Displacement and Commuting in the San Francisco Bay Area and Beyond: An Analysis of the Relationship Between the Housing Crisis, Displacement, and Long Commutes

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract

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Contents

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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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Principal Investigator, Co-Principal Investigators, others, conducted this research titled, "Displacement and Commuting in the San Francisco Bay Area and Beyond: An Analysis of the Relationship Between the Housing Crisis, Displacement, and Long Commutes" 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 August 16, 2020 to December 31, 2021 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

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Any opinions expressed in this report are those of the authors, not official positions of the California Franchise Tax Board.

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Abstract

We use four data sets to study supercommuting in the San Francisco Bay Area and Central Valley of California. We follow previous research in defining supercommuting as commutes longer than 50 miles or 90 minutes one-way. The San Francisco Bay Area has some of the highest housing costs in the United States, and anecdotal evidence has long suggested that households might move from the Bay Area to Central Valley counties, possibly enduring long commutes if they cannot move their job at the same time. Yet evidence on a link between supercommuting and house prices has been limited by data availability. We use the data first to demonstrate that the supercommute is far from uncommon, with some Central Valley counties having supercommuting rates that approach 10 percent of all county commutes. We use data on household moves, from zip code tabulation area to zip code tabulation area (ZCTA to ZCTA), to examine how supercommuting rates at the ZCTA level are linked to flows of in-migration from the Bay Area into the Central Valley. We find evidence that suggests that ZCTAs with higher in-migration flows from the Bay Area have higher supercommuting rates.

Research Report

Executive Summary

The phenomenon of supercommuting affects at least 3% of U.S. commuters (1), and more in the California's San Francisco Bay Area and Central Valley regions, but had not been studied in detail, to date. This report uses four different datasets to compile a descriptive portrait of supercommuting, taking into account different definitions, trends over time, demographic and mode comparisons, and the COVID-19 pandemic. Links between datasets enable analytical comparisons between supercommuting and demographic and socioeconomic characteristics at the household and neighborhood levels.

We find that supercommuting is a growing phenomenon, especially in the Central Valley, and that it clusters spatially. Whether measured as commutes over 50 miles or 90 minutes in one direction, the Central Valley counties nearest the Bay Area and in and around Sacramento have supercommuting shares of up to 8%, more than double the national average and generally two to four times more than Bay Area counties. The supercommuting share has grown the most in Merced, San Joaquin, and Stanislaus counties from 2012 to 2020 (according to travel survey and StreetLight data sources), and even within those counties, specific zip codes (as measured by Census Bureau's Zip Code Tabulation Areas) have particularly high shares of supercommuters.

The commute flow from the Central Valley to Bay Area has stayed remarkably consistent from 2002 to 2018, though increasing in absolute terms due to population growth in the Central Valley. However, the share of supercommuters among those commuting from Central Valley to Bay Area counties has increased by 3 to 9 percentage points by county (LODES).

At the household level, employment factors affect supercommuting at the household level: households employed in manufacturing, construction, maintenance, and farm jobs are more likely to supercommute, controlling for other factors. Households with larger numbers of children were also more likely to supercommute. Income, age, education, and housing characteristics have no statistically significant effect on the decision to supercommute. At the neighborhood level, measured by census Zip Code Tabulation Areas, higher renter shares, higher public transit mode shares, and higher shares of in-migration from the Bay Area are correlated with higher rates of supercommutes.

In terms of COVID-19, we document a large drop in overall traffic volume immediately after the start of the pandemic in California (March 15, 2020), relative to pre-pandemic baselines, using GPS-derived data from StreetLight. This is in line with other estimates such as Google Community Mobility reports. We find, however, that supercommute shares remained resilient during the same time period. In fact, supercommute shares decreased only in San

Francisco County, but increased in all other Bay Area and Central Valley counties under study and went up by as much as 1.5 percentage points (20-25% increase) in San Joaquin and Yolo counties. These possibly reflect different policy reactions to the pandemic, the distribution of essential employees and job sites, and shifting migration patterns during the pandemic.

This study provides a large step forward in understanding supercommuting as a phenomenon, from multiple standpoints, datasets, and definitions. The data provide specific estimates of levels and trends over time at the county level; we discuss dataset differences, strengths, and weaknesses. Travel surveys, the census American Community Survey (ACS), census LEHD Origin-Destination Employment Statistics (LODES), and mobile-derived data (StreetLight) all provide different snapshots, but we illustrate that together, they yield a more comprehensive picture.

Our findings suggest several takeaways for transportation planning in the Bay Area and Central Valley, California, and nationally:

- Analyzing multiple data sources is *necessary* when looking at supercommuting, as no single dataset provides thorough enough coverage.
- Supercommutes are resilient (either by choice or necessity) and have not been generally deterred by the COVID-19 pandemic, at least in 2020.
- Supercommutes are much more prevalent among Central Valley to Bay Area commuters, and much more so among carpool and public transit mode shares. This is in context of very low public transit mode shares. Thus, the burden of long duration (and distance) commutes falls heaviest on transit commuters in the region, most of whom are already of lower socioeconomic status.
- In-migration from the Bay Area is correlated with increased supercommuting in receiving Central Valley neighborhoods. Strategies to better connect employees with employers whether to commute, telecommute, or switch to more local employment may relieve these commuting burdens, and should at least be explored.
- Megaregional transportation planning across the regions of Northern California is an important level of intergovernmental coordination to increase wellbeing by managing and possibly decreasing supercommuting.

Chapter 1: Introduction

Background

Policy analysts and urban planners have begun to link extreme commuting with a lack of housing affordability in the urban core. Nearly 3 of every 100 U.S. commuters travelled longer than 90 minutes to work in 2016 (1). Yet is there a link between long commutes and housing affordability in the urban core? We study California's San Francisco Bay Area and the northern part of the Central Valley to explore long commutes (which we call supercommuting) and migration patterns from the Bay Area to the Central Valley.

