# 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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## Project Objective

This project looks at mobility patterns and experiences using alternative modes of transportation for disadvantaged workers during COVID-19 in California's Bay Area and Central Valley.

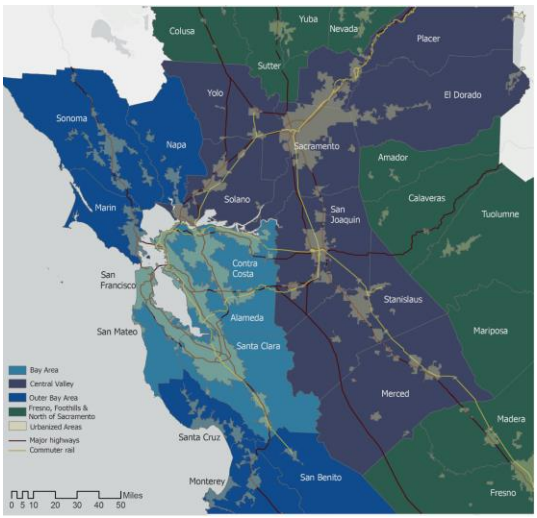
## Problem Statement

The analysis focuses on understanding the changes in peak period travel during the COVID pandemic, and how those changes link to income and occupation structures.

## Research Methodology

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 (a mobility analysis firm), to document mobility patterns between the Central Valley and the Bay Area throughout the pandemic.

The study area is shown in Figure 1, below.




We use a regression model to explain traffic volumes, to-from zip-code tabulation areas (ZCTA's), as shown below:

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

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. $D_i$ 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*. $v_{it}$ represents the share of the population fully vaccinated in ZCTA *i*, for day *t*. $bp_{it}$ indicates the assigned blueprint tiers (which the state government used to categorize COVID risk) for ZCTA *i*, for day *t*. Blueprint tiers originally reported weekly at the county level, which we link to ZCTAs, and weeks are assigned to days. We include several socioeconomic variables that measure income levels of ZCTAs and occupation structure, also of ZCTAs. More detail on variables and data sources is in the full report.

## Results

Our primary result is that after COVID, the peak morning traffic volume by income and by occupation flipped orders. (See Figures 2 and 3, which summarize regression results.) Low income ZCTAs generated more travel post-COVID, and tracts with concentrations of service work generated fewer trips post-COVID. Both are reversals from pre-COVID trends. We interpret this as evidence of the greater ability of high-income, knowledge workers to shelter at home and work remotely during the COVID pandemic.

Figure 2: Estimated Differences in Trips Per Day by Stage and by Income Level of ZCTA. All estimates shown are statistically significant at the p < 0.001 level.

