survey

Pre-Covid Mode	18 to 24	25 to 34	35 to 44	45 to 54	55 to 64	65 to 74	All Ages
Drive Alone	33%	93%	63%	56%	76%	44%	67% (61)
Carpool/Vanpool	33%	0%	21%	19%	0%	11%	11% (10)
Bike/Walk	0%	7%	13%	19%	8%	22%	12% (11)
Public Transit	33%	0%	4%	6%	16%	22%	10% (9)
Telecommute							
Total Respondents	***3***	***14***	***24***	***16***	***25***	***9***	***91***

The dibs survey had a comparably larger share of lower-income respondents than the ACT survey (Table 3.2). Public transit use was highest in the lowest income group in both surveys, 15% of ACT survey respondents and 14% of dibs survey respondents making less than $50,000 used public transit as their primary mode of transportation. Carpool / Vanpool shares were relatively comparable by income across both surveys, similar to the dibs results in Figure 2 above. The highest income category in the dibs survey suffers from low sample size.

Table 3.2: dibs v. ACT: Primary Mode of Transportation by Income

ACT survey

Pre-Covid Mode	Less than $50,000	$50,000 - $75,000	$75,000 - $100,000	$100,000 - $150,000	Above $150,000	All Incomes
Drive Alone	38%	41%	56%	46%	51%	46% (125)
Carpool/Vanpool	35%	36%	32%	36%	26%	33% (90)
Bike/Walk	13%	14%	4%	7%	13%	10% (28)
Public Transit	15%	8%	6%	11%	11%	10% (27)
Telecommute	0%	2%	2%	0%	0%	1% (2)
Total Respondents	***55***	***64***	***50***	***56***	***47***	***272***

dibs survey

Pre-Covid Mode	Less than $50,000	$50,000 - $75,000	$75,000 - $100,000	$100,000 - $150,000	Above $150,000	All Incomes
Drive Alone	68%	67%	74%	59%	67%	46% (59)
Carpool/Vanpool	11%	10%	5%	18%	33%	33% (10)
Bike/Walk	7%	14%	16%	18%	0%	10% (11)
Public Transit	14%	10%	5%	6%	0%	10% (8)
Telecommute						
Total Respondents	***28***	***21***	***19***	***17***	***3***	***88***

Survey respondents indicated a primary occupation, in both surveys. The occupation classifications in both surveys were reclassified and harmonized to compare between surveys. Several response options were combined including health and education, business, financial, and tech, and government and civil service jobs (Table 3.3). In both surveys government and civil service had the largest number of responses. In the ACT survey 42% of respondents were working in the government sector and 45% of dibs respondents worked in the same field. The government / civil service employees had the highest carpool / vanpool use among all respondents in all surveys. Construction / Utilities / Warehouse workers also had high responses in terms of carpool / vanpool use. Certain occupation categories had very low sample sizes.

Table 3.3: dibs v. ACT: Primary Mode of Transportation by Occupation

ACT Survey

Pre-Covid Mode	Government/ Civil Service	Health and Education	Construction, Utilities, Warehouse	Business/ financial/tech	Retail and Hospitality	Other	All Incomes
Drive Alone	39%	53%	40%	41%	56%	57%	45% (135)
Carpool/Vanpool	47%	15%	43%	25%	11%	21%	33% (98)
Bike/Walk	7%	19%	0%	13%	11%	11%	10% (31)
Public Transit	6%	12%	17%	22%	22%	11%	10% (34)
Telecommute	1%	1%	0%	0%	0%	0%	1% (2)
Total Respondents	**126**	**75**	**30**	**32**	**9**	**28**	**300**

dibs Survey

Pre-Covid Mode	Government/ Civil Service	Health and Education	Construction, Utilities, Warehouse	Business/ financial/tech	Retail and Hospitality	Other	All Incomes
Drive Alone	60%	60%	90%	71%	25%	75%	67% (67)
Carpool/Vanpool	20%	0%	10%	14%	0%	13%	13% (13)
Bike/Walk	9%	20%	0%	14%	50%	13%	11% (11)
Public Transit	11%	20%	0%	0%	25%	0%	9% (9)
Telecommute							
Total Respondents	**45**	**15**	**21**	**7**	**4**	**8**	***100***

Survey Results and Analysis

The dibs survey provides an understanding of the impact of dibs program registration on transportation mode choice. This includes how often a particular mode is used before and after registering for the program. It also involves an understanding of how such choices changed after the Covid-19 pandemic started. We are also able to disaggregate data by age, gender, income, and race/ethnicity to shed some light on how socioeconomic and demographic characteristics affect the impact of the dibs program on mode choice and frequency.

Summary Survey Statistics on dibs Program Registration Impact on Mode Choice

Table 3.4 reports how many times dibs members indicated using carpool/vanpool before and after registering with dibs and during the pandemic, by number of days per week. The share of respondents using carpool / vanpool to any extent increased by 22% after joining dibs: before joining dibs, only 26% of respondents had used carpool / vanpool, while 48% reported using it after joining dibs. Total carpool / vanpool usage decreased from 48% to 37% during Covid-19 (March 15, 2020 – September 2021), but not to pre-dibs registration levels. For those who carpool/vanpool, the plurality of users pre-Covid, used carpool / vanpool 5 or more days per week (i.e., full-time). During Covid-19, among those who carpool/vanpool, the frequency of use decreased slightly. Note that the most common response was “Never”: that just because dibs was available or the respondent was registered, did not mean they use the program.

Table 3.4: Impact of dibs Registration on use of carpool/vanpool (dibs Survey 2021)

Carpool/Vanpool	Never	1-2 days per week	3-4 days per week	5-6 days per week	Everyday	Grand Total
Before registering with dibs, how often did you carpool or vanpool?	78	5	9	9	5	106
	74%	5%	8%	8%	5%	100%
After registering with dibs, how often did you carpool or vanpool?	54	9	11	14	15	103
	52%	9%	11%	14%	15%	100%
During the COVID-19 pandemic (March 15,2020 – today), how often did you carpool or vanpool	66	8	11	10	9	104
	63%	8%	11%	10%	9%	100%

To better evaluate the impact of dibs registration and of Covid-19 on carpool / vanpool usage, a statistical test was utilized to assess whether the differences were by chance or due to either dibs registration or Covid-19, in Table 3.5. The statistical test indicates that we can be 95% confident that the 22% increase in carpool / vanpool usage is due to dibs registration and not due to random chance. Moreover, the statistical test indicates that we can be 95% confident that dibs registration decreased the share of driving along by 15%. dibs registration did not statistically significantly change biking or public transit use. For dibs registrants, the changes to carpooling/vanpooling, biking, or driving alone during the Covid-19 timeline were not statistically significantly different than pre-Covid. This is likely due to the relatively low sample size of the dibs survey. At the same time, among dibs registrants, we can be 90% confident that Covid-19 reduced public transit use by 15%. During Covid-19, among those who carpool/vanpool, the frequency of use decreased slightly. Note that the most common response was “Never”, meaning that just because dibs was available or the respondent was registered, did not mean they use the program. Overall, this table reveals that dibs had a statistically significant impact on the use of carpooling and vanpooling.

Table 3.5: Impact of dibs Registration on Method of Transportation (dibs Survey 2021)

	Carpool/ Vanpool	Biking	Public Transit	Drive Alone
Before registering with dibs, how often did you carpool or vanpool?	26%	33%	23%	78%
After registering with dibs, how often did you carpool or vanpool?	48%*	41%	28%	63%*
During the COVID-19 pandemic (March 15,2020 – today), how often did you carpool or vanpool	37%	33%	13%^	64%

*Statistically significant difference between After and Before dibs
^Statistically significant difference between After and Covid

The survey also evaluated whether dibs generally influenced transportation choices along certain demographic characteristics of respondents, including gender, age, income, and race / ethnicity (Table 3.6). Table 3 presents the responses to the following question survey "Do you feel dibs has or will influence your transportation choices?" along these characteristics. Generally, about 60% of respondents reported that dibs influenced their transportation choices. There was little difference between males and females, and these differences were not statistically significant. The number of respondents for "prefer not to answer" was too low to draw conclusions. Lower and middle household income respondents (<$75,000) were slightly more likely to report that dibs changed their transportation choices, but these were not statistically significantly different by category – so they may have occurred by chance even without dibs. Black / Other respondents were more likely to respond that dibs changed their transportation choices, but this was the smallest category of respondents, and was not a statistically significant difference. By age, respondents under 55 years old were 20+% more likely to report dibs impacting their transportation choices. This was a statistically significant differences between age categories.

Table 3.6: "Do you feel dibs has or will influence your transportation choices?" by Demographic Categories (dibs Survey 2021)

		No	Yes	Sample Size
Gender	Female	32%	68%	50
	Male	42%	58%	55
	Prefer not to Answer	67%	33%	3
	All Genders			108
Income Category	<$50K	36%	63%	33
	$50-75K	33%	67%	24
	$75-100K	43%	57%	21
	>$100K	48%	52%	25
	All Incomes			103
Age Category**	18-34	26%	74%	19
	35-44	33%	67%	27
	45-54	26%	74%	23
	55+	57%	43%	37
	All Ages			106
** Chi-squared test statistically significant for p<0.05				

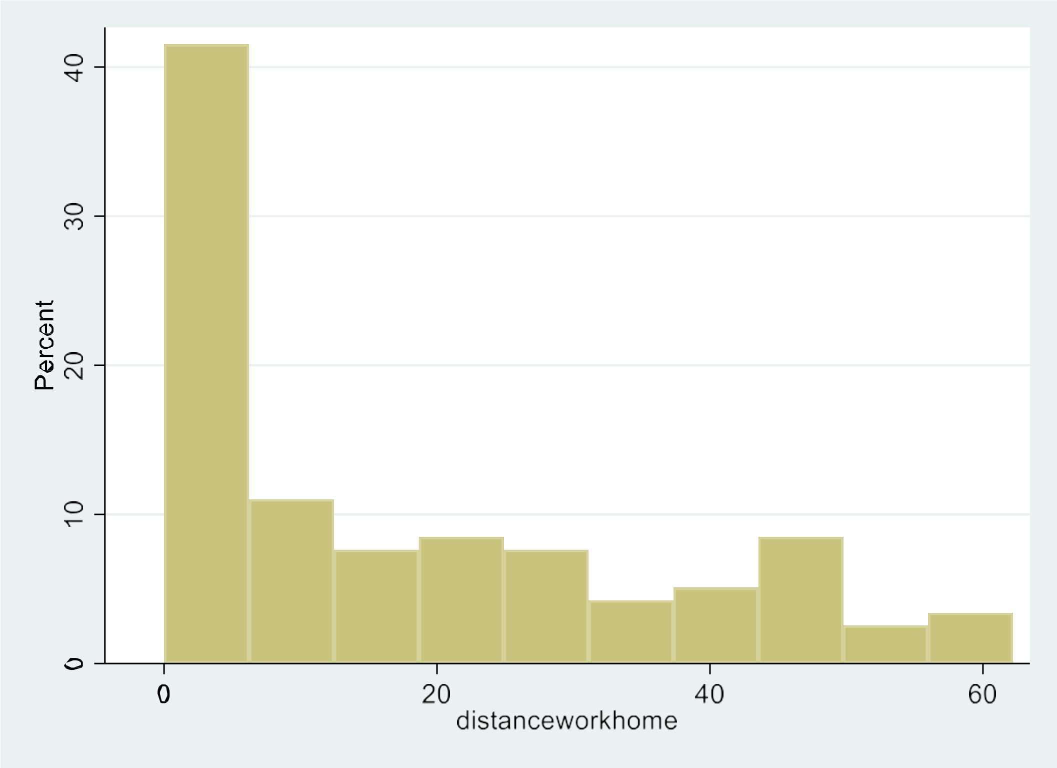
Race / Ethnicity	White	44%	56%	48
	Hispanic	39%	61%	28
	Asian	46%	54%	13
	Black/Other	21%	79%	14
	All Race / Ethnicity			103

Commute Distance

Figure 3.1 depicts the distance between respondents' home and primary workplace in miles for each survey, with miles on the x-axis and the share of distances falling in a particular mileage on the y-axis. The dibs survey interface allowed respondents to place pins on the location of their home and of their workplace or school and the survey then logged the latitude and longitude associated with these pins. Then, we calculate the distance between the home and workplace location in miles. The median distance across all respondents was 10.5 miles for the dibs survey. About 10% of respondents commuted over 50 miles, in line with supercommuting estimates for this region (Boarnet et al., 2022).

The ACT survey precludes a direct comparison on commute distance, due to differences in the way the question was asked. ACT survey asked for the home and work zip codes. Calculating distances between zip code centroids introduces quite a bit of measurement error, when comparing to distances between known latitude and longitude coordinates (as in dibs survey). For example, the ACT median distance based on zip code centroids is 19.6 miles (nearly double the dibs median). This is possibly because zip codes in the study region are quite large in area, making centroid distance similarly large. However, population and work locations are clustered in certain parts of zip codes, making these calculations less relevant.

Figure 3.1: How Far do dibs Respondents Commute? (dibs Survey 2021)



Median commute distance provides a different measure of dibs program impact. Respondents indicated that after registering with dibs, drive alone, transit, and carpool median distances changed. Specifically, median carpool distance went up by 3.5 miles and median transit distance more than doubled, while median drive alone distance fell by 3.8 miles (Table 3.7). This suggests that dibs impacted commute travel by reducing the number of miles respondents drove alone, and increasing shared mobility (transit or carpool / vanpool), in line with findings in Tables 1 and 2. During the pandemic, median commute distances stayed largely the same, except for transit where they dropped dramatically. This suggests that those who drove alone, carpooled, and biked generally did so for distances in line with pre-pandemic medians.

Table 3.7. Median Distance by Mode for dibs Survey Time Periods (dibs Survey 2021)

Median distance (miles)	Pre-dibs	Post-dibs	During Covid-19
Drive Alone	12.2	8.4	9.8
Transit	7.8	16.6	6.6
Carpool	17.2	20.7	20.4
Biking	4.3	4.3	3.7

Regression Analysis of dibs Program Impact

The descriptive survey results above provide some directional indication that dibs registration impacts (1) registrants' transportation mode choice and mode use frequency and (2) that the pandemic did not seriously dampen this impact. This section uses regression analysis to attempt to tease out what is driving the descriptive results, to better understand the impact of programs like dibs.

To more finely measure the impact of the dibs program on shared mobility use specifically, we calculate an increment to see the number of respondents who indicated a change in carpool/vanpool use frequency following dibs registration and then again following the onset of the Covid-19 pandemic. This increment takes a value of 0 if no change in use frequency was indicated, a value of 1 if respondent increased carpool/vanpool use from for example "Never" to "1 or 2 days per week" or from "3 to 4 days per week" to "5 to 6 days per week", a value of 2 if respondent increased carpool/vanpool use from "Never" to "3 to 4 days per week", and so on.

Table 3.8 shows these increments for both changes (registration, pandemic). Per Table 3.4 above, most respondents have not changed their use. But, following dibs registration, we see some relatively committed new users with high positive increment changes. As the pandemic started, increment changes were more modest.

Table 3.8. Incremental change from dibs registration and from onset of Covid-19 (dibs Survey 2021)

increment	dibs registration	Covid-19 pandemic onset
-2	0	1
-1	2	4
0	72	72
1	8	12
2	5	4
3	5	4
4	10	4

Next, we measure what variables (if any) correlate with incremental changes in carpool usage following (1) dibs program registration and (2) the onset of the Covid-19 pandemic? The explanatory variables include socioeconomic characteristics (gender, income category, age category, and race / ethnicity), work characteristics (occupation type, commute distance, commute frequency), and household characteristics (household size, number of young children in the house, and number of cars available in the household) available in the dibs survey. Because of the small sample size of the dibs survey, we run and report separate regressions for socioeconomics only and then for household and commute characteristics (Table 3.9 and 3.10).

There are few statistically significant socioeconomic factors that drive incremental change in shared mobility use in this sample (Table 3.9). Being Black / Other race relative to being White is statistically significant (at the 10% level) and has a magnitude of nearly 1 increment. This means that after registering for dibs, Black / Other respondents increased carpool use by 1-2 days more relative to the reference group.

Among household and commute characteristics, being employed in a government occupation relative to all other occupations increased carpool use by 0.83 increments. Commute distance is also positively associated with incremental changes in carpool use: a 10-mile commute distance suggests a 0.2 incremental increase in shared mobility. Both impacts are statistically significant at the 5% level. Commute distance remains positively associated with incremental increases in carpool use once the pandemic starts, but government employment is no longer statistically significant.