This study defines a supercommmute as a one-way commute longer than 90 minutes (2,3) or at least 50 miles (4), following existing literature. California's Central Valley has several metropolitan areas within the top ten of the highest shares of supercommuters in the U.S. and the San Francisco Bay Area has seen rapid increases in its share of super-commuters, growing from a 2.3% share of all Bay Area commutes in 2005 to a 4.8% share in 2016, based on American Community Survey (ACS) data (1). Several areas of the Central Valley surrounding the Bay Area have even higher proportions of super-commuters: 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).

Researchers have suggested that the imbalance between affordable housing in the Central Valley and thriving job opportunities in the Bay Area increases the need for long-distance commuting (5). They hypothesize that restrictive housing supply in the San Francisco metro forces workers to migrate throughout and outside of the Bay Area (7). However, excess commuting is much higher than can be explained by jobs-housing mismatch or imbalance and there has been little evidence on such an association between unaffordable housing and extreme commutes. Furthermore, past literature has identified two types of supercommuters: 1) lower-income workers who live in the metropolitan area's periphery and travel frequently to the workplaces in more central locations and 2) higher-income workers who live farther away but tend to have more flexible schedules and hence travel to work less frequently (3). At times policy discussions have confounded or combined the two groups, failing to disentangle what might be households who live far from jobs by necessity from those who live far from jobs by choice. The COVID-19 pandemic and its attendant changes in commute flows, patterns, and mode shares further underscore the need to disentangle choice versus necessity in supercommuting behavior.

Although the relationship between housing affordability and supercommmuting cannot be directly examined in this research, this study fills several voids indirectly by measuring the changes in commuting and supercommuting patterns over time and by looking at supercommuting by demographic characteristics. Due to the disruption of COVID-19, the study also analyzes the pandemic's impact on people's travel behavior. Our purpose is fourfold:

1) To canvass several data sources to describe supercommuting in the combined San Francisco Bay Area / northern Central Valley regions of California,

2) To examine how income, occupation, age, and residence are associated with supercommuting,
3) To document pandemic related changes to commuting patterns, and
4) To explore how migration from the Bay Area to the Central Valley is associated with supercommuting, developing key evidence that, can illuminate how supercommuting is linked to households moving from an urban core to a fringe area, filling a key gap in literature and practice.

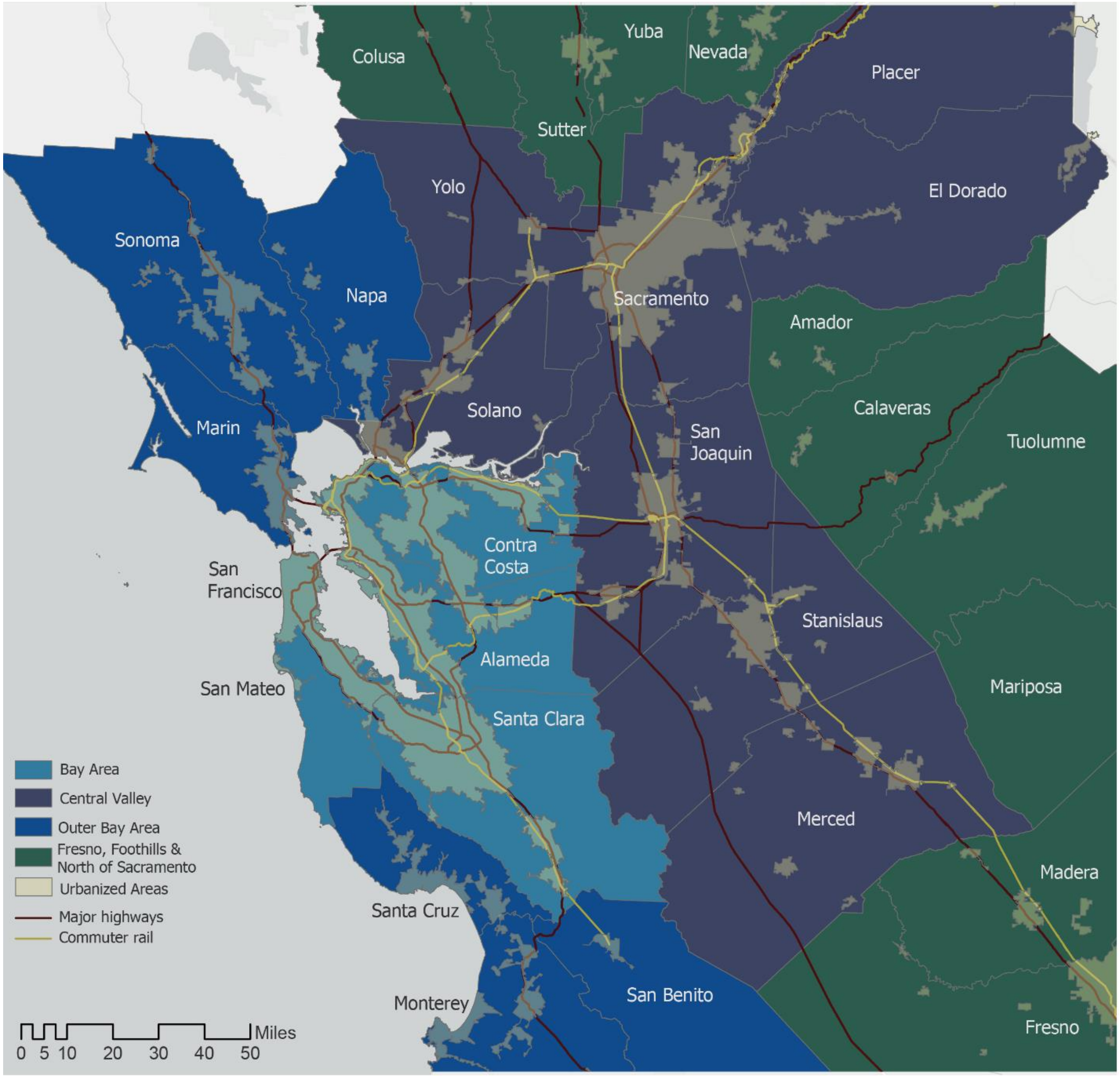
Chapter 3 of this report describes the data sources, Chapter 4 explores supercommute levels by region, county, and demographic characteristics, and also reports pandemic-related changes. Chapter 5 presents regression analysis that ties together migration and supercommuting.