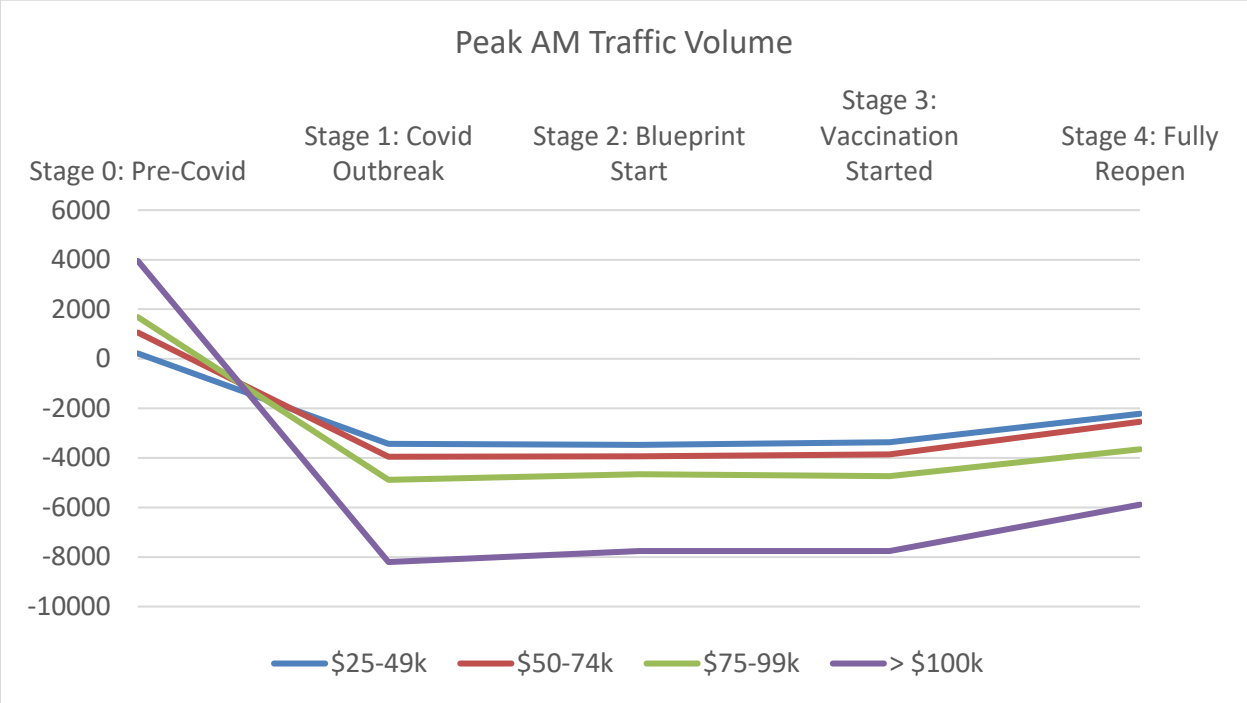
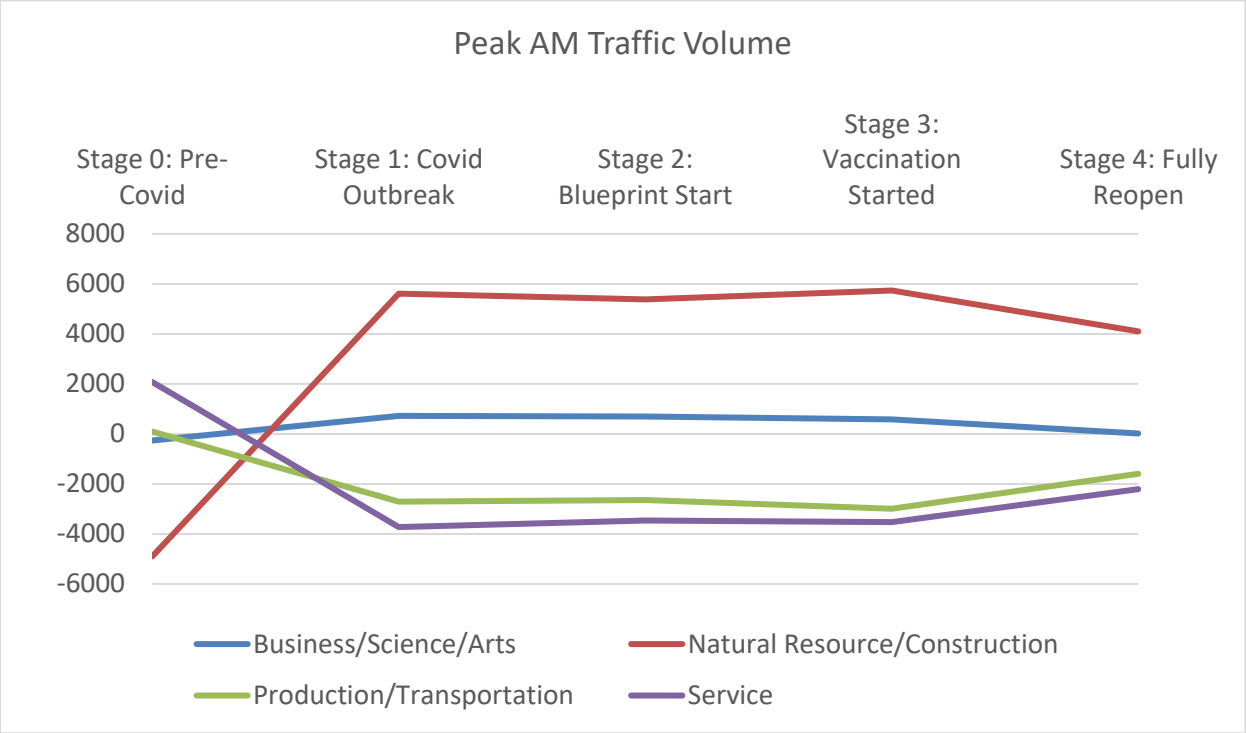


Figure 3: Estimated Differences in Trips Per Day by Stage and by Occupation of ZCTA residents. All estimates shown are statistically significant at the $p < 0.001$ level.




For more information, see both the full research report and the following article derived from this research: Bonnie S. Wang, Seva Rodnyansky, Marlon G. Boarnet, and Andre Comandon, "Measuring the Impact of COVID-19 Policies on Local Commute Traffic: Evidence from Mobile Data in Northern California," Travel Behaviour and Society, volume 34, Jan., 2024, DOI https://doi.org/10.1016/j.tbs.2023.100660.