Table 3.9. Incremental Change in Carpool / Vanpool Use: Socioeconomic Variables

DV: Incremental Change in Carpool Use from Registering for Dibs						DV: Incremental Change in Carpool Use from Pandemic				
Variable	Coef.	Std. Err.	t	P>t		Variable	Coef.	Std. Err.	t	P>t
gender (female is baseline)	-0.03	0.35	-0.09	0.93		gender (female is baseline)	0.17	0.30	0.56	0.58
income (<$50K is baseline)						income (<$50K is baseline)				
$50-75K	-0.11	0.47	-0.24	0.81		$50-75K	0.16	0.40	0.41	0.68
$75-100K	-0.29	0.48	-0.61	0.55		$75-100K	0.18	0.41	0.45	0.66
>$100K	-0.52	0.50	-1.04	0.30		>$100K	-0.18	0.43	-0.42	0.68
age (<35 y.o. is baseline)						age (<35 y.o. is baseline)				
35-44	0.56	0.50	1.10	0.27		35-44	0.01	0.43	0.03	0.98
45-54	-0.33	0.55	-0.61	0.54		45-54	-0.31	0.46	-0.68	0.50
55+	0.11	0.52	0.21	0.83		55+	0.02	0.44	0.04	0.97
race (white is baseline)						race (white is baseline)				
Hispanic	0.62	0.42	1.50	0.14		Hispanic	0.12	0.36	0.33	0.74
Asian	0.86	0.58	1.50	0.14		Asian	-0.06	0.49	-0.11	0.91
Black/Other	0.98	0.53	1.86	0.07		Black/Other	0.44	0.44	0.99	0.33
Constant	0.39	0.48	0.80	0.43		_cons	0.35	0.41	0.86	0.39
# of Observations	77.00					# of Observations	76.00			
R-squared	0.14					R-squared	0.06			
P>F	0.38					P>F	0.93			

Table 3.10. Incremental Change in Carpool / Vanpool Use: Household and Commute Variables

DV: Incremental Change in Carpool Use from Registering for Dibs						DV: Incremental Change in Carpool Use from Pandemic				
Variable	Coef.	Std. Err.	t	P>t		Variable	Coef.	Std. Err.	t	P>t
Occupation in Government (vs all other)	0.83	0.35	2.40	0.02		Occupation in Government (vs all other)	0.17	0.27	0.62	0.54
Commute Distance	0.02	0.01	2.25	0.03		Commute Distance	0.02	0.01	3.48	0.00
3+ persons in household (vs <3)	0.16	0.34	0.48	0.63		3+ persons in household (vs <3)	-0.10	0.27	-0.39	0.70
3 or more cars in household	0.26	0.34	0.75	0.45		3 or more cars in household	0.41	0.27	1.53	0.13
Any children <4?	-0.29	0.54	-0.54	0.59		Any children <4?	-0.17	0.43	-0.40	0.69
Commute Fewer than 5 days per week?	-0.18	0.33	-0.56	0.58		Commute Fewer than 5 days per week?	0.37	0.25	1.47	0.15
Constant	0.01	0.33	0.03	0.98		Constant	-0.26	0.25	-1.03	0.31
# of Observations	77.00					# of Observations	76.00			
R-squared	0.21					R-squared	0.14			
P>F	0.01					P>F	0.09			

Pandemic Impact on Shared Mobility

The Covid-19 pandemic effectively curbed non-essential activity outside of the home for many places in California, starting in March 2020 and continuing to some extent into 2021 and beyond. Part of this was driven by state and local policy toward restricting mobility and social interaction to prevent the spread of the virus. These affected travel behavior across the country (Barbieri et al., 2020; De Vos, 2020). In Northern California megaregion, within two weeks of pandemic onset, workplace activity plunged by about 55% on average with significant variation. Bay Area counties surrounding San Francisco, San Jose, and Oakland decreased by 64% but in Central Valley counties like Sacramento, its suburbs, and the Stockton area, the decrease was 44%, according to the analysis of Google Community Mobility Reports (McKinney, Morton, and Rodnyansky 2021). Stanislaus and Merced counties, in particular, saw lower drops in both weekday and weekend workplace activity, and recovery was a bit faster in these counties than the megaregion generally.

Lower-income workers, however, tended to be less likely to have remote work options, more likely to be classified as “essential workers”, and also more likely to be affected by the virus. Traditionally, lower-income workers as a group use carpool / vanpool services more than higher-income workers. At the same time, lower-income workers are overrepresented in industries like Leisure / Hospitality and Retail, both of which suffered large cutbacks during the pandemic, leading to unemployment and furloughs especially for lower-income workers. Our study area, however, had fewer losses in these industry sectors compared to the Bay Area (McKinney, Morton, and Rodnyansky 2021).

So, how did commuters in this region react to pandemic? We combine the dibs and ACT surveys to better understand the relative incidence of remote work during the pandemic and the impact of the pandemic on carpool / vanpool usage. Combining these surveys increases the sample size. However, the surveys do not have many variables in common, so we only use and harmonize variables found in both surveys.

What variables are correlated with working from home, in the Central Valley, among the populations surveyed by the ACT and dibs surveys? We estimate in equation 1 the correlates of working remotely in our combined survey sample using a logit model. Table 3.11 presents findings with coefficients transformed to odds ratios.

(2) $Remote\ Work = \alpha + \beta_1 * Commute\ Distance + \beta_2 * Car\ Availability + \beta_3 * PreCovid\ Mode + \beta_4 * Income\ Category + \beta_5 * Age\ Category + \beta_6 * Occupation\ Category + \varepsilon$

Commute distance is positively associated with working remotely. Respondents with incomes of $75,000 - $100,000 had nearly five times higher odds of remote work than those with incomes below $50,000. Note that median household incomes in the study area ranged from ~$59,000 (Merced County) to ~$75,000 (San Joaquin County), but were well below Bay Area medians (e.g., Alameda County's was $112,000) according to the 2017-2021 5-year average of the American Community Survey (Census Bureau QuickFacts). Respondents who worked in the construction, utilities, warehouse sector had 1/5 the odds of working remotely and government / civil service had 1/3 the odds of working remotely, compared to all other category (that excludes government / civil service, health and education, business / finance / tech). The government sector makes up 14-22% of the study area counties' workforce, in line with California's 16% average (Table 3.13). The Construction / Utilities / Warehouse sector makes up 34% of San Joaquin County's workforce, while it is only 10% in Stanislaus and 8% in Merced counties (and 23% state average) (Table 3.13). The rest of the variables were not statistically significant.

Table 3.11. Remote Work and the Pandemic

Dependent Variable: Currently Working Remotely (yes = 1, no = 0)	**Odds Ratio**	**Std. Err.**	**z**	**P>z**
Distance (miles) from Home to Work	1.01	0.00	2.31	0.02
Any Cars at Home? (No is baseline)	0.47	0.30	-1.17	0.24
Principal Commute Mode Pre-Covid (Drive Alone is baseline)				
Carpool/Vanpool	0.76	0.28	-0.77	0.44
Transit	1.01	0.54	0.02	0.99
Bike/Walk	1.30	0.63	0.53	0.59
Income (<$50K is baseline)				
$50-75K	2.04	1.06	1.36	0.17
$75-100K	4.98	2.67	3.00	0.00
$100-150K	2.19	1.14	1.50	0.13
>$150K	1.88	1.07	1.10	0.27
Age (<35 y.o. is baseline)				
35-44	1.44	0.71	0.74	0.46
45-54	1.53	0.76	0.86	0.39
55+	1.00	0.49	-0.01	1.00
Occupation (All Other is baseline)				
Government/Civil Service	0.30	0.15	-2.34	0.02
Health and Education	0.64	0.34	-0.84	0.40
Construction, Utilities, Warehouse	0.21	0.14	-2.36	0.02
Business/financial/tech	0.97	0.56	-0.05	0.96
Survey (ACT is baseline)	1.24	0.54	0.49	0.62
Constant	0.48	0.39	-0.90	0.37
# of Observations	280.00			
Pseudo R-squared	0.12			
Prob>chi2	0.00			

What variables are correlated with using carpool / vanpool as the primary commute mode (pre-covid), in the Central Valley, among the populations surveyed by the ACT and dibs surveys? We estimate in equation 2 the correlates of using carpool or vanpool as the primary commute mode in our combined survey sample using a logit model. Table 3.12 presents findings with coefficients transformed to odds ratios.

(2) $Carpool\ is\ Primary\ Mode = \alpha + \beta_1 * Commute\ Distance + \beta_2 * Car\ Availability + \beta_3 * Current\ Work\ Arrangement + \beta_4 * Income\ Category + \beta_5 * Age\ Category + \beta_6 * Occupation\ Category + \varepsilon$

Similar to the results above, commute distance as well as employment in government / civil service and construction, utilities, and warehouse sectors are positively associated with carpooling as a primary mode, among our sample. The occupation findings indicate that government and construction /

warehouse sector workers have nearly 3 times the odds of carpooling than the all other occupation category. Car availability at the household is also strongly positively correlated with carpooling – with 10 times the odds of carpooling as with carless households. The highest income category (annual income greater than $150,000), which is more than double the median for these counties, has a 1/3 lower odds of carpooling than respondents in the below $50,000 category.

Note also that the survey binary is statistically significant, with dibs respondents having 1/3 the odds of ACT respondents of having carpool as the primary mode. This is likely to be a function of the sample. Running the same regressions on the ACT survey sample only gives the same set of statistically significant variables and magnitudes.

Table 3.12. Shared Mobility and the Pandemic

Dependent Variable: Carpool / Vanpool is primary commute mode (yes = 1, no = 0)	Odds Ratio	Std. Err.	z	P>z
Distance (miles) from Home to Work	1.01	0.00	2.73	0.01
Any Cars at Home? (No is baseline)	10.33	10.96	2.20	0.03
Current Work Arrangement (Full time at office is baseline)				
part-time	0.51	0.23	-1.49	0.14
fully remote	0.65	0.23	-1.21	0.23
Income (<$50K is baseline)				
$50-75K	0.75	0.35	-0.61	0.54
$75-100K	0.61	0.31	-0.98	0.33
$100-150K	0.85	0.40	-0.34	0.73
>$150K	0.34	0.18	-2.07	0.04
Age (<35 y.o. is baseline)				
35-44	1.56	0.74	0.93	0.35
45-54	1.44	0.71	0.74	0.46
55+	1.01	0.47	0.03	0.98
Occupation (All Other is baseline)				
Government/Civil Service	3.26	1.72	2.24	0.03
Health and Education	0.66	0.41	-0.67	0.50
Construction, Utilities, Warehouse	2.65	1.58	1.63	0.10
Business/financial/tech	1.40	0.89	0.52	0.60
Survey (ACT is baseline)	0.31	0.15	-2.43	0.02
Constant	0.03	0.03	-3.02	0.00
# of Observations	280			
Pseudo R-squared	0.13			
Prob>chi2	0			

Table 3.13. Employment by Industry Classification for Study Region Counties in September 2021
(California EDD Department CES
https://www.labormarketinfo.edd.ca.gov/cgi/dataanalysis/AreaSelection.asp?tableName=ces)

	San Joaquin	Stanislaus	Merced	California
Government/Civil Service	16%	14%	22%	14%
Health and Education	14%	18%	12%	16%
Construction, Utilities, Warehouse	34%	10%	8%	23%
Business/Financial/Tech	12%	11%	7%	24%
All Other Industries	24%	47%	52%	23%
Total Employment (persons)	271,600	195,800	89,000	17,362,500

Findings on Shared Mobility

What do we learn from these analyses? First, from a program level, the dibs program appears to be effective at decreasing driving alone and increasing carpool use among registrants, even with a very small sample and response rate, and controlling for demographic and socioeconomic characteristics. Upon the onset of Covid-19, dibs registrants did not significantly turn back toward driving alone or away from carpooling. Thus, among the population it serves, the program can be considered “sticky” in terms of travel behavior and mode choice. Moreover, more than half of respondents who indicated an increase in carpool / vanpool use after having registered for dibs, increased use up to 5 or more days per week, suggesting a wholesale switch in commute mode, generally away from driving alone.

Second, the dibs program and carpool / vanpool use more generally appear to be more prevalent in two industry sectors: government / civil service and construction / utilities / warehouse, which together make up half of San Joaquin County’s workforce and 24% and 30% of Stanislaus and Merced Counties’ workforce. It is possible that the nature of these types of work are more amenable to a carpool / vanpool setup. Both types of work are place-based, with work having stable hours and stable locations for many government services, warehouses, utilities, and in some cases construction sites. Or, the dibs service is specifically designed for industries like these – large regional employers (like county, state, or federal government offices; warehouse clusters; power plants) – or that the program has been more heavily marketed toward such users.

Third, remote work during the pandemic – and the lack of need to commute – were least prevalent among the same employment sectors (government, construction) that indicated highest carpool use. Hence, these jobs were much more likely to continue in place and/or have an “essential designation”, potentially explaining the success of dibs and similar programs in retaining carpool use during the pandemic. Higher income respondents were also more likely to work remotely, in line with other findings (Brynjolfsson et al. 2020, Yilmazkuday, 2020; Srichan et al., 2020, Baker et al., 2020)

Chapter 4: Commuting During and after COVID-19

This study analyzes the effects of evolving policy interventions in California, one of the states with the earliest and strictest set of orders. The analysis relates policy changes to Zip Code-level socioeconomic composition to better understand variation across income and industry categories.

Data

Travel Data

The analysis focuses on the variation in trip generation at the Zip Code level. We used data from StreetLight InSight® to estimate the daily trip generation out of Zip Codes in the study area. StreetLight is a private firm specializing in mobility metrics and analysis, using Global Positioning System data from phones to create measures of flow between locations. The platform provides information about travelers' origin and destination, travel distance, and travel purpose, and has gone through extensive validation using transportation data. The data is available from 2016 and is updated monthly.

We used the platform's Origin-Destination capabilities to estimate the daily total number of trips out of every Zip Code during peak AM time (6am-10am) and for all home-based work trips (excluding weekends and national holidays). Home-based work trips were estimated by StreetLight's own Location-Based Services algorithm. The two definitions serve as proxies for commute trips and offer a more transparent and easier definition for replication. The definitions also address the shifting commuting pattern over the course of the pandemic. Data have shown a flattening of peak congestion in the morning without a decrease in the overall number of trips in the later phases of the pandemic. This flattening suggests that many workers retained some flexibility for when they drive, which may muddle the connection between peak AM trips and commuting (Smith, 2021).[1]

The license for these data limits the number of included geographic units available to the research team. We, therefore, use the Zip Code Tabulation Area (ZCTA) as the main unit of analysis. ZCTA is the U.S. Census equivalent to the U.S. Postal Service's (USPS's) 5-digit zip codes (U.S. Census Bureau, 2018). They provide a next step up from the smaller census tract that allows us to maximize coverage without sacrificing geographic specificity and the ability to link to other data sources. Unlike other census geographies, however, Zip Codes have no standard population targets and vary in both population and area. The analysis includes only ZCTA that intersect urbanized areas or have a population over 3,000.

COVID-19 Data

The analysis integrates both the prevalence of COVID-19 throughout the period and the changes in policy. The California Department of Public Health provides access to daily counts of COVID-19 cases, deaths, and testing at the county level since February 1, 2020. The data is not reported on weekends or state holidays. The vaccine progress dataset provides weekly updates on full, partial, and at least one vaccine dose coverage rate by ZCTA for the whole state since January 5, 2021.

[1] These patterns were noted after significant recoveries in trip volume were recorded, most of which happened after our study period.

The Blueprint for a Safer Economy[2] is the main policy tool California has used to guide counties in implementing restrictions for a safe progression to reopen business and activities during the pandemic. The framework assigned one of four safety tiers to each county weekly. Tier 1 is the widespread disease transmission stage (least safe to re-open), tier 2 is substantial, tier 3 is moderate, and tier 4 is minimal (most safe to re-open). The state of California announced this policy on August 31, 2020, and retired it on June 15, 2021, because the whole State had met the criteria to fully reopen. All datasets are publicly available on the California Open Data Portal.

Socioeconomic Data

COVID-19 policies (and prevalence) did not affect everyone equally. We use Census data from U.S. Census Bureau's American Community Survey (ACS) 5-year average for the years 2015-2019 to examine the interactions between policy and demographics. The main variables focus on economic status as measured by income and occupation. We also include other variables that stand out in the literature: race and ethnicity, employment, reliance on public transit, housing tenure, and educational attainment. We add data on the 2020 election to capture the political leaning of ZCTA. The 2020 Election data from the Voting and Election Science Team at the University of Florida and Wichita State University is available at the precinct level for all States. We use the presidential election result in California and aggregate precinct-level data into ZCTA-level data (see Appendix D). The ratio of Biden to Trump votes is one potential proxy for voters' attitudes toward candidates' COVID-19 policies. The dataset is publicly available on the Harvard Dataverse.

We complement data on the demographic composition of ZCTA with contextual variables. Existing research shows that density and how urban a place was relevant to how people adjusted their behavior during the pandemic. We include population density as a measure of development compactness. We also calculate the distance between the population-weighted median center of every ZCTA to the closest job center and the city hall of all principal cities.[3] Table 4.1 shows summary statistics for each variable.

[2] Blueprint for a Safer Economy. California Department of Public Health https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/COVID-19/COVID-1919CountyMonitoringOverview.aspx

[3] Job centers are defined as block with employment density over 5,000 per km^2 within a job cluster larger than 10,000 total jobs. We included the city hall location of all cities that were listed in the name of each metropolitan statistical area (MSA). For example, the San Francisco MSA lists San Francisco, Oakland, and Fremont.

Table 4.1. Summary statistics of variables

Category	Variable	Obs.	Mean	Std. dev.
Trips	Peak AM trips	225,178	13,701.38	10389.99
	Home-based work trips (all day)	225,178	14,060.22	10350.49
	Average travel distance (mile)	225,178	2.13	0.37
COVID-19	Daily COVID-19 cases per 100,000	225,178	10.36	17.58
	% Population fully vaccinated	225,178	0.11	0.24
Demographics	Total population	225,178	30,761.41	19,491.63
	Median household income	222,913	98,591.68	43,344.08
	% Asian	224,346	0.20	0.17
	% Black	224,346	0.06	0.07
	% Hispanic	224,346	0.26	0.18
	% Commute by public transit	223,963	0.08	0.10
	% Renter	223,459	0.42	0.20
	% Below poverty	224,346	0.11	0.09
	% College graduated	224,346	0.41	0.22
Occupation	Total employment	225,178	15,212.58	9,940.32
	business/science/arts	225,178	0.45	0.18
	Service	225,178	0.16	0.07
	Sales and office	225,178	0.19	0.05
	natural resource/construction	225,178	0.09	0.07
	production/transportation	225,178	0.11	0.07
2020 presidential election	Total votes	216,075	14,800.94	8,834.05
	Biden votes	216,075	10,209.13	6,507.57
	Trump votes	216,075	4,269.06	3,513.66
	Biden/Trump ratio	216,075	3.95	4.65
Neighborhood	Population density	224,346	2,057.28	2,780.82
	Distance to nearest job center	224,346	9,249.98	14,273.77
	Distance to nearest city hall of principal/secondary city of each MSA	224,346	15,856.76	14,482.39

Methodology

COVID-19 stages

Figure 4.1 compares the overall trend of workday (without weekends and national holidays) peak AM traffic volume and COVID-19 cases per 100,000 by county from March 4, 2019 to September 25, 2021.[4] The first confirmed case of COVID-19 in California was on January 26, 2020 and the number jumped to two digits around March 6th to 9th in the Bay Area counties. Although California did not issue a statewide shelter-in-place order until March 19, 2020, the data show a cliff-like drop in peak AM volume as early as March 10, 2020. Therefore, we use this day as the cutoff point of the COVID-19 outbreak.

Peak AM volume decreased more in the Bay Area than in the Central Valley initially. One possible reason for the quick response is that many tech companies had already announced remote working options to their employees in late February 2020. In contrast, workers in other industries might have had to continue commuting until the state-wide emergency order was issued.