This paper's methodology and implications are broader than just the Bay Area and Central Valley. They are generally applicable to other regions since the supercommute has become a growing trend nationally and globally. The discussion of data sources and limitations is illuminating for both transportation planners and researchers. We look at the three best available data sources on commuting (U.S. DOT's and Caltrans' Household Travel Surveys, the U.S. Census American Community Survey abbreviated ACS, and the census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics abbreviated LODES) to descriptively and statistically understand the incidence of supercommuting trends over time. We also use StreetLight InSight® data to explore how pandemic patterns have changed from past trends.

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



Research Questions

This study answers the following research questions.

1. **The trend of supercommuting**
   - What is the general commute pattern in the Bay Area and Central Valley?
   - What is the trend of supercommuting in the Bay Area and Central Valley? Is supercommuting growing? Where is supercommuting growing the most?
   - Does the supercommute pattern change from the past trend during COVID?
   - Which counties produce more supercommuters during COVID?

2. **The flow of Supercommuting**
   - Where are the supercommuters from?
   - Where are the supercommuters commuting to?
   - Are particular origin-destination pairs more popular for supercommuting?
   - Does the regional pattern of supercommute change during COVID?

3. **Supercommute, demographics, and industry**
   - Who bears the burden of supercommuting?
   - What type of households are more likely to supercommute? Lower or higher-income workers? Young or old workers?
   - What is the transit mode of supercommuters? Are supercommuters more likely to drive alone, carpool, or take public transit, and does it vary by income?
   - What kind of neighborhoods are more likely to produce supercommuters?
   - Do commute patterns vary between different industries? Which industries produces more supercommuters?

4. **Supercommute during COVID-19**
   - What is the distribution of supercommuters during COVID? (by ZCTA)
   - Are particular origin-destination pairs more popular for supercommuting during COVID?

Chapter 2: Literature Review

Extreme commuting (also known as super-commuting or long commuting) has a fluid definition. A 2012 report using Longitudinal Employer-Household Dynamics (LEHD) data examining commuting to Manhattan defined extreme commuting as one-way commutes longer than 90 minutes (2,3), as compared to the 26-minute average US commute in 2017 (4). Another report characterized super-commuters as those working in a core metropolitan county but living in counties that border the combined metropolitan statistical area (CMSA) or further away (3). Distance-based definitions show extreme commuting as at least 50 miles one-way, which is nearly double the average person trip length for work according to the 2017 US National Household Travel Survey (4).

Regardless of the definition, average commute times have increased by 1-2% per year in the US since 1983 (4, table 27). Supercommuting, or the share of those traveling over 90 minutes to work, has increased by 1.8% annually from 2005 to 2016, comprising nearly 3 of every 100 U.S. commuters in 2016, based on ACS data (1). The San Francisco Bay Area in particular has become the national leader in supercommuters (8). Based on ACS data, the Bay Area has seen rapid increases in its share of super-commuters, growing from a 2.3% share of all Bay Area commutes in 2005 to a 4.8% share in 2016 (1). Several areas of the Central Valley surrounding the Bay Area have even higher proportions of super-commuters: Stockton, CA and Modesto, CA had 10.0% and 7.3% share of super-commuters in 2016, the most of any US metropolitan area (1). Nearly 25% of all commuters in San Joaquin, CA, Stanislaus, CA, and Merced, CA travel to a different county to work; 14% of employed residents in these three counties commute to the Bay Area (5,6).

The standard urban model (9-12) predicts that households will trade long commutes for lower land prices (and hence lower housing prices) on the urban fringe. Similarly, Kain (1961) posits that households trade off commute costs for residential site costs (12). Decades of urban economics research has verified those predicted patterns (see, e.g., Mills and Tan, 1980 (14), for an early example). The standard urban model leads to predictions that persons will consume lower cost housing far from the urban core and in effect trade longer commutes for more land or, on a per unit basis, lower cost housing. Yet depending on how preferences for land and the time-cost of commuting vary across income levels, it is not clear whether persons living far from the core would be higher or lower income (12). Furthermore, unless land and housing costs perfectly compensate homeowners for commuting costs, long commutes will bring disadvantages.

A growing literature has examined the social and psychological costs of long commutes. As the extreme of the commute distribution, supercommuting is fraught with individual and societal costs over and above that of the average commute. Research suggests increased physiological and psychological costs from long commuting individuals (20), including worse self-reported health (15), and among long public transit commutes in particular negative health outcomes (16) and reduced sleep and increased hypertension (17). Long commuters face social and economic costs including reduced productivity and increased absenteeism (18), lower levels of life satisfaction and an increased sense of time pressure (19), sacrificed time and higher cost (20). Societally, long commutes contribute more to transportation-related pollution (20) and are costly in terms of wasted time (21). If the incidence of supercommuting is higher for lower-income or minority communities, this may increase the economic and health disadvantages already faced by these communities.

Policy analysts and urban planners have begun to link extreme commuting with a lack of housing affordability in the urban core. The central concept of jobs-housing balance assumes that workers choose to work as close to home as possible or workers choose homes as close to work as possible (22-23). It is measured by the ratio of resident workers per job in a defined catchment area. The more balance the community, the shorter the commute. If a given area has much greater numbers of jobs than its residents, workers need to be drawn from other areas, thus lead to longer commutes and worse traffic conditions. The assumption being that low-income persons, priced out of locations closer to the urban core, move to the fringe but continue to commute long distances (7). However, past literature fails to explain the mixed results between two types of supercommuters: 1) those who live in the metropolitan area's periphery and travel frequently to the workplace and 2) those who live farther away but tend to have more flexible schedules and travel less frequent to work (2,3). Some scholars believe that the high housing prices in employment centers displace workers to reside in other subregions (22), while other academic literature and commentary rarely made the link. This view of extreme commuting as a by-product of high housing prices implicitly assumes that extreme commuting is not a choice.

A related set of literature examines whether land use patterns empirically affect commuting (23) and how actual commutes compare to those predicted by the standard urban model (known as the "excess commuting" literature). Empirical evidence suggests actual commutes are in excess of predicted commutes by 47% to 87% depending on the context and measurement type (24-29), with the exception of White (1988) who finds only an 11% excess (30). In all, workers drive much more than expected (23) – is this because they are priced out of living where their jobs are (termed "mismatch") or the number of jobs and workers are very different in an area ("imbalance")? Giuliano and Small (1993) suggest that excess commuting is much higher than can be explained by jobs-housing mismatch or imbalance (23). As a result, policies toward correcting this mismatch may not meaningfully reduce commuting distance or time.

More recent work has improved on these initial estimates from a methodological perspective (see Ha et al., 2018 for a succinct literature review) and have confirmed the role of urban form on excess commuting (31). Ha et al. (2018) also confirmed that polycentric regions tend to have higher commuting and excess commuting due to cross-commuting tendencies and that regions with dominant central cities have lower commutes and excess commuting (31).

Moreover, their study finds that the impact of sprawl and jobs-housing imbalance is complicated and beset by methodological choices, as predicted by Giuliano and Small (1993) (23). This study dovetails well into our analysis of the Central Valley and Bay Area: two sprawling, polycentric regions with jobs-housing imbalance.

Researchers have suggested that the imbalance between affordable housing in the Central Valley and thriving job opportunities in the Bay Area increase the need for long-distance commuting (5,6). The restrictive housing supply in San Francisco metro forces workers to migrate out of the Bay Area (32). This is in line with Shoag and Muehlegger (2015) who find that across U.S. metropolitan areas, more stringent local land use regulation, which is often correlated with more restrictive housing supply, is associated with increased aggregate commute times (33). This is even more the case for college educated workers but can be mitigated by the presence of a well-functioning public transit system (33). The current policy debate and popular press have also begun to associate extreme commuting with a lack of affordable housing (see, 34), but there has been little evidence on such an association between unaffordable housing and extreme commutes.

Most COVID-19 pandemic-related research on transportation has dealt with logistics and supply chain issues (35-37) and the effect of transportation and commuting on COVID-19 transmission (e.g., 38-39), with only a few studies about disruptions to transportation systems (40) and the pandemic's impact on travel behavior (41-43). There are several academic studies that estimate the incidence of telecommuting due to the pandemic using survey data (e.g., 44-48), but by nature these cannot make a conclusion about the pandemic's effect on overall traffic flows, and most are not about the U.S. context. Since the pandemic continues, with subsequent strains of the coronavirus causing further disruption, this important policy and research question will take time to resolve (49).

Two papers stand out as providing a more comprehensive early lens on the impact of COVID-19 on commuting. Kar et al. (2021) document spatial patterns of essential workers' commutes by socioeconomic status (SES), in 2019 before the pandemic and in 2020 once the pandemic started in Columbus, OH (50). They find that the pandemic widened the travel disparities by SES groups that existed prior to the pandemic: low and moderate SES travelers made long and medium distance trips for work, while higher SES travelers traveled short distances for recreational or other non-work purposes (50). Liu et al. (2021) focused on public transit demand among essential and non-essential workers, before and during the pandemic (51). They find that places with higher shares of essential workers and vulnerable populations (African American, Hispanic, Female, those older than 45) and places with more "Coronavirus" Google searches had higher levels of public transit demand after the pandemic started (51).

The pandemic has increased remote working, with the daily work-from-home rate going from 8% in February 2020 to 35% in May 2020 (56). Brynjolfsson et al. (2020) conducted two waves of surveys in April and May 2020 using Google Consumer Surveys (GCS) to ask whether people have started work-from-home in the past 4 weeks. They found that workers who are white, young, highly educated, high income, employed in information work (management, professional and related occupations), or parents were more likely to switch to work-from-home. These groups were also less likely to have been laid off or furloughed. Bick et al (2020) suggested that lower-educated, Blacks or Hispanic workers are less likely to work-from-home due to their occupations. These group of people are also more likely to became unemployed during the pandemic (57). COVID-19 has caused enormous economic dislocation, but it is still unclear if its impact on work and commute patterns will be temporary or permanent. Many speculative discussions on work-from-home after the pandemic predicts that telecommuting will continue its growth. The changes in work and employment had an immediate impact on the economy and could lead to permanent shifts that last beyond the pandemic.

Given the negative individual and societal associations with long commutes, more research is needed to guide transportation policy that could provide environmental, fiscal, and economic development benefits to the region. This report helps fill this gap by exploring the supercommute from multiple angles, analyzing demographics associated with supercommuting, and looking at the effect of COVID-19 on the supercommute.

Chapter 3: Data

We draw from five data sources to compile summaries and analyses of supercommuting: four data sources relating to commuting - U.S. Department of Transportation's (DOT's) and California Department of Transportation's (Caltrans') Household Travel Surveys, the American Community Survey (ACS), the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LEHD-LODES), StreetLight Insight, and one data source related to migration - California Franchise Tax Board (FTB) records. Each of these data sources provides different definitions of commuting, geographies, and covariates. The following summarizes each source's methodology and main uses.

Transportation

1. Travel Surveys: Travel diary data from U.S. DOT's National Household Travel Survey (2017) and Caltrans' California Household Travel Survey (2012). Data include travel distance, mode, and time, as well as personal and household characteristics variables. Access to this database is obtained to the geocoded spatial data for the 2012 CHTS and 2017 NHTS through Dr. Marlon Boarnet's active National Center for Sustainable Transportation (NCST) and Pacific Southwest Region (PSR) University Transportation Center contracts with Caltrans. Researchers and transportation planners can obtain access to public use files from these datasets. Secure versions of the data include residential locations and trip origin and destination locations.