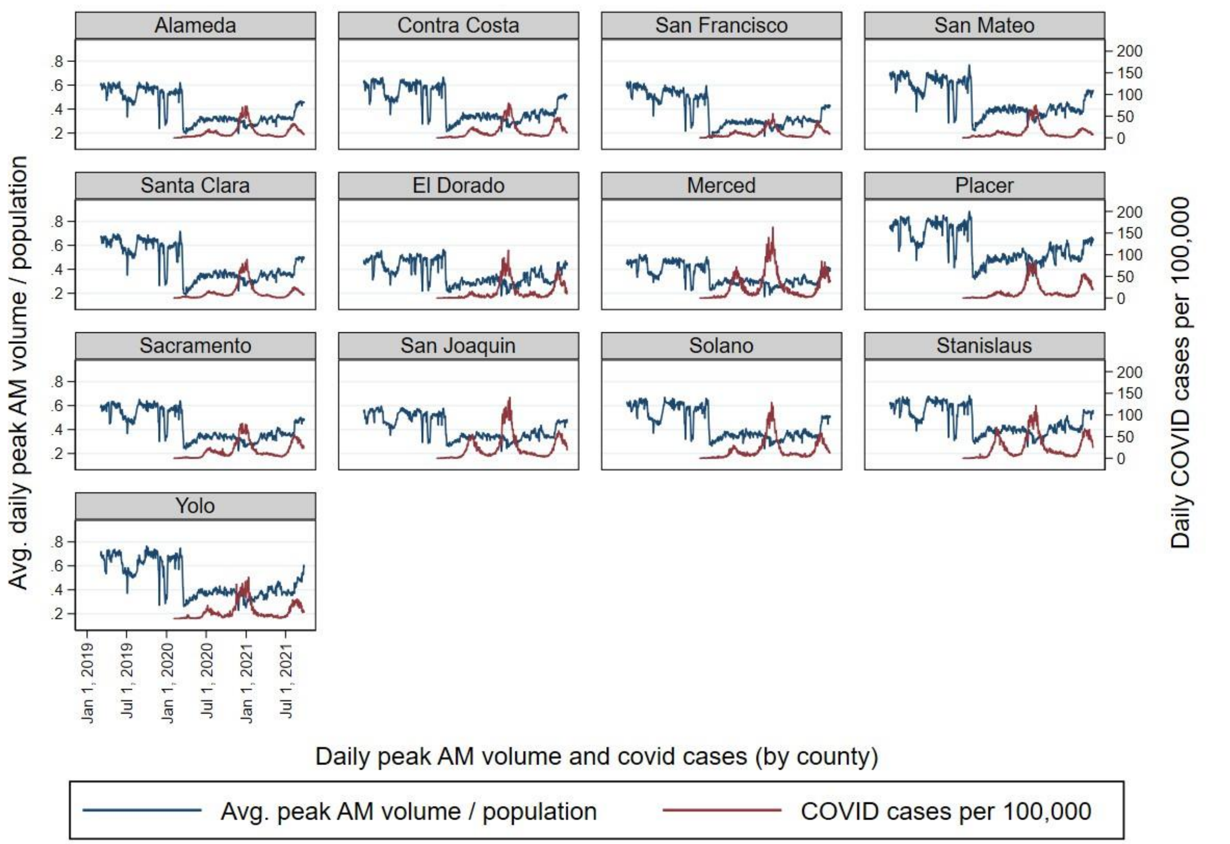


Figure 4.1. Daily peak AM traffic volume and COVID-19 cases

[4] See Appendix for home-based work trip trends by county over time

In light of the public health emergency, California Governor Gavin Newsom issued a broad stay-at-home order on March 19, 2020, for all residents outside of those working in the 16 federally-determined critical infrastructure sectors.[5] By August 31, 2020, the state government via the California Department of Public Health enacted the Blueprint for a Safer Economy to begin to loosen stay-at-home restrictions county by county. Table 4.2 provides an example of initial reopening tiers, based on new COVID-19 cases, test positivity, health equity, and eventually vaccine equity. Reopening tiers ranged from widespread risk (purple, tier 1) to minimal risk (yellow, tier 4). The lower the risk, the higher the possible resumption of in-person activity in the county. Counties' tiers were evaluated weekly; counties could advance to a less restrictive tier after 3 weeks in the prior tier.[6] The Blueprint tiers were in effect until June 14, 2021, at which point all counties were reopened to economic activity.

Table 4.2. Blueprint for a Safer Economy initial tier example[7]

Tier Level	New Cases per 100,000*	Positive Tests
Widespread Purple	More than 7	More than 8% testing positivity rate
Substantial Red	4 to 7	5 - 8%
Moderate Orange	1 to 3.9	2 - 4.9%
Minimal Yellow	Less than 1	Less than 2%

* Case numbers are adjusted up or down based on testing volume above or below the state median.

Trip volumes show a modest correlation to the COVID-19 case rate during the first half of 2020 and the Blueprint period. Peaks in transmission in the summer of 2020 and in January 2021 did not correspond to proportional decreases in trip volume. Times of lower transmission in the first halves of 2020 and 2021 do show a timid recovery in trip volume. Significant recovery was not visible until June 2021 when restrictions were lifted statewide.

A big part of this relaxation was the introduction of the COVID-19 vaccine. Figure 4.2 shows the weekly vaccination progress in the Bay Area and Central Valley California started to deliver vaccines on January 1, 2021. However, the majority of the general public did not receive their first dose until March 2021. The share of the population fully vaccinated reached 38% in the Bay Area and 30% in the Central Valley by late April 2021, while by that same date the share partially vaccinated (with one dose) was 20% and 10% respectively. By the end of June 2021, 70% of the Bay Area residents were fully vaccinated, 20 percentage points more than the Central Valley share.

[5] State of California Executive Order N-33-20. https://www.gov.ca.gov/wp-content/uploads/2020/03/3.19.20-attested-EO-N-33-20-COVID-19-HEALTH-ORDER.pdf
[6] California's Color-Coded County Tier System. California Department of Public Health. https://emd.saccounty.gov/EMD-COVID-19-Information/Documents/California-Color-Coded-Tier-System--en.pdf
[7] California's Color-Coded County Tier System. California Department of Public Health. https://emd.saccounty.gov/EMD-COVID-19-Information/Documents/California-Color-Coded-Tier-System--en.pdf

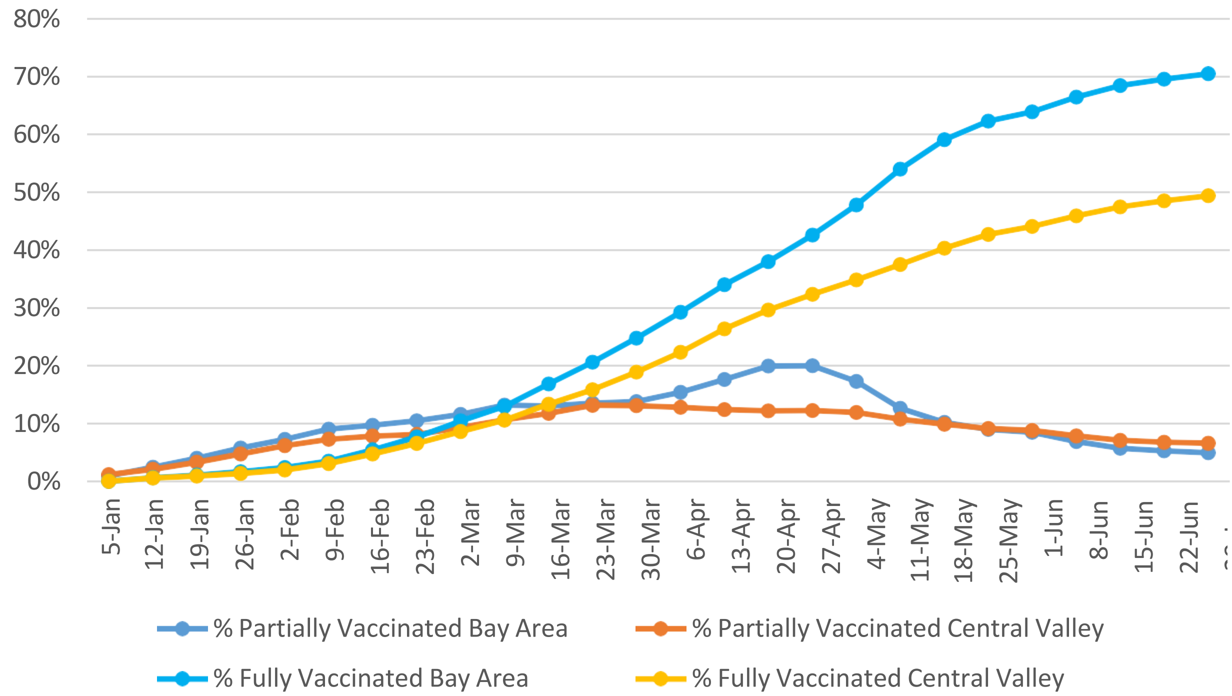


Figure 4.2. Weekly vaccination progress from January to June 2021

We defined five stages to analyze changes in trip volume based on the chronology of the pandemic and policy interventions in California:

- Stage 0. Pre-COVID-19: 03/04/2019 – 03/09/2020. This period is a full year before the COVID-19 outbreak, which can serve as a baseline representing pre-pandemic traffic patterns.
- Stage 1. COVID-19 outbreak: 03/10/2020 - 08/30/2020. This period is between the first day of the traffic decline and the announcement of the Blueprint framework.
- Stage 2. Start of Blueprint: 08/31/2020 - 12/31/2020. This period is between the launch of the Blueprint framework and the start of vaccination.
- Stage 3. Start of Vaccination: 01/01/2021 - 06/14/2021. This period is between the start of vaccination and the retirement of the Blueprint measurement.
- Stage 4. Fully Reopen: 06/15/2-21 - 09/25/2021. This period is between the lifting of all statewide restrictions (retirement of Blueprint) and the last day of the collected data

Descriptive Analysis

Table 4.3 shows the average number of peak AM trips per ZCTA by COVID-19 stage and Blueprint tiers in our study area (home-based work trips follow a similar pattern, see Appendix C). In the pre-COVID-19 period (stage 0), the average peak AM trips per ZCTA is 17,751. This number dropped to 10,402 (-40% from pre-COVID-19) after COVID-19 outbreak (stage 1) and remained similarly low in stages 2 (10,606) and 3 (10,692). After fully reopening on June 15, 2021, the average peak AM trips per ZCTA rebounded to 13,012 (73% of the pre-COVID-19 level). When looking at Blueprint tier assignments, in stage 2 (after the launch of Blueprint but before vaccine distribution) peak AM traffic volume between tiers 2, 3, and 4 was not much different. However, in stage 3, the average peak AM traffic volume of tier 4 is much higher than those in tier 1. Traffic volume recovery began with vaccine rollout and differed by location based on the degree of reopening.

Table 4.3. Average peak AM traffic volume per ZCTA by COVID-19 stages and blueprint tiers

COVID-19 Stages	Statistics	No tier assignment	Tier 1: Widespread Risk	Tier 2: Substantial Risk	Tier 3: Moderate Risk	Tier 4: Minimal Risk	Total
Stage 0: Pre-COVID-19	**Mean**	**17,751**	**.**	**.**	**.**	**.**	**17,751**
	Std. dev.	12,320	.	.	.	.	12,320
Stage 1: COVID-19 outbreak	**Mean**	**10,402**	**.**	**.**	**.**	**.**	**10,402**
	Std. dev.	7,393	.	.	.	.	7,393
Stage 2: Blueprint start	**Mean**	**.**	**9,937**	**11,119**	**11,698**	**10,416**	**10,606**
	Std. dev.	.	6,951	7,459	7,729	5,729	7,276
Stage 3: Vaccine rollout	**Mean**	**.**	**9,271**	**11,637**	**11,537**	**12,425**	**10,692**
	Std. dev.	.	6,440	7,991	7,811	7,266	7,380
Stage 4: Fully reopen	**Mean**	**13,012**	**.**	**.**	**.**	**.**	**13,012**
	Std. dev.	9,214	.	.	.	.	9,214
All Stages	**Mean**	**14,957**	**9,595**	**11,379**	**11,586**	**12,121**	**13,701**
	Std. dev.	11,174	6,702	7,734	7,786	7,091	10,390

Table 4.4 shows the average number of daily COVID-19 cases per 100,000 persons and the share of the population fully vaccinated per ZCTA during all five stages. Average daily COVID-19 cases were the highest (26.44) in stage 2; the case rate decreased to 16.16 in stage 3 and increased to 21.96 in stage 4. The average share of the population fully vaccinated is 0.25 in stage 3 and 0.64 in stage 4.

Table 4.4. Summary statistics of COVID-19 variables by COVID-19 stages

COVID-19 Stages	Daily COVID-19 cases per 100,000		% Population fully vaccinated	
	Mean	Std. dev.	Mean	Std. dev.
Stage 0: Pre-COVID-19	0.02	0.12	-	-
Stage 1: COVID-19 outbreak	8.75	10.27	-	-
Stage 2: Blueprint start	26.44	26.69	-	-
Stage 3: Vaccine rollout	16.16	19.96	0.25	0.23
Stage 4: Fully reopen	21.96	15.91	0.64	0.17

Regression Analysis

Model Specification

Daily traffic volume dropped precipitously throughout the study area in March 2020, just as California began to have double-digit COVID-19 case rates and issued a statewide shelter-in-place order (Table 2). As of September 2021 (latest Streetlight data available), neither workday peak AM traffic volumes nor all daily home-based work trip volumes had returned to pre-pandemic averages. This paper tests 4 broad hypotheses regarding the impact of the COVID-19 pandemic on commute volume.

Health risks and interventions: We test the hypothesis that traffic volumes followed COVID-19 case rates as people were afraid of catching and transmitting the virus. Once a health intervention (the vaccine) was available, people let down their guard and traffic volumes reverted to pre-pandemic norms.

Closing the economy: We test the hypothesis that traffic volumes responded to government action which shut down in-person economic activity for certain sectors of the economy and that traffic volumes increased following the economy reopening.

Differential impact of stay-at-home orders, health risks, and interventions by income and occupation: We test the hypothesis that travel behavior and response to health and policy interventions followed income and occupation characteristics. Higher-income households and knowledge-intensive workers were, in this hypothesis, more flexibly able to adjust their commute behavior to engage in social-distancing order during COVID-19. Lower-income households and essential workers were less flexibly able to change the way they commuted and end up with less participation in the social-distancing order.

Unpacking these hypotheses, we believe, sheds light on the continued evolution of travel as pandemic recovery continues and provides guideposts for future pandemics or similar-scale economic disruptions.

We set up a regression model to capture the change in trip volume across socioeconomic groups in different COVID-19 periods. The focus is on estimating the interaction between income, occupation, travel distance, and the five stages we defined while controlling for a variety of ZCTA characteristics. We use OLS regression with time-fixed effects to estimate traffic volume across the population of ZCTAs. Time-fixed effects are applied to control for the variance that is constant across observations but varies over time. We also use robust standard errors to allow non-constant variance across observations. The regression model is defined as follows:

$$Vol_{it} = \beta_0 + \beta_1 C_j + \beta_2 \sum (C_j * I_i) + \beta_3 \sum (C_j * O_i) + \beta_4 \sum (C_j * D_{it}) + \beta_5 \sum (C_j * bp_{it}) + \beta_6 w_{it} + \beta_7 v_{it} + \beta_8 x_i + \beta_8 n_i + \varepsilon_{it}$$

The dependent variable, Vol_{it}, is two traffic volume measures: daily peak AM trips and home-based work trips from ZCTA *i*, for day t. We run the equation with daily fixed effects, to control the daily variance that is constant across all ZCTAs. C_j indicates one of five COVID-19 stages. The pre-COVID-19 time period dummy is the omitted category. D_i is the average travel distance of the traffic departing/leaving ZCTA *i* for day t. w_{it} represents the daily COVID-19 cases per 100,000 in ZCTA *i*, for day t. COVID-19 cases are originally reported daily at the county level. Each ZCTA within the same county is assigned with the same county-level daily covid rate. v_{it} represents the share of the population fully vaccinated in ZCTA *i*, for day t. The vaccination rate is originally reported weekly at the ZCTA level and so each day has the vaccination rate for the ZCTA for the week. bp_{it} indicates the assigned blueprint tiers of ZCTA *i*, for day t. Blueprint tiers are originally reported weekly at the county level, and weeks are assigned to days.

All socioeconomic variables are measured pre-COVID-19. I_i indicates the median household income of ZCTA *i*. ZCTA income is divided into five categories: <$25k (omitted category), $25-49k, $50-74k, $75-99k, and > $100k. O_i represents the ratio of the number of workers for each occupation to the number of workers in sales and office occupations in ZCTA *i*. ACS provides the number of workers (civilian employed population 16 years and over) under five occupation types: 1) management, business, science, and arts occupations, 2) service occupations, 3) sales and office occupations, 4) natural resources, construction, and maintenance occupations, and 5) production, transportation, and material moving occupations. Occupation categories of the 2015-2019 ACS are based on the 2018 Standard Occupational Classification (SOC) system. According to the U.S. Bureau of Labor Statistics, SOC describes the occupation held by individuals but not the industries (NAICS codes) in which people work. We choose sales and office occupation as the baseline for normalization because the share of workers in sales and office varies the least across ZCTAs among all five occupation categories.

To assess the impact of health and policy interventions across incomes and occupations, we interact COVID-19 stage (C_j) with ZCTA income (I_i) and occupation (O_i). We interact COVID-19 stages with Blueprint tiers (bp_{it}) to separate the role of vaccination versus economic reopening. We also interact COVID-19 stage with ZCTA average distance to test whether locations, where people tend to drive greater distances, were more resilient on commute trips than places with shorter commutes.

x_i is a set of pre-COVID-19 demographic control variables at the ZCTA level which may affect traffic volume and/or response to health or policy interventions, including total population, total employment, percentage of Asians, African Americans, and Latinos, percentage of workers commuting by public transit, percentage of renters, percentage of population below poverty, percentage of people with a college degree or above, and the ratio of Biden to Trump votes in the 2020 presidential election. n_i is a set of variables to control for the geographic context of ZCTA, population density, distance from the closest job center, and distance to the closest primary city center.

Regression Results

Table 4.5 shows the regression results for all four commute traffic models with daily fixed effects. Models 1 and 2 focus on examining only the COVID-19-related variables. Models 3 and 4 run the full equation with all explanatory variables. The dependent variable for models 1 and 3 is peak AM volume, which we consider our primary model. The dependent variable for models 2 and 4 is the StreetLight-defined home-based work trip, which serves as a robustness check. The results of the explanatory variables are discussed below.