2. ACS: Census data from U.S. Census Bureau's American Community Survey (ACS) 5-year average commuting characteristics, available at the Zip Code Tabulation Area (ZCTA) level from 2006-2010 to 2015-2019. ACS data can be aggregated to the county and state levels. Commuting data include travel time, travel mode, and workplace location, as well as key demographic variables. This database is free to the public. We access the data through IPUMS NHGIS (IPUMS NHGIS, University of Minnesota, www.nhgis.org) (57).

3. LEHD LODES: State-level employment and administrative data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES), available from 2002 – 2018 (https://lehd.ces.census.gov/data/). The Origin-Destination (OD) data contains information on census block to census block home to work flows, which aggregate to the ZCTA, county, or state levels. OD data also includes high-level demographic and industry group characteristics.

4. StreetLight InSight®: 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. They temporarily licensed their data platform to academics researching the impact of COVID-19, providing a valuable up-to-date source. Their system uses a

machine learning algorithm trained with Census data to infer demographic information about commuters from a sample of phones. The platform provides information about travelers' origin and destination, travel distance, travel purpose, and basic demographic information (income, ethnicity, educational level, etc.) and has gone through extensive validation using transportation data (28). Unlike the ACS and LEHD-LODES, StreetLight data includes all trips, not just work commutes. It is available from 2016 and continues updating every month. We use this data to measure the changes in ZCTA to ZCTA commuting flows before and during the COVID-19 pandemic. Because the data rely on sampling and impose limits on the total number of ZCTAs included, we only use ZCTAs that intersect urbanized areas in our study area or that have a population over 3,000 and are in our study area.

Migration

5. FTB: The Franchise Tax Board compiles tax records for all people who file state income taxes in California. We used those records to measure migration from the Bay Area to the Central Valley. For each year from 2002 (the first year of the LODES data) to 2015 (the last year in our FTB data), we counted as a move any record that was in a Bay Area Zip Code in one year and in a Central Valley Zip Code in the next year. The unit of measurement is the number of *moves* rather than number of *movers* as records may be for an individual or a family. For sparsely populated zip codes, FTB data was aggregated as required by FTB's data usage policies. We normalized the data by standardizing the record to ZCTA geography and dividing the number of moves by the population in the appropriate year.

Chapter 4: Exploring the Supercommute

This section documents the characteristics of the supercommute from the four different data sources listed in the previous section: travel surveys, ACS, LODES, and StreetLight. The four datasets are collected and sampled with different methods, and each enables different understandings of long commutes. No previous studies have analyzed supercommuting with cross-comparison datasets and it is important to sort out what is similar and different about the results.

This section first documents the historic trend of supercommuting with datasets gathered between 2012 and 2020. We then look at commute patterns over time by analyzing commute flow between the Bay Area and Central Valley. Following that, we study detailed demographics of supercommuters to understand the characteristics of these long commute trips. Last, we review the effect of COVID-19 on supercommute patterns in the region.

This section explores the characteristics of supercommute with cross-sourced data.

Methods & Limitations

We only focus on analyzing the “commute trip” (known as home-based work trip) in this study. In the travel diaries, we identified commute trips as those where an employed worker starts a trip from home (trip origin=home), ends at a workplace (trip destination=workplace), and has a trip purpose of “work”. For ACS, we use the travel time to work variable, whose universe are employed persons over age 16. For LODES, we identify commutes by looking at flows between residence blocks and work blocks. For Streetlight, we use trips during Peak AM hours (6AM – 10AM) as proxies for commute trips on a typical weekday because the dataset does not provide trips by activity type.

Recall, this study defines a supercommute as a one-way commute longer than 90 minutes (2,3) or at least 50 miles (4), following existing literature. We amend this definition where necessary based on data availability. With travel diaries (2012 CHTS and 2017 NHTS), we calculate and aggregate the average incidence of supercommuting at the household level. With the ACS, we calculate the proportion of supercommuters by ZCTA by year. With the LODES data, we calculate the network distance for each origin and destination pair using ArcGIS’ Network Analyst tool. We then calculate the proportion of origin-destination pairs that indicate over 50 miles of one-way network distance for each ZCTA. Streetlight provides trip distance and duration data by origin-destination pair (ZCTA to ZCTA). We calculate the proportion of origin-destination pairs that have an average trip length over 50 miles or trip duration over 90 minutes during morning peak hour for each origin ZCTA.

The differences in data collection and presentation make cross-source comparisons hard. The sample size varies significantly (10 times difference) across different data sources. ACS 2015-2019 5-year estimates and LODES 2018 contain large sample sizes, while travel survey data (NHTS 2017 and CHTS 2012) provide a very small sample view of commuting. These data are also collected at different geographical units, making it challenging to find a unified aggregation level that could be applied across different data sources. Moreover, data sources differ in the degree of additional demographic, socioeconomic, and travel mode details provided. As a result, we aggregate findings at the county and region level to compare across sources. Where possible, we report descriptive statistics at the city level (LODES) and use ZCTAs as the unit of analysis for regressions (ACS, Streetlight, FTB).

Supercommute Trends

Commute Distance and Duration by Region

This part of the analysis focuses on the overall patterns of commute as reported by all four data sources available (travel diaries from CHTS and NHTS, ACS, LODES, and StreetLight).

Table 1 compares the results of commute distance from CHTS, NHTS, LODES, and StreetLight by region. All data sources show that more than half of the commuters travel fewer than 15 miles or 30 minutes to work regardless of the year of data collection. The share of supercommuters by distance (commute more than 50 miles one way) is around 2% in the Bay Area, a number consistent across sources except for LODES, where it over 9%. In the Central Valley, the supercommute share of 3% is consistent between NHTS 2017 and StreetLight, but around 8% in the 2012 CHTS and again much higher at 22% in LODES results.

The fact that LODES reports much higher shares of supercommute likely reflects the difference in data collection methodology. The LODES Origin-Destination (OD) data delineate the number of workers for each pair of residential and work census blocks. Because LEHD data are based on voluntary reporting by employers, it has several well-known limitations (52,53). Notably, it is an imperfect measure of commutes because the place of work assigned is not necessarily where a worker works but, in some cases, the headquarters of the organization or business, although the Census Bureau makes an effort to avoid such incorrect assignments.

Table 2 compares the results of commute duration from CHTS, NHTS, ACS, and StreetLight by region. Supercommute patterns are more consistent and have less variation for duration than for distance across all datasets. By duration, 2012 CHTS and Streetlight show supercommute levels around from 1-2%, while 2017 NHTS and ACS show 4.5-5%. In the Central Valley, the share of supercommute by duration is reported at 1.8% in StreetLight, 3.1% in NHTS, 4.5% in CHTS, and 5.9% in ACS. These tables highlight differences in supercomputing incidence depending on definition. While distance-based measures are common, duration measures may provide a more complex picture. This is because commute distance only shows the direct network distance from home to workplace, but commute duration captures other confounders that could affect commute time such as traffic and mode choice.

Table 1. General commute distance from CHTS, NHTS, LODES, and Streetlight

Data	CHTS (2012)				NHTS (2017)				LODES (2018)				Streetlight (2020)			
Region	Bay Area		Central Valley		Bay Area		Central Valley		Bay Area		Central Valley		Bay Area		Central Valley	
Mile	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
0	6	0.2	7	0.3	7	0.3	6	0.2	3,015	0	1,667	0.1	-	-	-	-
<1	172	5.1	88	4.0	154	6.0	205	5.4	1,977,444	63.3	952,027	53.0	1,735	0.05	0	0
1-14	2,135	62.8	1,163	52.6	1,636	63.4	2,457	64.4					3,047,284	80.5	2,032,912	77.9
15-24	616	18.1	370	16.7	418	16.2	686	18.0	458,607	14.7	211,501	11.8	400,098	10.6	320,392	12.3
25-49	414	12.2	407	18.4	324	12.6	348	9.1	397,931	12.7	230,550	12.8	283,223	7.5	188,141	7.2
>=50	57	1.7	175	7.9	42	1.6	112	2.9	288,128	9.2	399,536	22.3	50,959	1.3	67,144	2.6
Subtotal	3,400	100	2,210	100	2,581	100	3,814	100	3,125,125	100	1,795,281	100	3,783,299	100	2,608,589	100
Total trips	5,610				6,395				4,920,406				6,391,888			

*Streetlight sample: time period: 01/01/2020-03/10/2020; daytype: Tuesday (Tu-Tu); daypart: Peak AM (6am-10am)

Table 2 General commute duration from CHTS, NHTS, ACS, and Streetlight

Data	CHTS (2012)				NHTS (2017)				ACS (2015-2019)				Streetlight (2020)			
Region	Bay Area		Central Valley		Bay Area		Central Valley		Bay Area		Central Valley		Bay Area		Central Valley	
Minute	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	Percent	Freq.	Percent
1-29	1,925	57.4	1,163	53.4	1,131	43.8	2,248	58.9	1,457,924	48.3	1,057,264	59.8	2,217,142	58.6	1,611,297	61.8
30-59	1,165	34.7	701	32.2	979	37.9	1,200	31.5	1,085,627	35.9	485,746	27.5	1,251,970	33.1	852,383	32.7
60-89	225	6.7	216	9.9	343	13.3	247	6.5	340,876	11.3	119,053	6.7	250,069	6.6	96,297	3.7
>=90	40	1.2	99	4.5	127	4.9	119	3.1	136,853	4.5	104,473	5.9	63,553	1.7	48,133	1.8
subtotal	3,355	100	2,179	100	2,580	100	3,814	100	3,021,280	100	1,766,536	100	3,782,734	100	2,608,110	100
Total trips	5,534				6,394				4,787,816				6,390,844			

*Streetlight sample: time period: 01/01/2020-03/10/2020; daytype: Tuesday (Tu-Tu); daypart: Peak AM (6am-10am)

Commute Distance and Duration by County

To further understand supercommuting trends by distance and duration between the Bay Area and Central Valley, we focus the analysis at the county level.

Table 3 compares the trend of supercommutes by travel distance (miles) by county. While the supercommute levels vary by county and data source, the counties with the highest supercommute share do not: Stanislaus, Merced, San Joaquin, and Solano. These four Central Valley counties have the highest supercommute shares by distance, shares that are at least 2-3 times higher than those of Bay Area counties or Sacramento County. The suburban Sacramento region counties of El Dorado and Placer also exhibit slightly higher supercommute shares, but only according to some datasets (2017 NHTS, 2018 LODES), but not others.

Within each data source, the variation across counties is higher across regions than within regions. Comparatively, cross-source comparisons follow the regional trends. The reason LODES still reports the highest shares is because the methodology used to calculate supercommute with LODES data is the percent of home-to-job pairs that are more than 50 miles.

The county-level patterns by commute duration parallel those of commute distance. Here too, Stanislaus, Merced, San Joaquin, and Solano counties have consistently higher supercommute shares than Bay Area or Sacramento counties, in almost every dataset. El Dorado county again joins this group except for in Streetlight. However, using the duration definition, several Bay Area counties have higher supercommute shares than by distance, including San Mateo and San Francisco (in 2017 NHTS) and Alameda and Contra Costa (in ACS).

Figure 2 takes a deeper dive into the Central Valley counties with the highest supercommuting shares, by looking at supercommuting by distance at the city level using LODES. While LODES may overestimate supercommutes relative to other sources, Figure 2 only looks at LODES, but over time. For each of these cities, supercommute shares follow a relatively steady upward trend. In each of these (except Modesto) this is a case of both growing populations of commuters (see table 7 below) but also growing supercommuting shares. In essence – since 2002, these cities have added 10-60% more commuters and more of these now commute over 50 miles in one direction.