COVID-19

Model 1 focuses on the relationship between Peak AM traffic and COVID-19-related variables. Using pre-COVID-19 peak AM traffic volume (19,663) as the baseline, ZCTA peak AM trips decreased by 40% in stage 1 (-8,060), and stage 2 (-8,741). The number remained low (-8,557) in the first 6 months since vaccine distribution. The peak AM traffic grew back to 80% of the pre-COVID-19 level in the fully reopened stage 4 (-3,904). Similar patterns are seen in models 2, 3, and 4.

The COVID-19 rate (daily COVID-19 cases per 100,000) is significantly negatively related to peak AM and home-based work trips in all four models. Fully vaccination rate is significantly positively related to peak AM and home-based work trips in three models (Model 1, 3, and 4). The magnitude of the coefficient of the COVID-19 rate is relatively small, while the full vaccination rate is relatively large when compared with other explanatory variables. In models 3 and 4, results indicate that a one percentage point increase in the share of the population fully vaccinated is associated with an increase of 60-80 (depending on the model) peak AM or home-based work trips per day.

When looking at Blueprint assignment in stage 2, ZCTA traffic volumes in the riskiest tier (tier 1) ZCTAs decreased most (-8,349), followed by tier 2 (-7,838) and then tier 3 (-7,390), compared to the lowest risk tier (tier 4). However, in stage 3, after vaccines were available, the difference between each tier became less obvious. In the COVID-19-focus model 1, peak AM traffic decreased by 11,319 for tier 1, 9,293 for tier 2, and 9,375 for tier 3. With the full equation of model 3, peak AM traffic decreased by 12,926 for tier 1, 12,537 for tier 2, and 13,186 for tier 3.

Lower COVID-19 rates and higher vaccination rates provided workers more confidence to go back to work and the higher blueprint tiers allowed more business and activities to reopen. The regression results suggest that vaccination progress is most influential to peak AM traffic and home-based work trips compared with Blueprint assignment and COVID-19 case rate.

Travel Distance

ZCTAs with Peak AM and home-based work trips of longer average travel distance generated fewer peak AM and home-based work trips during COVID-19. ZCTAs with shorter peak AM and home-based work trip distances recovered more than longer peak AM and home-based work trip ZCTAs in the post-vaccine period. In stage 0, the pre-COVID-19 period, one additional mile in average ZCTA travel distance is associated with -3,186 peak AM trips departing from a ZCTA. One mile addition on average travel distance is associated with +766 peak AM trips departing from a ZCTA in stage 1. This number gradually decreased in stage 2 and stage 3. In the fully opened stage 4, one-mile addition on average travel distance is associated with -207 peak AM trips departing from a ZCTA.

Income

In the pre-COVID-19 period (stage 0), ZCTAs with higher median household income produced more peak AM and home-based work trips than ZCTAs with lower median household income. Based on the result of model 3, ZCTAs with median household income >$100k are associated with 3,949 more peak AM trips than ZCTAs with median household income <$25k in stage 0.

Throughout COVID-19 (stages 1-4), ZCTA median household income was negatively associated with traffic volume. ZCTAs in the highest income band (>$100k) had the largest traffic volume decreases, relative to the lowest income band (<$25k) (Figure 5). These highest income ZCTAs decreased traffic volume by a factor of two relative to those with a median income of $25-100k. In the post-vaccine period (stages 3 and 4), peak AM trips in ZCTAs with lower median household income recovered more than ZCTAs with higher median household income.

This result is in line with findings from previous research that higher-income households have higher flexibility to work-from-home and are more likely to engage in social-distancing orders, while lower-income households are less likely to engage in social-distancing orders due to fear of losing income (Yilmazkuday, 2020; Srichan et al., 2020, Baker et al., 2020, Austrian et al., 2020).

Occupation

Before the COVID-19 outbreak, ZCTAs with higher ratios of service workers to sales / office workers had larger traffic volumes, while those with higher ratios of natural resources, construction, and maintenance had the lowest traffic volumes.

Throughout COVID-19, ZCTAs with higher ratios of natural resource / construction relative to sales and office had increased traffic volumes (Figure 4.3). The results indicate that, although primary and secondary industries generate fewer commutes pre-COVID-19, the commutes in those industries were most likely to remain during COVID-19. In contrast, ZCTAs with higher ratios of service and production / transportation occupations had the largest decrease in peak AM traffic volume. The reason for such decline could relate to fact that service activities involve a lot of face-to-face interactions, which was highly restricted during the COVID-19 outbreak. Interestingly, the home-based-work results show service occupations more in line with sales and office, potentially indicating that service workers still commuted, but shifted their commutes outside of the peak AM time window. Business / science / arts traffic volumes were largely in line with those for sales and office occupations. Occupations associated with natural resources / construction / maintenance, had relatively higher peak AM volume during COVID-19.

In post-vaccine period, the peak AM trips of service occupations bounced back the most. The relative peak AM volume of service occupation grew back in stage 4. The peak AM trips of natural resources, construction, and maintenance occupations remain high in stage 3. The comparative difference between them and other tertiary industries went closer to the pre-COVID-19 level in stage 4.

Political Orientation and Location

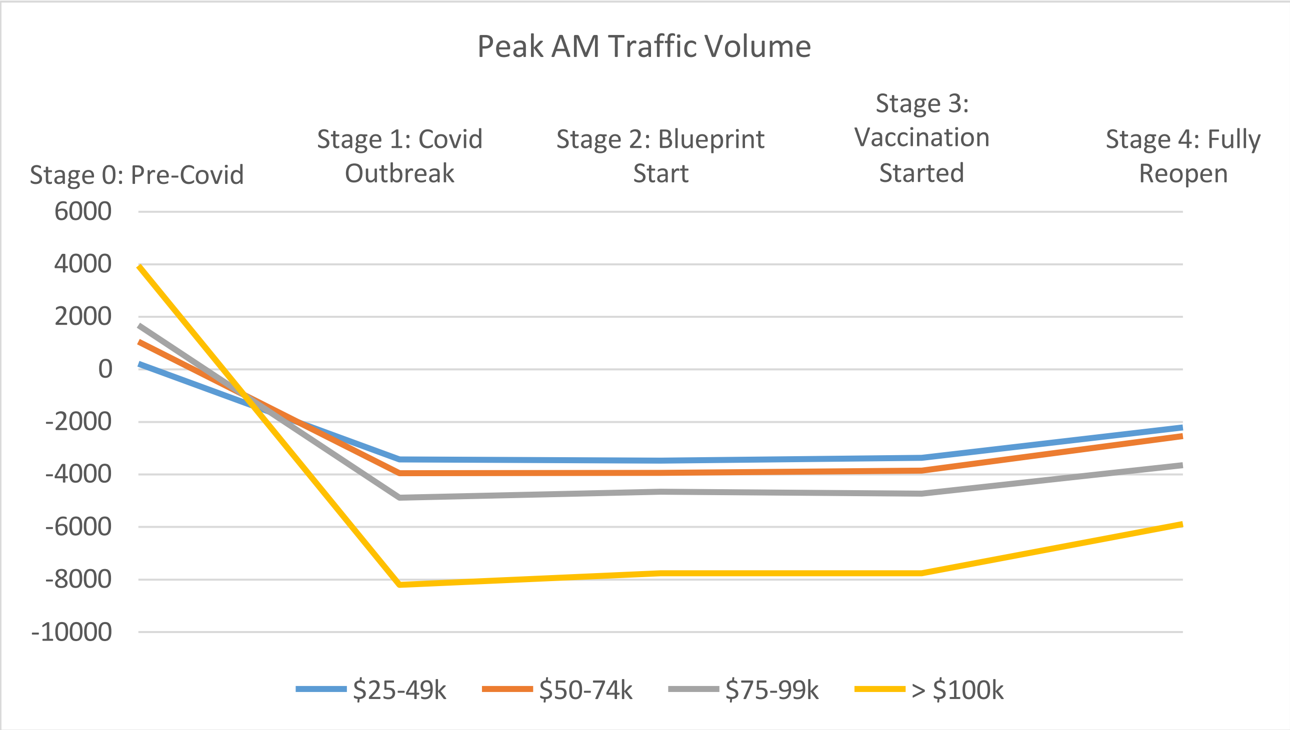
ZCTAs with more Biden votes than Trump votes were negatively associated with traffic volume. However, magnitudes were relatively low: doubling the Biden to Trump ratio was associated with a decrease in 136 – 182 daily trips (models 3 and 4). We also controlled for population density, which may be correlated with partisan voting in California (Figure 4.4). The population density was also negatively associated with traffic volume, with a 1000 person / km increase estimated to decrease the ZCTA trips per day by 671 – 797 (models 3 and 4), in line with Hamidi and Zandiatashbar (2021). The lower-density, Trump-voting ZCTAs also may be further from job centers and downtowns, in our study area. Distance to the nearest job center was not strongly statistically significant in the model. Distance to downtown (principal city of each MSA) was statistically significant, but signs diverged between peak AM and home-based-work trips. The magnitudes were low as well (a 100-mile distance was associated with a +0.7 peak AM trips and -1.4 home-based work trips). Taken together, partisan voting and population density were more important in explaining ZCTAs traffic volumes than its location within a regional hierarchy. Yet, partisanship and population density magnitudes were generally lower than those of income, occupation, and COVID-19-related variables.

Other Demographics Controls

ZCTA population, employment, and renter share are significantly positively related to peak AM and home-based work traffic volume. Magnitudes are on the order of income and occupation effects for population size (a 10,000 person population increase is associated with +3550 daily trips) and is double that of employment. Every percentage point increase in renter share is associated with an increase of 50 – 120 trips (models 3 and 4). In essence, larger ZCTAs with higher employment maintained proportionately higher levels of economic activity and thus traffic volume. Higher college education shares were negatively correlated with traffic volume (1 p.p. increase led to 57 – 117 fewer trips (models 3 and 4).

Higher non-white proportions were negatively correlated with traffic volume. A one percentage point increase in African American share was associated with -114 – 139 daily trips, and for Hispanic share -29 – 40. Signs diverged for Asian share. Signs also diverged for public transit commute share: one percentage point increases were associated with 42 more peak AM trips but 69 fewer home-based work trips.

Figure 4.3: Estimated differences in trips per day by stage by income group, relative to lowest income ($0-25k group). All estimates shown are statistically significant at the p<0.001 level (see Table 4.5).



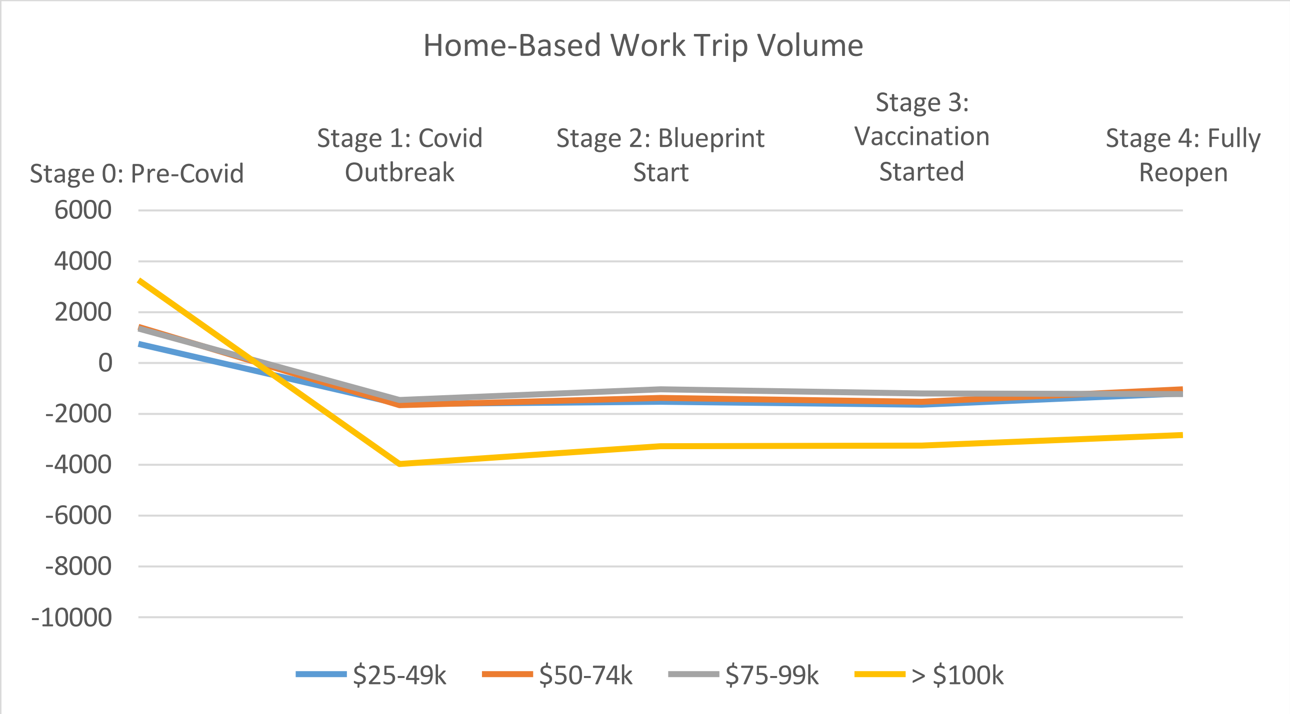
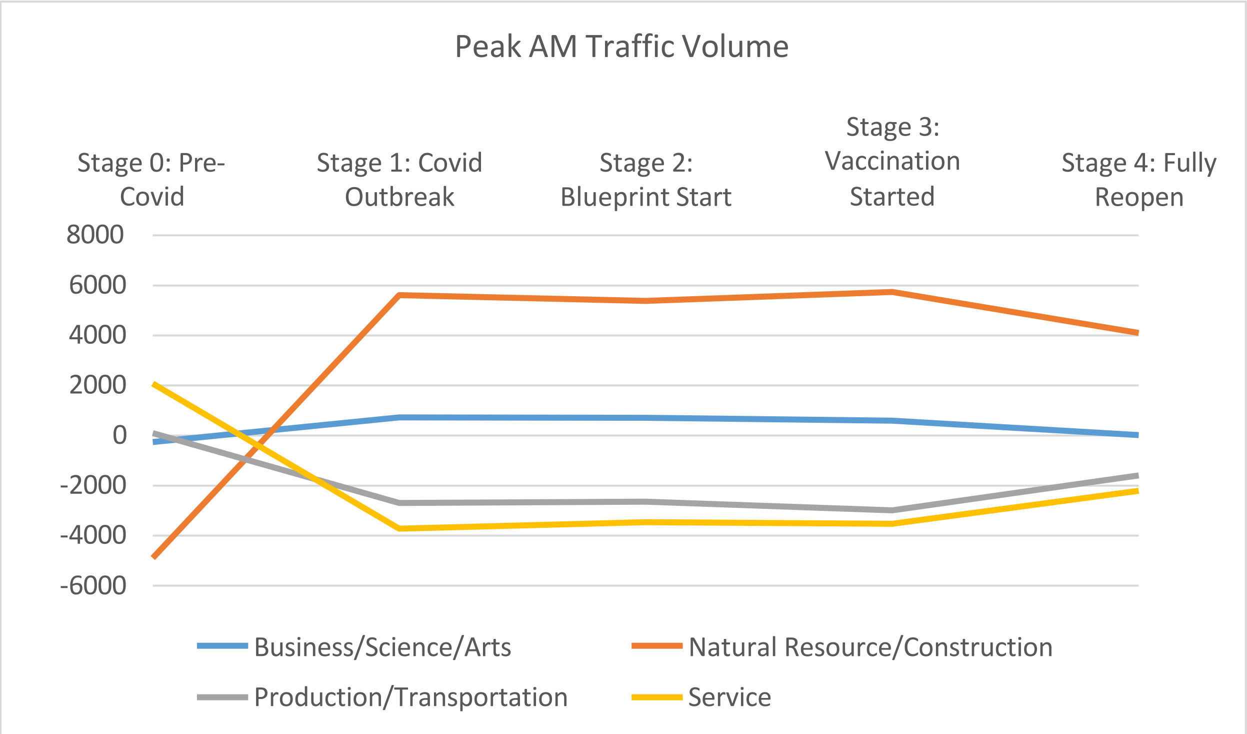


Figure 4.4: Estimated differences in trips per day by stage by ratio of occupation share to Sales / Office occupation share. All estimates shown are statistically significant at the p<0.001 level (see Table 4.5).



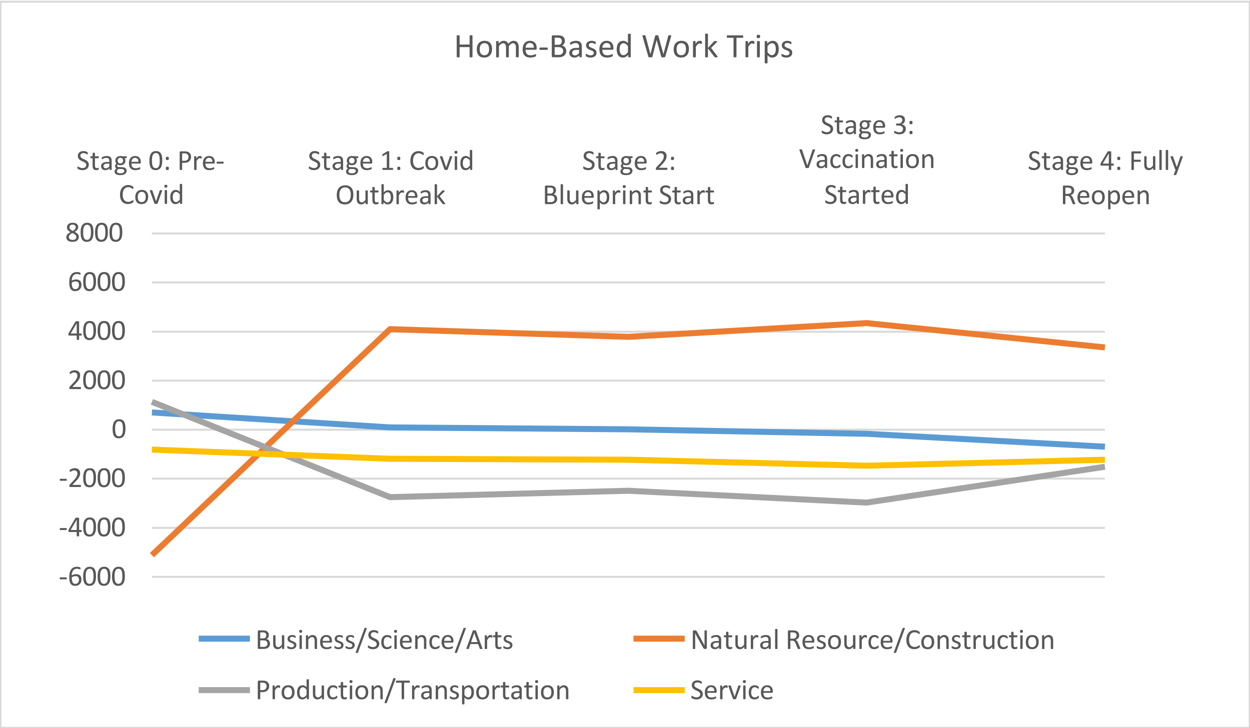


Table 4.5. Regression Results

Category	Description		w/ daily dummy			
Y=	Trips depart from origin ZCTA		(1) Peak AM vol	(2) HBW vol	(3) Peak AM vol	(4) HBW vol
COVID-19 stages (base=stage 0: pre-COVID-19: 03/04/2019 – 03/09/2020)	stage 1: COVID-19 (03/10/2020 - 08/30/2020)		-8060.226***	-7460.071***	-10842.089***	-11475.507***
	stage 2: blueprint started (08/31/2020 - 12/31/2020)		-8741.211***	-13451.860***	-12231.883***	-14466.963***
	stage 3: vaccination started (01/01/2021 - 06/14/2021)		-8556.899***	-5141.784***	-13498.543***	-13650.003***
	stage 4: fully reopen (06/15/2-21 - 09/25/2021)		-3904.365***	-708.866	-8841.179***	-7666.254***
Blueprint (base = Tier 4)	stage 2: blueprint started	Tier 1	392.515	3017.681***	-1166.199***	-1068.125***
		Tier 2	903.438**	2891.764***	-644.876**	-677.623**
		Tier 3	1351.034***	2663.431***	-202.736	-248.461
	stage 3: vaccination started	Tier 1	-2761.763***	-1817.589***	571.939***	1136.628***
		Tier 2	-735.693***	-104.335	960.922***	1421.195***
		Tier 3	-817.681***	-580.539**	312.421***	839.122***
COVID-19 rate	Daily COVID-19 cases per 100,000		-48.928***	-22.775***	-6.845***	-5.130***
Vaccination rate	% Population fully vaccinated		1103.296***	-865.724**	5825.835***	8096.134***
Travel distance	stage 0: pre-COVID-19	average travel distance (mile)			-3167.944***	-2640.057***
	stage 1: COVID-19	average travel distance (mile)			3933.523***	3140.006***
	stage 2: blueprint started	average travel distance (mile)			3750.625***	3013.545***
	stage 3: vaccination started	average travel distance (mile)			3445.740***	2697.748***
	stage 4: fully reopen	average travel distance (mile)			2960.550***	2240.538***
COVID-19 stages * Household income (base= stage 0: pre-COVID-19* income<$25k)	Stage 0: pre-COVID-19: (03/04/2019 – 03/09/2020)	$25-49k			215.614	751.312***
		$50-74k			1057.629***	1420.346***
		$75-99k			1681.957***	1355.806***
		> $100k			3948.505***	3265.386***
	stage 1: COVID-19 outbreak (03/10/2020 - 08/30/2020)	$25-49k			-3430.055***	-1612.644***
		$50-74k			-3952.431***	-1658.921***
		$75-99k			-4885.029***	-1455.767***
		> $100k			-8203.711***	-3973.885***
	stage 2: blueprint started (08/31/2020 - 12/31/2020)	$25-49k			-3474.090***	-1531.215***
		$50-74k			-3938.519***	-1370.208***
		$75-99k			-4662.672***	-1031.068***
		> $100k			-7757.594***	-3268.151***
	stage 3: vaccination started (01/01/2021 - 06/14/2021)	$25-49k			-3367.913***	-1640.151***
		$50-74k			-3858.299***	-1521.122***
		$75-99k			-4733.582***	-1200.881***
		> $100k			-7757.082***	-3253.247***
	stage 4: fully reopen (06/15/2021 - 09/25/2021)	$25-49k			-2215.647***	-1198.754***
		$50-74k			-2538.921***	-1041.368***
		$75-99k			-3651.314***	-1223.160***
		> $100k			-5892.300***	-2832.789***

Table 4.5. Regression Results (continued)

Category	Description		w/ daily dummy			
Y=	Trips depart from origin ZCTA		(1) Peak AM vol	(2) HBW vol	(3) Peak AM vol	(4) HBW vol
COVID-19 stages * Occupation (base=stage 0: pre-COVID-19*sales/office occupation)	Stage 0: pre-COVID-19: (03/04/2019 – 03/09/2020)	business/science/arts			-260.191***	703.088***
		Service			2077.297***	-810.852***
		natural resource/construction			-4895.189***	-5115.276***
		production/transportation			96.539	1134.659***
	stage 1: COVID-19 outbreak (03/10/2020 - 08/30/2020)	business/science/arts			724.097***	98.013***
		Service			-3722.524***	-1186.076***
		natural resource/construction			5613.993***	4103.209***
		production/transportation			-2701.373***	-2751.974***
	stage 2: blueprint started (08/31/2020 - 12/31/2020)	business/science/arts			704.407***	16.194
		Service			-3462.409***	-1226.726***
		natural resource/construction			5381.823***	3787.514***
		production/transportation			-2641.075***	-2483.401***
	stage 3: vaccination started (01/01/2021 - 06/14/2021)	business/science/arts			588.255***	-171.334***
		Service			-3522.479***	-1469.361***
		natural resource/construction			5737.538***	4344.664***
		production/transportation			-2989.464***	-2972.656***
	stage 4: fully reopen (06/15/2-21 - 09/25/2021)	business/science/arts			15.246	-692.417***
		Service			-2205.128***	-1220.838***
		natural resource/construction			4100.878***	3355.363***
		production/transportation			-1590.355***	-1516.116***
Demographic controls	Total population				0.356***	0.354***
	Total employment				0.166***	0.168***
	% Asian				-1176.731***	281.480**
	% Black				-11456.884***	-13917.372***
	% Hispanic				-2948.582***	-4028.874***
	% Commute by public transit				4245.198***	-6909.860***
	% Renter				5073.897***	12220.516***
	% Below poverty				-1096.524***	1410.232***
	% College graduated				-5727.721***	-11704.821***
	2020 presidential election	Biden/Trump ratio			-182.439***	-136.291***
Neighborhood controls	Population density				-0.671***	-0.797***
	Distance to nearest job center				-0.003	0.004*
	Distance to nearest city hall of principal city of each MSA				0.007***	-0.014***
Constant			19663.936***	18351.999***	15287.265***	13202.600***
Observations			215510	215510	206337	206337
R-squared			0.147	0.092	0.834	0.812
Adjusted R-squared			0.145	0.089	0.833	0.812

*** p<0.001, ** p<0.01, * p<0.05

Chapter 5: Conclusion

This project looks at the mobility patterns and experience in using alternative modes of transportation for disadvantaged workers during COVID-19 in California's Central Valley, a region with a large proportion of low income and nonwhite workers and a region where many commute long distances to jobs in the San Francisco Bay Area and elsewhere. We use three sources of data: (1) Survey data of vanpool and app-based rideshare users from the San Joaquin Council of Governments (SJCOG) dibs program, (2) survey data of commuters from the National Association for Commuter Transportation (ACT), and (3) traffic data from StreetLight, Inc., a mobility analysis firm, to document mobility patterns between the Central Valley and the Bay Area throughout the pandemic.

Our study helps gain an understanding of the state of alternative commuting solutions during the pandemic, through the lens of the carpool / vanpool users in the study region. Registering to be part of the dibs program generally shifted mode choice toward carpool / vanpool and away from driving alone pre-pandemic. During the pandemic, these mode choice shifts remained sticky, with no statistically significant shifts back to driving alone for this group. Our analysis was limited by a low sample size in this case.

Combining the dibs survey data with another external survey (ACT) in the study region provides further detail on the characteristics of households who continued to use rideshare during Covid-19. Households who lived further from their workplace, who had car access, or who were employed in Government / Civil Service or Construction / Utilities / Warehousing had higher likelihood of using carpool / vanpool modes during the pandemic, while households with annual incomes above $150,000 had lower likelihood. In many ways, these correlations describe the typical carpool / vanpool user in this region, pre-pandemic. This shows again the resilience of this mode even during a public health calamity like Covid-19.

We also contribute to the long-term understanding of commute behavior before, during, and after the pandemic. In the COVID and commute section, we examine traffic volume trends before and throughout the COVID-19 pandemic to understand key drivers of differences in traffic volume changes at a fine geographic level. We test the impact of health risks and interventions, economic shutdown and reopening policy, political ideology and metropolitan location, and differential impacts by income and occupation.

Traffic volumes dropped by 40% in the average ZCTA relative to pre-COVID-19 norms and had not fully recovered as of September 2021. Vaccine penetration was a necessary, but not sufficient driver in traffic volume recovery. California's Blueprint reopening policy which assessed county-level risk was of secondary importance: ZCTAs in lower risk counties had faster traffic volume recovery. Once people felt some level of health protection from the virus, they were guided by policy considerations like the economic reopening.

We found substantial differences in COVID-19's impact on traffic volume by income and occupation. As hypothesized, ZCTAs with the highest median incomes decreased peak AM and home-based-work trips the most, relative to those with the lowest median incomes. This persisted throughout the various COVID-19 stages, with low and moderate income ZCTAs recovering faster than high-income ones. ZCTAs with high natural resource and construction employment relative to sales and office saw large increases in traffic volume, likely as a result of essential designation and inability to work remotely. In contrast, ZCTAs with higher service and production / transportation ratios saw decreases in traffic volume. We also found that higher density ZCTAs, and those with a higher share of votes for Biden, generated fewer peak AM and home-based-work trips, although we did not interact either variable with the COVID-19 stage.

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Data Management Plan

***Note to PI**: <u>This section is required</u>: Data and schema must be submitted with final report. You can access our DMP instructions here*:
https://www.metrans.org/sites/default/files/PSR_DMP_Instructions.pdf

Products of Research
We used data from five sources, two of which can be released to the public and three of which, due to data confidentiality, cannot be released.

<u>Public data sources:</u>

1. California Department of Public Health, Open Data Portal (Covid cases, vaccination, and Blueprint for a Safer Economy data, at county level)
2. Census American Community Survey, 2015-2019 (socioeconomic data, at ZCTA level)

<u>Data with restrictions on data release</u>

1. Survey data of vanpool and app-based rideshare users from the San Joaquin Council of Governments (SJCOG) dibs program
2. Survey data of commuters from the National Association for Commuter Transportation (ACT)

Data release for both survey data requires further confirmation with the San Joaquin Council of Governments (SJCOG)

<u>Data that cannot be released:</u>
StreetLight

Data Format and Content
We will deposit the Covid related data and ACS socioeconomic data used in this study in the Dataverse data repository. The files will contain information about the data and variables.

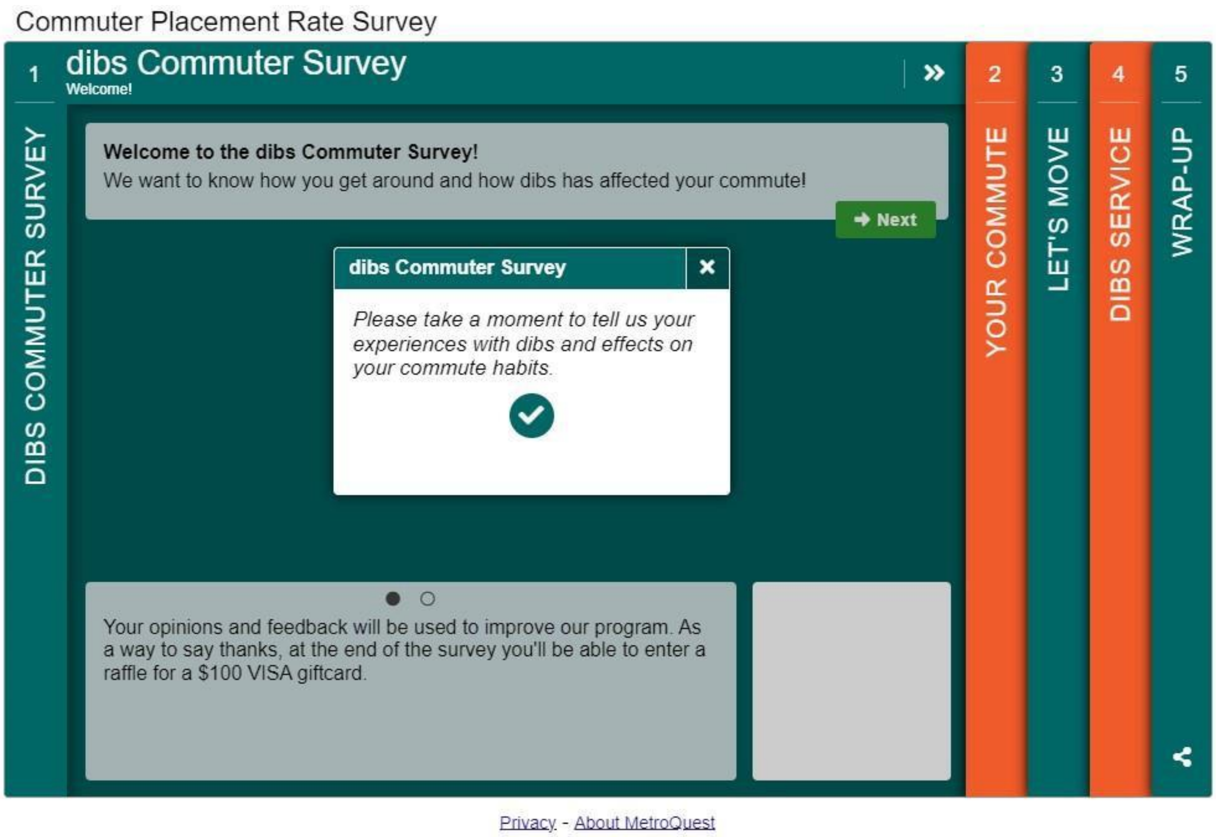
Data Access and Sharing
The public can access the data via Dataverse.

Reuse and Redistribution
Traffic data from StreetLight was made available to the research team through agreements that require that those data not be released publicly, to protect subject confidentiality. The release of dibs and ACT survey data needs further confirmation with the San Joaquin Council of Governments (SJCOG).

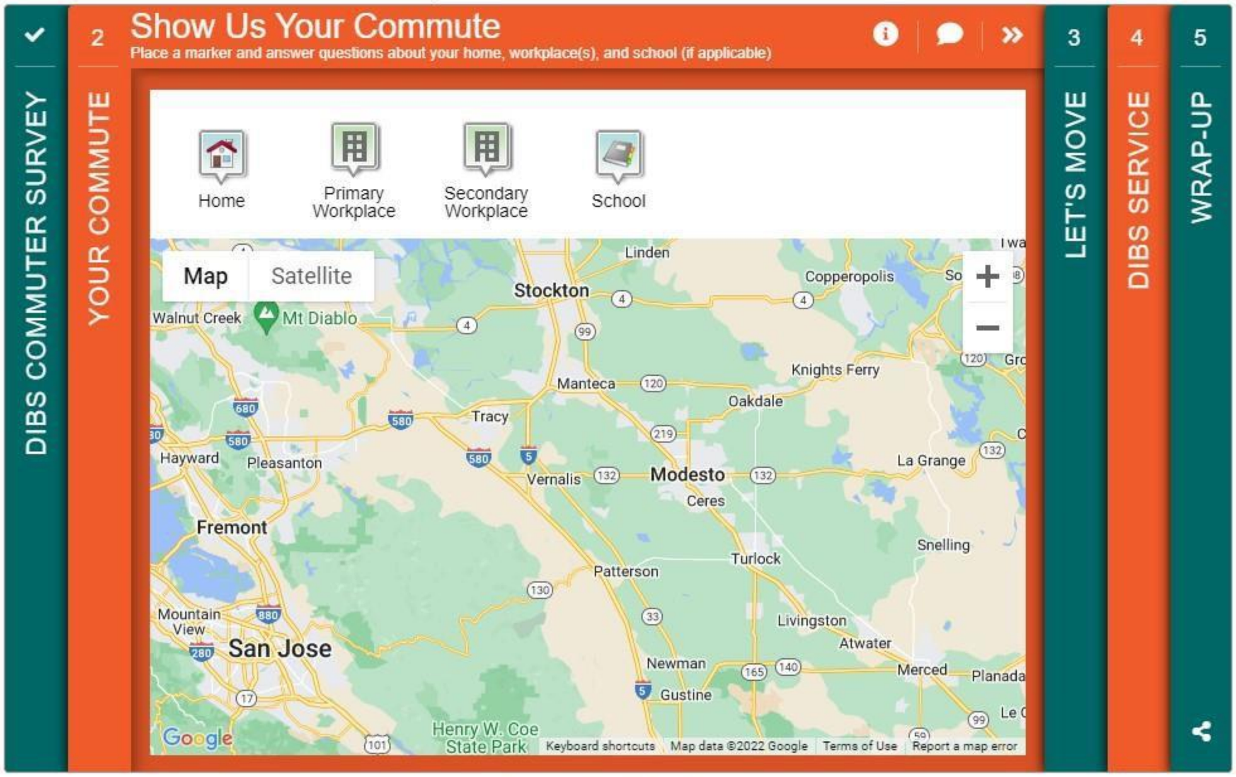
Appendix

Appendix A: dibs Survey Questionnaire

This appendix provides screenshots of the dibs survey questionnaire. A demo version of the survey is available here:
https://demo.metroquestsurvey.com/?u=bm4p4l#!/?p=web&pm=dynamic&s=1&popup=WTD