In sum, in the counties with the highest shares of supercommuting (i.e., Stanislaus, Merced, San Joaquin, and Solano), anywhere from 5 to 10% percent of commuters go at least 50 miles one way and 4 to 10% of commuters go at least 90 minutes one way, when looking at 2017 and later. We see these estimates as providing a lower bound, given that LODES, for example, estimates much higher levels. As a result, up to 10% of commuters in these Central Valley counties spend at least 3 hours on the road and cover 100 miles or more each day. The time spent has undoubted social costs. For example, the distance covered likely plays out in higher CO_2 emissions, unless these commuters are taking low emission forms of mass transit.

Table 3. Supercommuters by travel distance (>=50 miles): CHTS, NHTS, LODES and Streetlight

Region	County	CHTS 2012		NHTS 2017		LODES 2018		Streetlight 2020 (Q1)			
		% of super-commuters (>=50 miles)	# of all commuters (all distance)	% of super-commuters (>=50 miles)	# of all commuters (all distance)	% of Jobs (>=50 miles)	# of jobs (all distance)	% of peak AM super-trips (>=50 miles)	# of all peak AM trips (all distance)	% of early+peak AM super-trips (>=50 miles)	# of all early+peak AM trips (all distance)
Bay Area	Alameda	0.7%	28,246	2.9%	5,707	9.3%	805,131	1.3%	935,588	1.7%	1,079,860
	Contra Costa	1.2%	21,988	2.9%	3,881	11.2%	515,000	1.9%	697,309	3.2%	807,841
	San Francisco	0.6%	17,159	3.0%	3,899	7.3%	473,702	1.2%	457,910	1.4%	511,938
	San Mateo	0.7%	18,286	3.6%	3,272	8.5%	385,644	0.8%	506,706	1.1%	562,552
	Santa Clara	1.2%	37,643	2.3%	7,384	9.4%	945,648	1.3%	1,185,786	1.7%	1,332,161
Central Valley	El Dorado	2.4%	5,140	4.1%	1,967	27.5%	76,335	1.8%	96,706	2.8%	108,100
	Merced	3.0%	6,711	8.4%	868	32.0%	98,140	6.0%	123,241	10.0%	149,079
	Placer	2.3%	6,142	2.0%	5,517	23.7%	160,558	1.5%	313,126	2.3%	349,012
	Sacramento	1.7%	12,191	2.1%	16,976	19.7%	662,007	1.5%	910,657	2.3%	1,045,685
	San Joaquin	3.3%	8,675	3.8%	3,145	24.5%	296,147	4.5%	409,856	7.7%	507,064
	Solano	2.6%	8,866	5.8%	1,375	15.5%	199,831	2.9%	261,133	4.9%	313,951
	Stanislaus	3.1%	7,605	4.3%	2,774	28.0%	217,126	3.0%	343,621	5.3%	410,407
	Yolo	2.7%	3,667	2.5%	2,615	17.1%	85,137	2.1%	150,249	3.5%	171,732

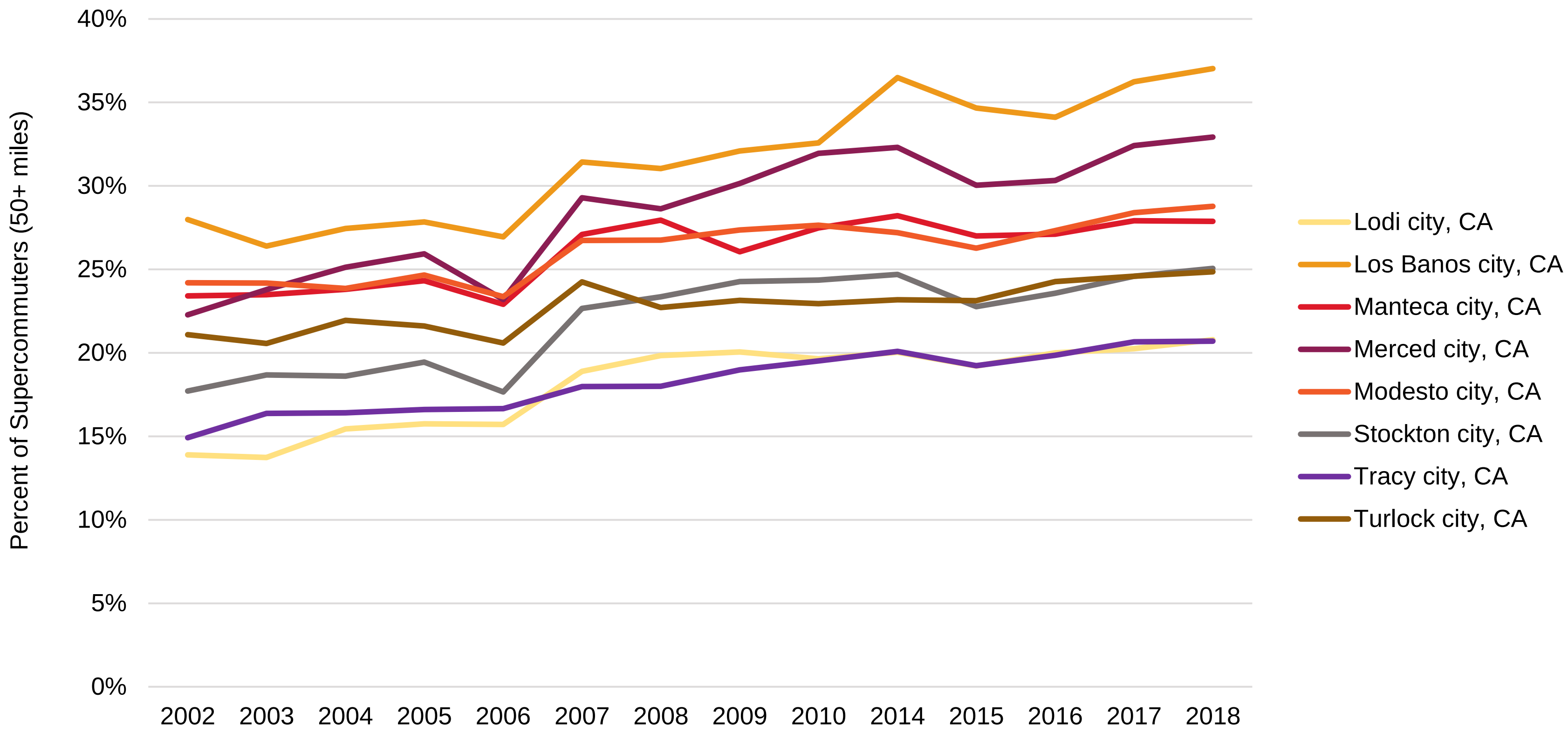
*Streetlight sample: time period: 01/01/2020-03/10/2020; daytype: Tuesday (Tu-Tu) ; daypart: Early AM (12am-6am); Peak AM (6am-10am)