Commuter Placement Rate Survey



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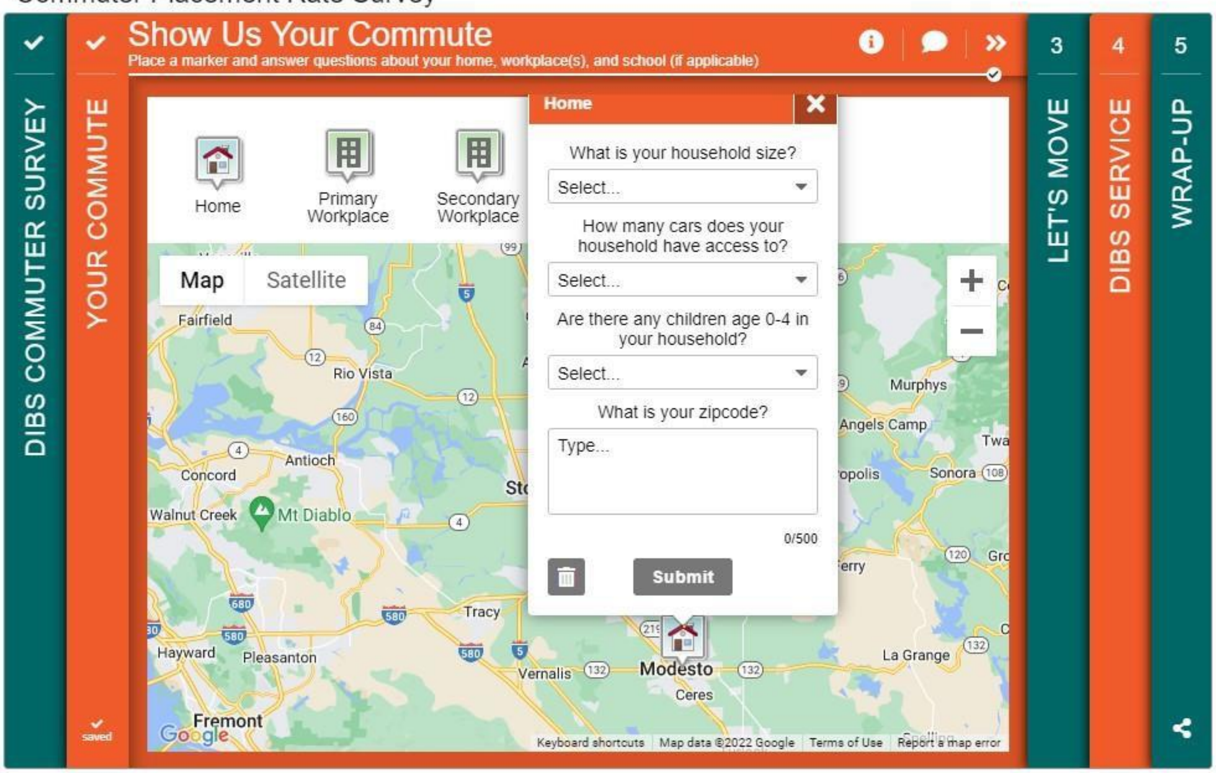
Commuter Placement Rate Survey



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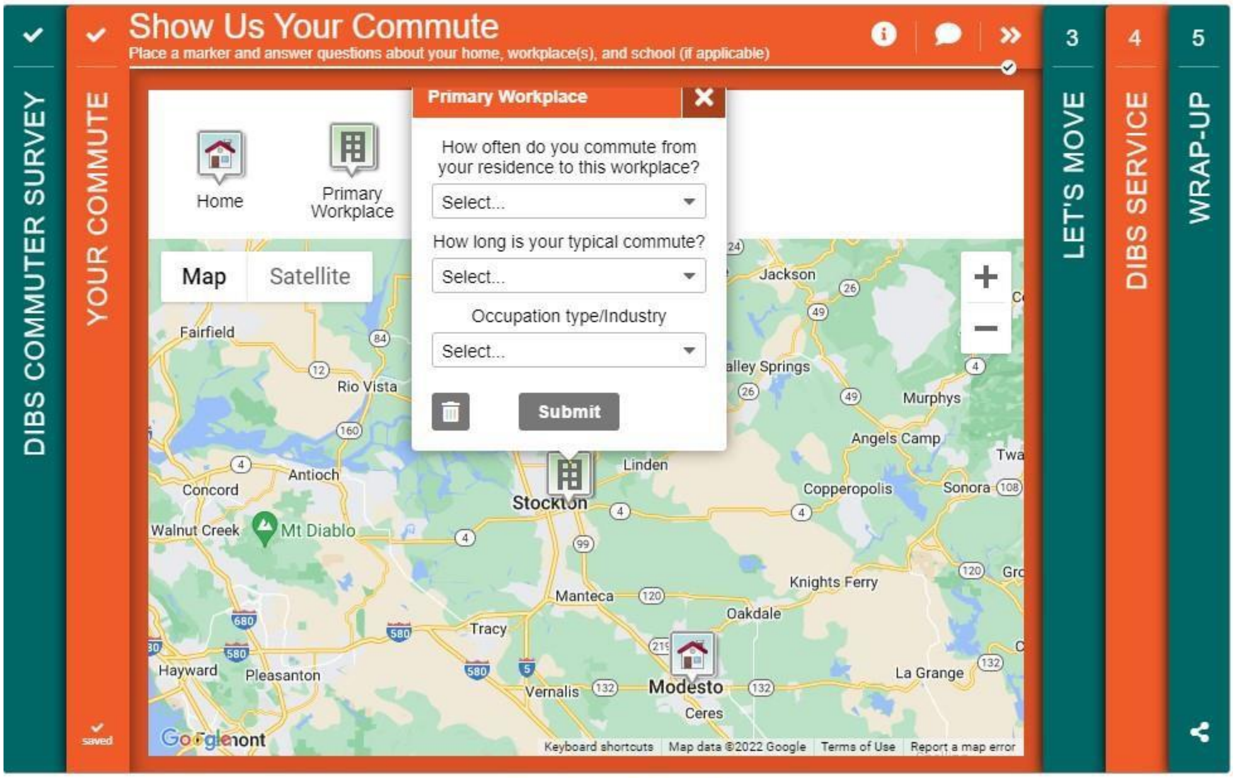

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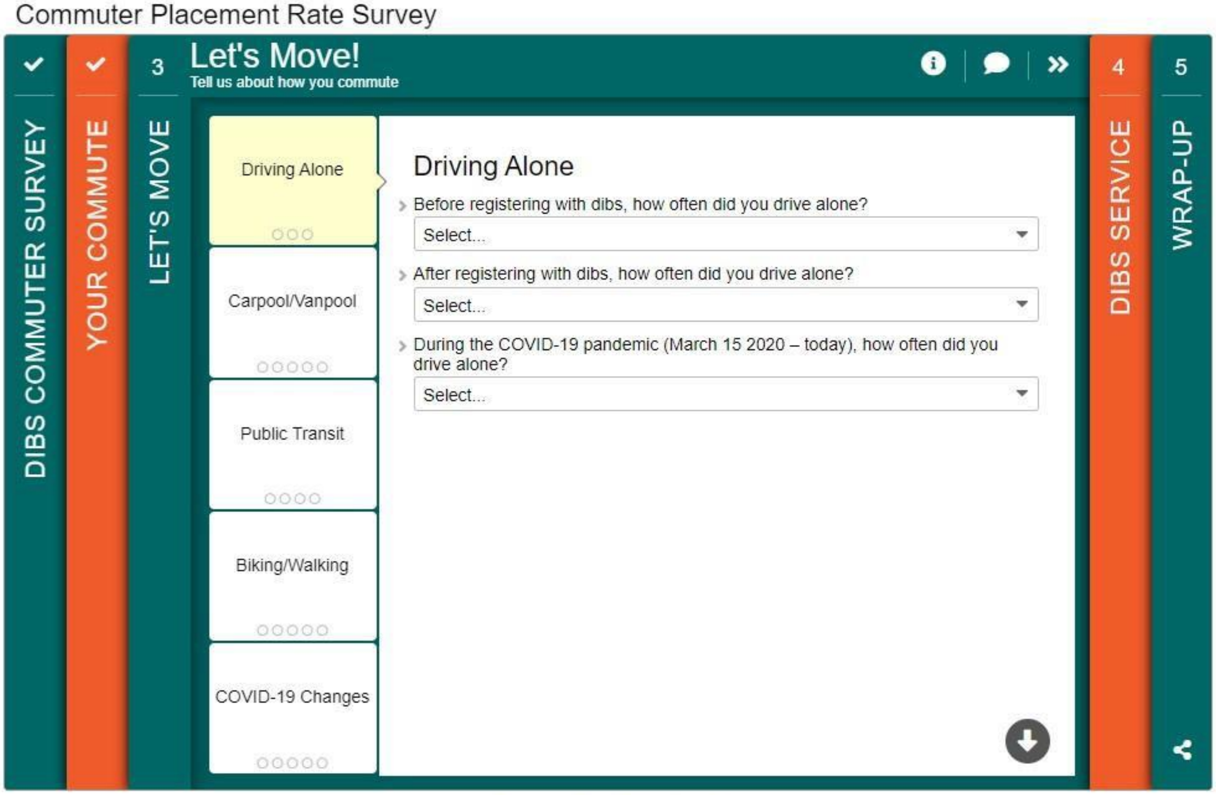

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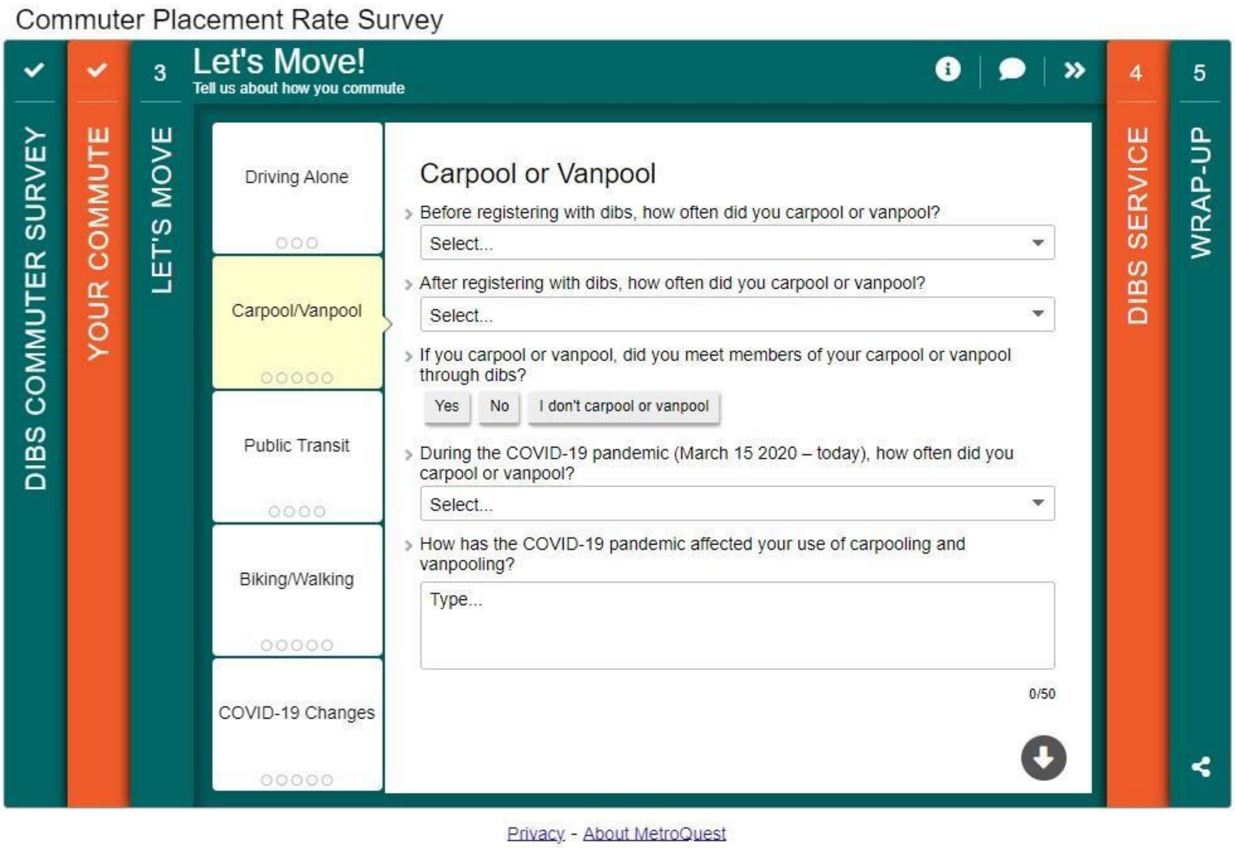
Commuter Placement Rate Survey
3
Let's Move!
Tell us about how you commute
4
5
DIBS COMMUTER SURVEY
YOUR COMMUTE
LET'S MOVE
DIBS SERVICE
WRAP-UP
Driving Alone
Carpool/Vanpool
Public Transit
Biking/Walking
COVID-19 Changes
Carpool or Vanpool
Before registering with dibs, how often did you carpool or vanpool?
Select...
After registering with dibs, how often did you carpool or vanpool?
Select...
If you carpool or vanpool, did you meet members of your carpool or vanpool through dibs?
Yes
No
I don't carpool or vanpool
During the COVID-19 pandemic (March 15 2020 – today), how often did you carpool or vanpool?
Select...
How has the COVID-19 pandemic affected your use of carpooling and vanpooling?
Type...
0/50
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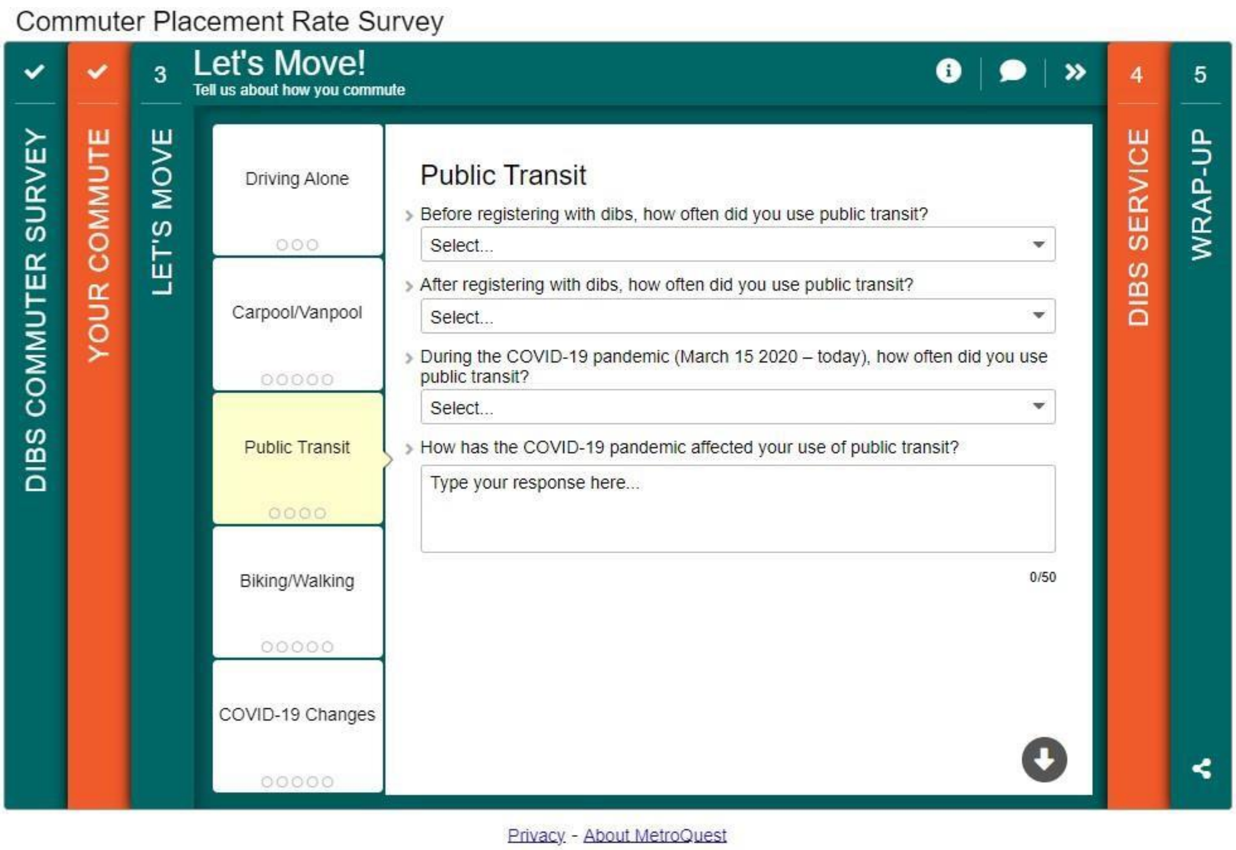
Commuter Placement Rate Survey
3
Let's Move!
Tell us about how you commute
4
5
DIBS COMMUTER SURVEY
YOUR COMMUTE
LET'S MOVE
DIBS SERVICE
WRAP-UP
Driving Alone
Carpool/Vanpool
Public Transit
Biking/Walking
COVID-19 Changes
Public Transit
Before registering with dibs, how often did you use public transit?
Select...
After registering with dibs, how often did you use public transit?
Select...
During the COVID-19 pandemic (March 15 2020 – today), how often did you use public transit?
Select...
How has the COVID-19 pandemic affected your use of public transit?
Type your response here...
0/50
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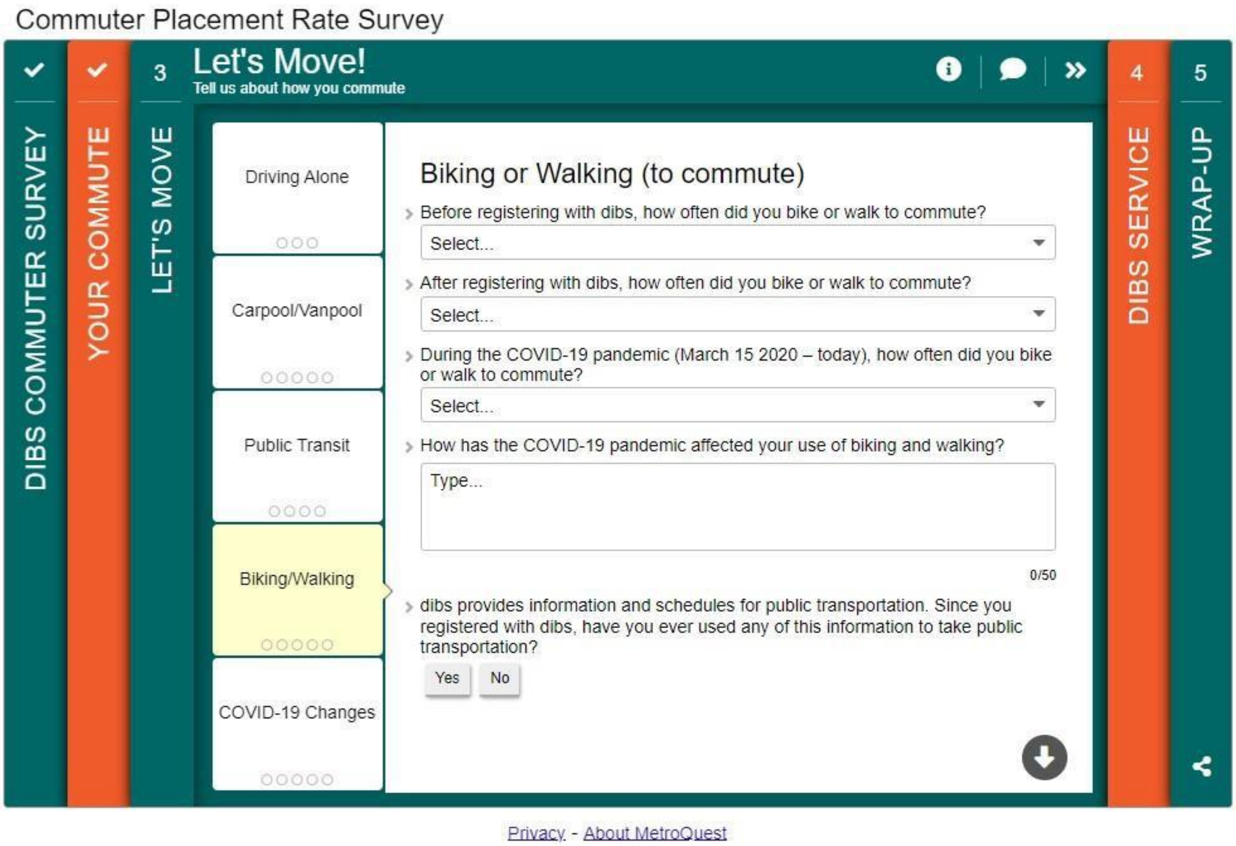
Commuter Placement Rate Survey
3
Let's Move!
Tell us about how you commute
4
5
DIBS COMMUTER SURVEY
YOUR COMMUTE
LET'S MOVE
DIBS SERVICE
WRAP-UP
Driving Alone
Carpool/Vanpool
Public Transit
Biking/Walking
COVID-19 Changes
Biking or Walking (to commute)
Before registering with dibs, how often did you bike or walk to commute?
Select...
After registering with dibs, how often did you bike or walk to commute?
Select...
During the COVID-19 pandemic (March 15 2020 – today), how often did you bike or walk to commute?
Select...
How has the COVID-19 pandemic affected your use of biking and walking?
Type...
0/50
dibs provides information and schedules for public transportation. Since you registered with dibs, have you ever used any of this information to take public transportation?
Yes
No
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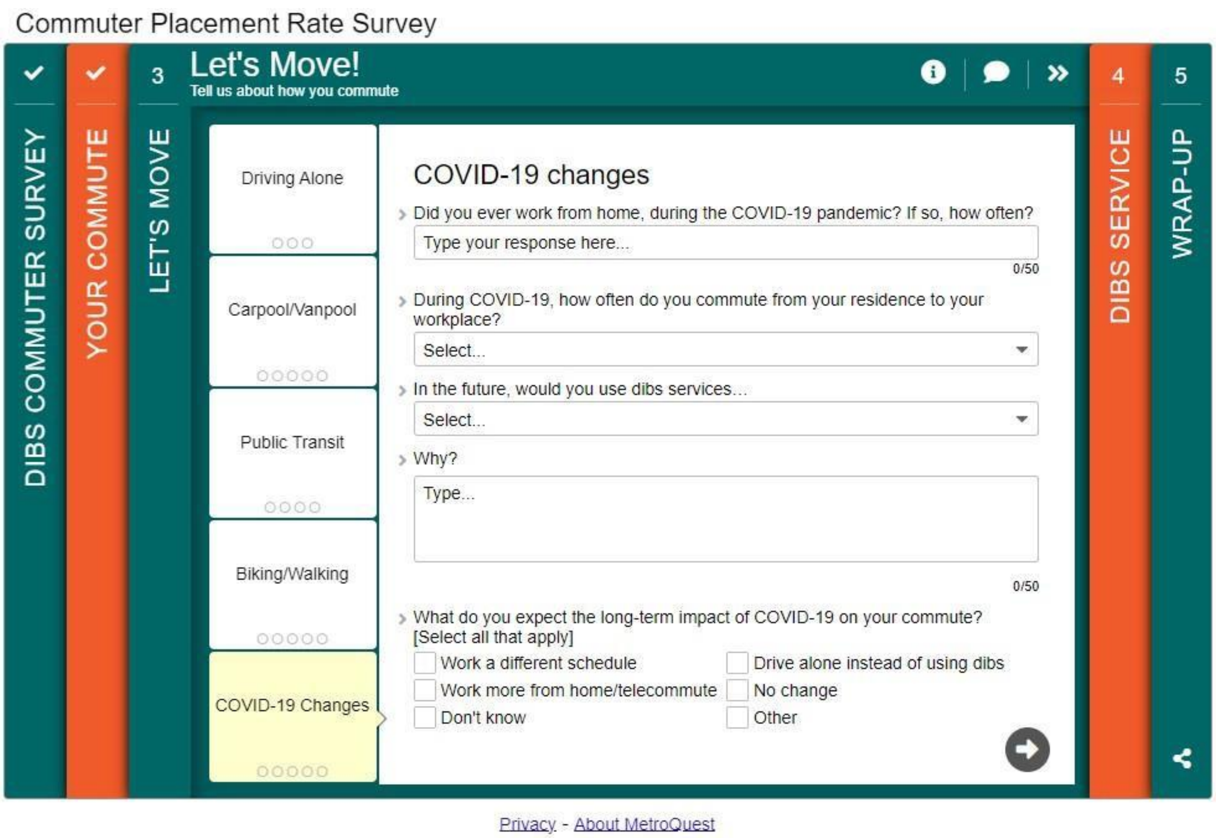
Commuter Placement Rate Survey
3
Let's Move!
Tell us about how you commute
4
5
DIBS COMMUTER SURVEY
YOUR COMMUTE
LET'S MOVE
DIBS SERVICE
WRAP-UP
Driving Alone
Carpool/Vanpool
Public Transit
Biking/Walking
COVID-19 Changes
COVID-19 changes
Did you ever work from home, during the COVID-19 pandemic? If so, how often?
Type your response here...
0/50
During COVID-19, how often do you commute from your residence to your workplace?
Select...
In the future, would you use dibs services...
Select...
Why?
Type...
0/50
What do you expect the long-term impact of COVID-19 on your commute? [Select all that apply]
Work a different schedule
Drive alone instead of using dibs
Work more from home/telecommute
No change
Don't know
Other
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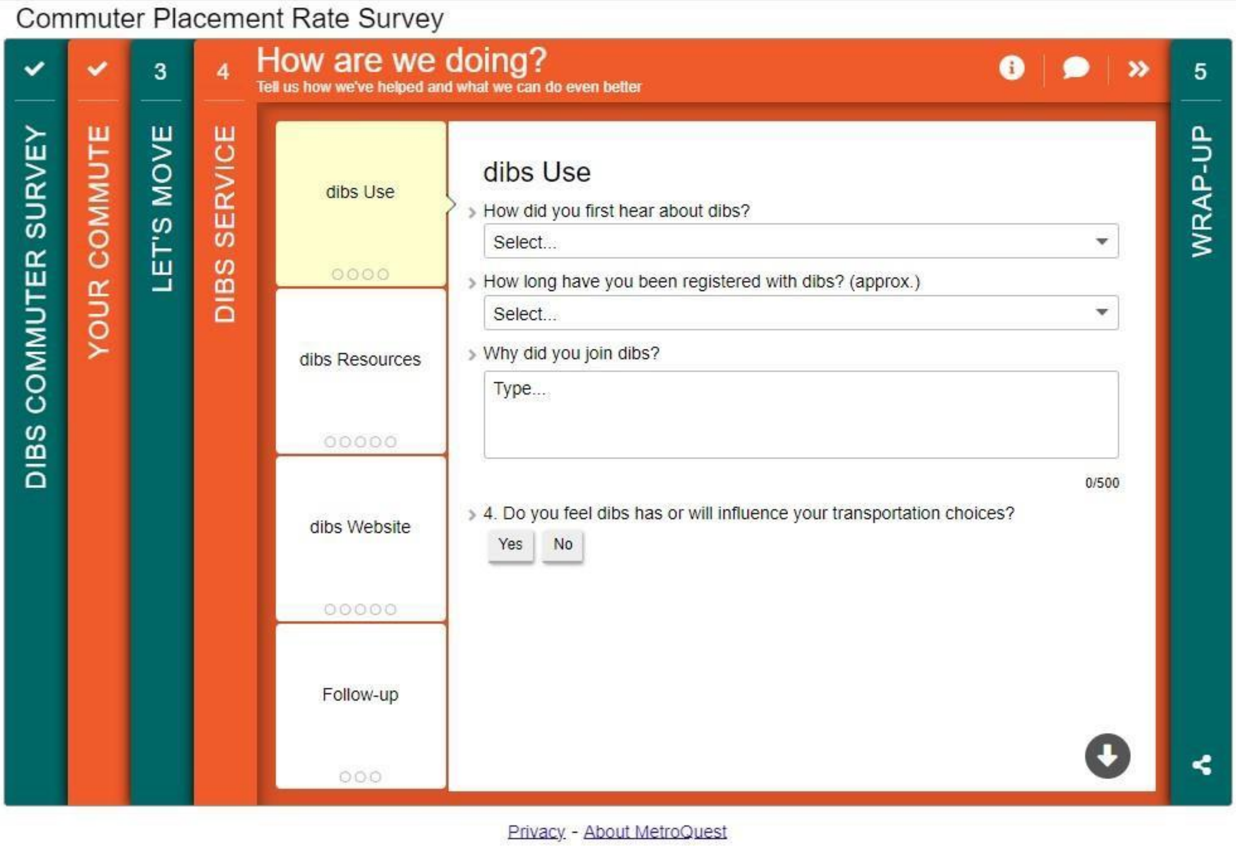
Commuter Placement Rate Survey
DIBS COMMUTER SURVEY
YOUR COMMUTE
3
LET'S MOVE
4
DIBS SERVICE
How are we doing?
Tell us how we've helped and what we can do even better
5
WRAP-UP
dibs Use
dibs Resources
dibs Website
Follow-up
dibs Use
How did you first hear about dibs?
Select...
How long have you been registered with dibs? (approx.)
Select...
Why did you join dibs?
Type...
0/500
4. Do you feel dibs has or will influence your transportation choices?
Yes
No
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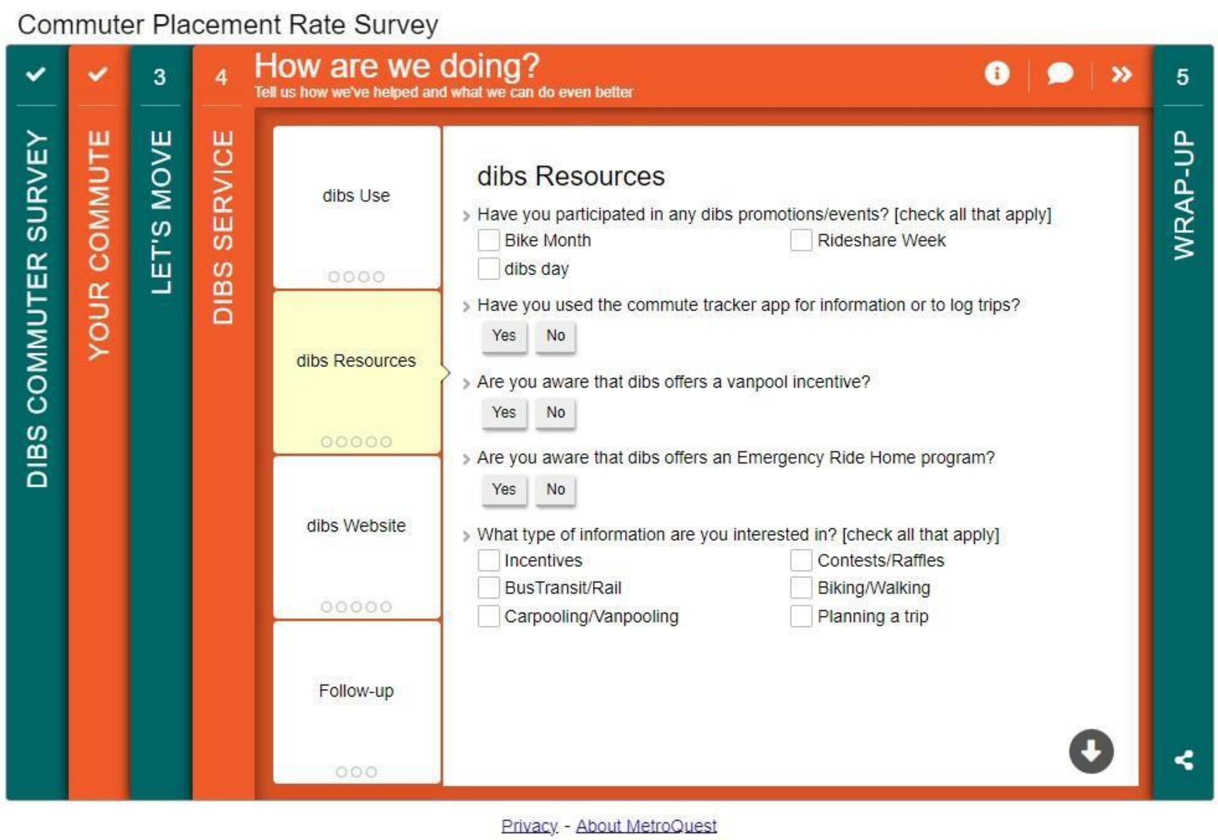
Commuter Placement Rate Survey
DIBS COMMUTER SURVEY
YOUR COMMUTE
3
LET'S MOVE
4
DIBS SERVICE
How are we doing?
Tell us how we've helped and what we can do even better
5
WRAP-UP
dibs Use
dibs Resources
dibs Website
Follow-up
dibs Resources
Have you participated in any dibs promotions/events? [check all that apply]
Bike Month
Rideshare Week
dibs day
Have you used the commute tracker app for information or to log trips?
Yes
No
Are you aware that dibs offers a vanpool incentive?
Yes
No
Are you aware that dibs offers an Emergency Ride Home program?
Yes
No
What type of information are you interested in? [check all that apply]
Incentives
Contests/Raffles
BusTransit/Rail
Biking/Walking
Carpooling/Vanpooling
Planning a trip
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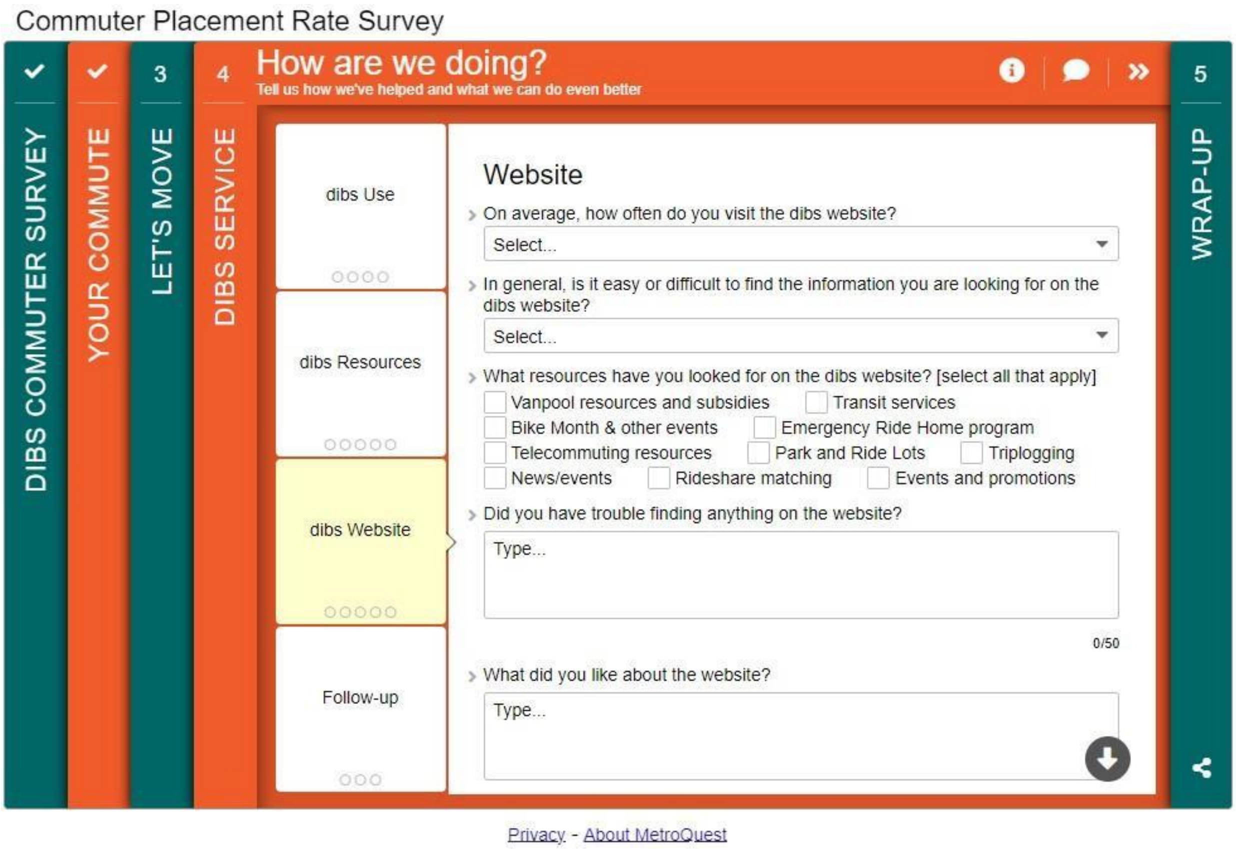
Commuter Placement Rate Survey
How are we doing?
Tell us how we've helped and what we can do even better
DIBS COMMUTER SURVEY
YOUR COMMUTE
3
LET'S MOVE
4
DIBS SERVICE
5
WRAP-UP
dibs Use
dibs Resources
dibs Website
Follow-up
Website
On average, how often do you visit the dibs website?
Select...
In general, is it easy or difficult to find the information you are looking for on the dibs website?
Select...
What resources have you looked for on the dibs website? [select all that apply]
Vanpool resources and subsidies
Transit services
Bike Month & other events
Emergency Ride Home program
Telecommuting resources
Park and Ride Lots
Triplogging
News/events
Rideshare matching
Events and promotions
Did you have trouble finding anything on the website?
Type...
0/50
What did you like about the website?
Type...
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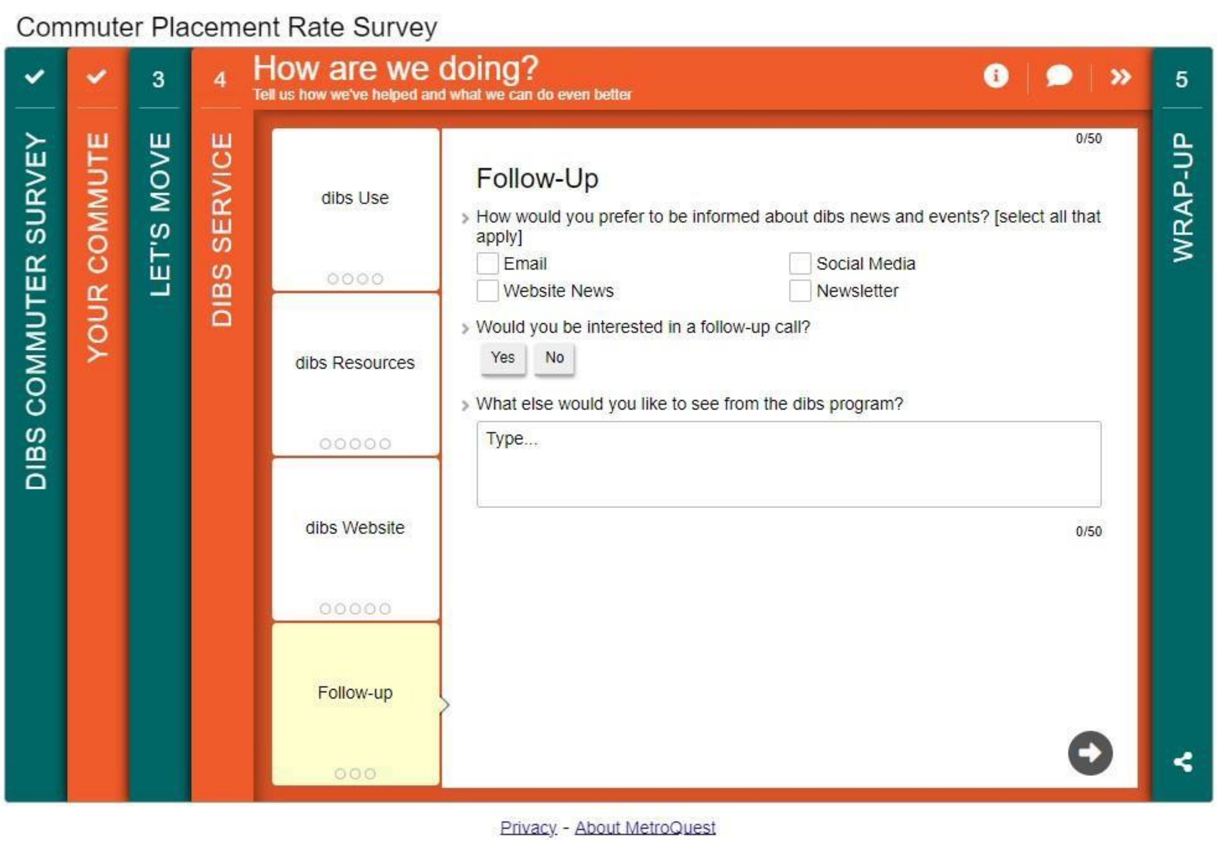
Commuter Placement Rate Survey
How are we doing?
Tell us how we've helped and what we can do even better
DIBS COMMUTER SURVEY
YOUR COMMUTE
3
LET'S MOVE
4
DIBS SERVICE
5
WRAP-UP
dibs Use
dibs Resources
dibs Website
Follow-up
0/50
Follow-Up
How would you prefer to be informed about dibs news and events? [select all that apply]
Email
Social Media
Website News
Newsletter
Would you be interested in a follow-up call?
Yes
No
What else would you like to see from the dibs program?
Type...
0/50
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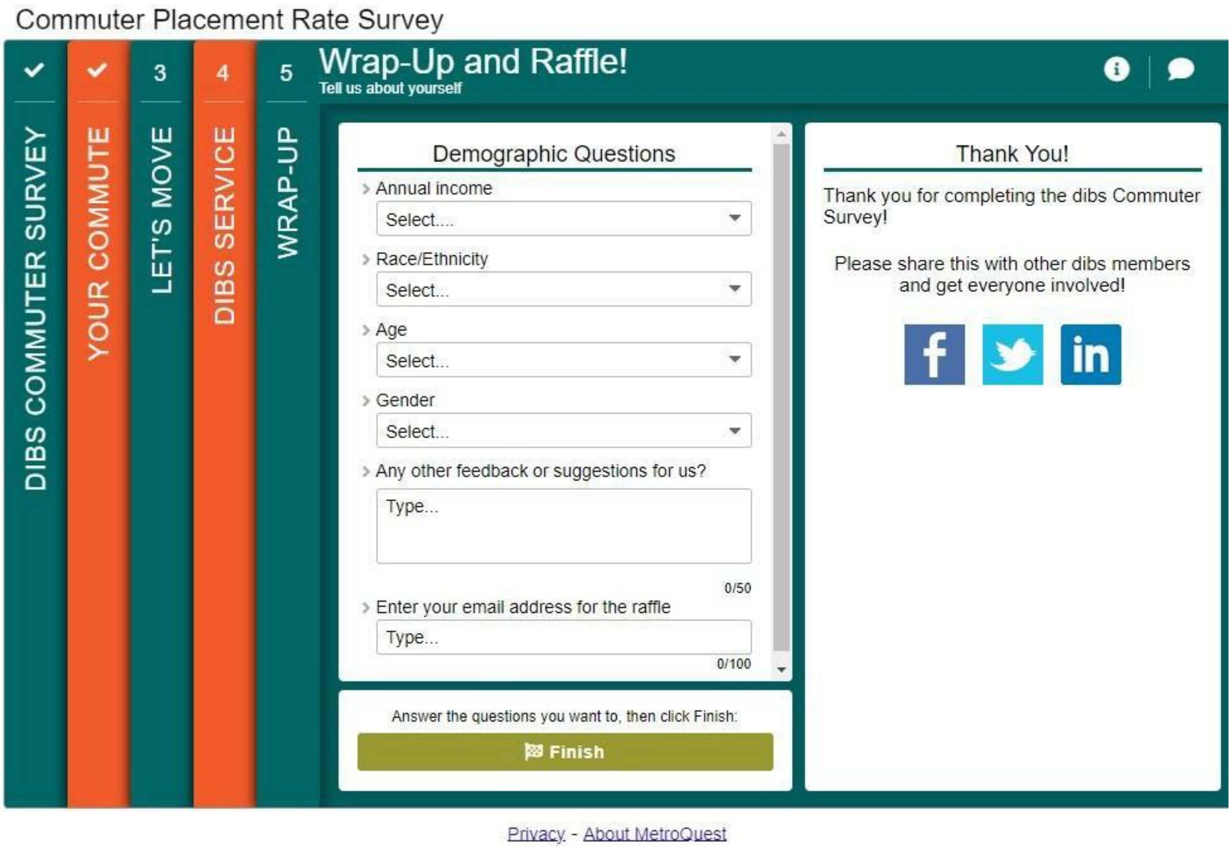
Commuter Placement Rate Survey
DIBS COMMUTER SURVEY
YOUR COMMUTE
3
LET'S MOVE
4
DIBS SERVICE
5
WRAP-UP
Wrap-Up and Raffle!
Tell us about yourself
Demographic Questions
Annual income
Select....
Race/Ethnicity
Select...
Age
Select...
Gender
Select...
Any other feedback or suggestions for us?
Type...
0/50
Enter your email address for the raffle
Type...
0/100
Answer the questions you want to, then click Finish:
Finish
Thank You!
Thank you for completing the dibs Commuter Survey!
Please share this with other dibs members and get everyone involved!
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Appendix B: ACT Survey Questionnaire

The National Association for Commuter Transportation (ACT) queried commuters' responses to Covid-19 in 2020 (SJCOG 2020). SJCOG provided us with survey responses for San Joaquin, Stanislaus, and Merced counties. This appendix provides the questionnaire.

1. Which of the following categories best describes your current employment status?
    - Employed, working full-time
    - Employed, working part-time
    - Retired
    - Furloughed/Not employed, but anticipate going back to the same position
    - Other
    - Furloughed/Not employed, but DO NOT anticipate going back to the same position
    - Student
    - Disabled, not able to work
2. Home Zip / Postal Code
3. Work Zip / Postal Code
4. Which of the following best describes your primary occupation prior to the outbreak of COVID-19?
    - Business Owner/Self Employed
    - Business Professional
    - Education/Academic
    - Government/Civil Services
    - Hospitality/Restaurant
    - Manufacturing/Warehouse
    - Medical/Healthcare/Social Services
    - Not Employed
    - Other
    - Retail
    - Student
5. Please select your primary mode of commuting before the pandemic (the mode you used for the longest distance of your commute to work):
    - Bike/Scooter
    - Carpool (2-6 people in a vehicle)
    - Commuter Rail
    - Drive alone
    - Other (please specify) __________
    - Public Bus
    - Subway, Light Rail, Tram
    - Telecommute/Work from Home
    - Vanpool (7-15 people in a coordinated van group)
    - Walk
6. Do you have a car available to you for your commute to work?

- No, never

- Sometimes
- Yes, always

7. During the COVID-19 outbreak, were you considered an essential worker (requiring you to report to the work site)?
    a. Yes
    b. No
8. Which best describes your situation?

- I am a student
- I am currently not employed/furloughed
- I am still working from home temporarily
- I am working at my physical workplace part-time
- I previously worked from home and have continued to do so
- I am working at my physical workplace full-time

9. Are you currently or planning to use the same mode of transportation to commute to work due to COVID-19?
    - I don't know yet
    - No, I plan to use a different mode
    - Yes, I plan to use the same mode (from Question 5)
10. Please select no more than three (3) reasons why you may use a different commute mode or are undecided. If not listed, please use other:
    a. Concern about crowds
    b. Concern about the ability to clean/sanitize/disinfect appropriately
    c. Concern about sharing spaces with strangers
    d. Cost of former option is high
    e. Former option is not available
    f. My employer is allowing me to continue working from home
    g. I will be returning to a new place of work or work site location
    h. I am in a high risk category
    i. Other (please specify) ___________
11. What might be (or is) your primary commute mode when you return(ed) to your work place?
    a. Bike/Scooter
    b. Carpool (2-6 people in a vehicle)
    c. Commuter Rail
    d. Drive alone
    e. Other (please specify)
    f. Public Bus
    g. Subway, Light Rail, Tram
    h. Telecommute/Work from Home
    i. Vanpool (7-15 people in a coordinated van group)
    j. Walk
12. Over the next 2-3 months, how comfortable would you be using each of the following modes of transportation to commute to work? Choose from among the following options for each mode: Not Comfortable, Somewhat Comfortable, Very Comfortable, Not Available for My Commute
    a. Bike/Scooter

b. Carpool (2-6 people in a vehicle)
c. Commuter Rail
d. Drive alone
e. Other (please specify)
f. Public Bus
g. Subway, Light Rail, Tram
h. Telecommute/Work from Home
i. Vanpool (7-15 people in a coordinated van group)
j. Walk

13. For the modes you marked in the last question as "somewhat comfortable" or "not comfortable", please indicate if the following actions would increase your willingness to use the modes:
    a. Requirements to wear masks
    b. Routine cleaning
    c. Reduced crowding (via physical distancing)
    d. Reserved/assigned seating
    e. Reduced fares
    f. Driver/passenger testing for COVID-19 symptoms
    g. Use of contact tracing
    h. Increase frequency of service during rush hour
    i. Prioritize road space for non-car traffic (bus, bike, walk)
    j. Other (please specify) ___________
14. What could your employer do to make your return to the work site easier? Please select your top 3 choices.:
    a. Allow me to continue to work from home (telecommute)
    b. Allow me to have a flexible schedule to reduce days in the office
    c. Allow me to have flexible hours to reduce travel time during rush hour
    d. Provide a co-working space in my neighborhood with Covid protocols
    e. Allow for virtual meetings/conferences
    f. Reduce the cost of commuting via public transit
    g. Add shuttle services for employees
    h. Provide onsite childcare
    i. Offer preferential parking for carpools
    j. Allow for daily parking vs monthly parking
    k. Separate desks and work stations to allow for distancing
    l. Allow me more time to commute to work
    m. Other (please specify) __________
15. What is your age?

- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 to 74

- 75 or older

16. What is the highest level of education you have completed?

- Associates Degree
- Bachelor's Degree
- Did not attend school
- Grade school
- Graduated from high school
- Master's Degree or higher

17. What is your approximate annual household income?

- $0-$24,999
- $25,000-$49,999
- $50,000-$74,999
- $75,000-$99,999
- $100,000-$124,999
- $125,000-$149,999
- $150,000-$174,999
- $175,000-$199,999
- $200,000 and up

Appendix C: Home-based Work Trip Statistics

Table C1. Home-based work trip per ZCTA by COVID-19 stages and blueprint tiers

COVID-19 Stages	Statistics	No tier assignment	Tier 1: Widespread Risk	Tier 2: Substantial Risk	Tier 3: Moderate Risk	Tier 4: Minimal Risk	Total
Stage 0: Pre-COVID-19	**Mean**	**16,879**	**.**	**.**	**.**	**.**	**16,879**
	Std. dev.	11,968	.	.	.	.	11,968
Stage 1: COVID-19 outbreak	**Mean**	**11,462**	**.**	**.**	**.**	**.**	**11,462**
	Std. dev.	8,057	.	.	.	.	8,057
Stage 2: Blueprint start	**Mean**	**.**	**11,142**	**12,731**	**12,898**	**10,269**	**11,881**
	Std. dev.	.	7,915	8,650	8,772	5,311	8,305
Stage 3: Vaccine rollout	**Mean**	**.**	**10,917**	**13,339**	**12,523**	**12,971**	**12,088**
	Std. dev.	.	7,627	9,136	8,625	7,657	8,349
Stage 4: Fully reopen	**Mean**	**13,934**	**.**	**.**	**.**	**.**	**13,934**
	Std. dev.	9,990	.	.	.	.	9,990
All Stages	**Mean**	**14,905**	**11,026**	**13,036**	**12,636**	**12,563**	**14,060**
	Std. dev.	10,965	7,769	8,902	8,671	7,414	10,350

Appendix D: 2020 Presidential Election Results

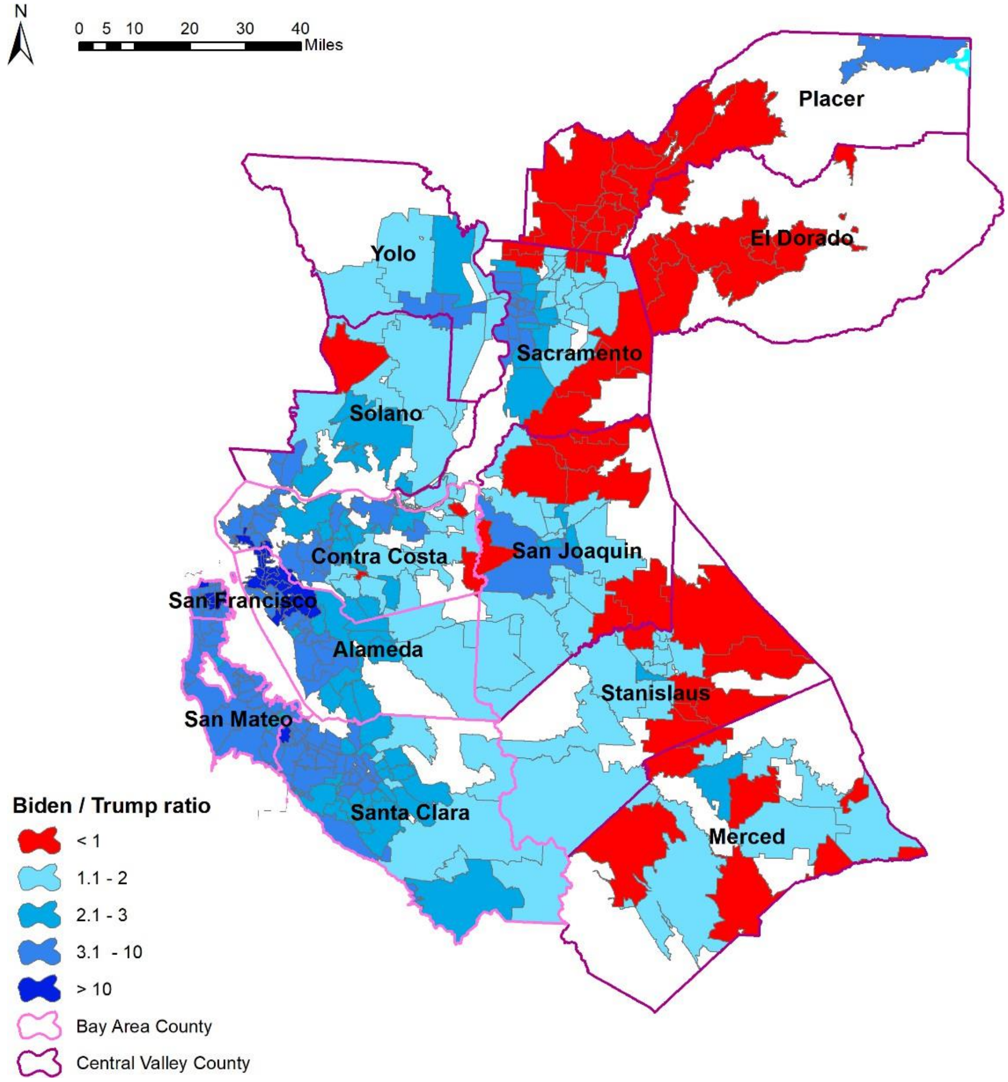

Figure D1. Ratio of Biden to Trump votes in the 2020 Presidential election at ZCTA level