Table 4. Supercommuters by travel duration (>=90 minutes): CHTS, NHTS, ACS and Streetlight

Region	County	CHTS 2012		NHTS 2017		ACS 2015-2019 5-year estimates		Streetlight 2020 (Q1)			
		% of super-commuters (>=90 min & < 240 min)	# of all commuters (all duration)	% of super-commuters (>=90 min)	# of all commuters (all duration)	% of super-commuters (>=90 min)	# of commuters (all duration)	% of peak AM super-trips (>=90 min)	# of all peak AM trips (all duration)	% of early+peak AM super-trips (>=90 min)	# of all early+peak AM trips (all duration)
Bay Area	Alameda	1.1%	21,235	3.2%	5,702	4.9%	741,906	2.0%	935,426	2.2%	1,079,576
	Contra Costa	1.6%	16,329	3.3%	3,879	9.2%	522,772	2.6%	697,210	3.2%	807,604
	San Francisco	0.9%	13,384	5.9%	3,899	3.9%	491,725	1.6%	457,836	1.7%	511,775
	San Mateo	0.9%	13,678	4.3%	3,268	1.9%	385,595	0.9%	506,622	1.1%	562,382
	Santa Clara	1.2%	27,975	3.0%	7,381	3.0%	942,148	1.2%	1,185,640	1.3%	1,331,889
Central Valley	El Dorado	3.0%	3,558	4.2%	1,961	4.8%	76,127	1.3%	96,691	1.9%	108,067
	Merced	2.7%	4,563	6.7%	868	8.6%	105,622	3.4%	123,223	6.1%	149,012
	Placer	2.6%	4,282	2.0%	5,510	3.5%	158,236	1.1%	313,032	1.7%	348,825
	Sacramento	2.0%	8,676	2.1%	16,953	3.4%	664,958	1.0%	910,521	1.6%	1,045,454
	San Joaquin	2.8%	6,040	3.1%	3,142	10.2%	305,061	3.5%	409,728	5.6%	506,887
	Solano	2.1%	6,377	4.4%	1,373	7.4%	203,509	2.5%	261,107	3.1%	313,879
	Stanislaus	4.2%	5,209	3.6%	2,772	8.6%	208,425	2.1%	343,581	4.1%	410,295
	Yolo	2.6%	2,622	2.9%	2,615	3.0%	89,974	1.3%	150,227	2.2%	171,696

*Streetlight sample: time period: 01/01/2020-03/10/2020; daytype: Tuesday (Tu-Tu); daypart: Early AM (12am-6am); Peak AM (6am-10am)

Figure 2. Supercommuter share by travel distance (>=50 miles) (LODES) for 8 largest incorporated cities in Central Valley, that are not part of the Sacramento metropolitan area (SACOG)



Supercommute Flows

Researchers have suggested that the relatively more affordable housing in the Central Valley and thriving job opportunities in the Bay Area increase the need for long-distance commuting and thus lead to an imbalance traffic between the two areas (4). This section presents the analysis of commute flow by region and county across multiple data sources.

Table 5 shows the share of outbound commute of workers living in the Central Valley counties and traveling to Bay Area counties for work using 6 cross-sections of Census-based estimates, including the US Census (1990, 2000), ACS (2006-2010, 2009-2013, 2011-2015), and the Census Transportation Planning Package (CTPP) (2012-2016). There are no more recent data sources on this topic from the census. According to the 2012-2016 CTPP, counties that have the highest share of outbound commuters are Solano (23.5%) and San Joaquin (18.1%), followed by Stanislaus (7.5%) and Merced (6.5%). However, outbound commuters decreased by 4.9% in Solano while growing in other counties in the Central Valley from 1990 to 2012/16.

Table 5. Share of outbound commuters going to Bay Area from the Central Valley (Census, ACS, and CTPP)

Region	Residence County	1990 Census	2000 Census	2006-2010 ACS	2009-2013 ACS	2011-2015 ACS	2012-2016 CTPP	P.P. Difference: 2012/16 minus 1990
Central Valley	El Dorado	1.30%	2.00%	2.30%	2.30%	1.90%	2.16%	0.86%
	Merced	1.40%	6.00%	6.20%	5.80%	6.30%	6.52%	5.12%
	Placer	1.20%	1.90%	1.60%	1.90%	1.90%	1.91%	0.71%
	Sacramento	1.20%	1.30%	1.60%	1.50%	1.60%	1.61%	0.41%
	San Joaquin	10.40%	15.70%	16.90%	16.60%	17.20%	18.14%	7.74%
	Solano	28.40%	28.60%	24.90%	23.10%	23.40%	23.47%	-4.93%
	Stanislaus	6.90%	7.90%	7.90%	7.50%	7.50%	7.47%	0.57%
	Yolo	1.60%	2.10%	2.50%	2.50%	2.60%	2.41%	0.81%

Data source: US Census: 1990, 2000; ACS 5-year estimates: 2006-2010, 2009-2013, 2011-2015; CTPP estimates 2012-2016

Table 6 shows the outbound commuters from LODES (2002 and 2018). Total employment grows by 32% (443,024 persons) from 2002 to 2018 in the Central Valley. The proportion commuting from Central Valley to Bay Area remain steady between 2002 (16.4%) and 2018 (16.6%). This is in line with Census-based estimates in Table 5 over the same approximate time period, though Census reports a drop in Solano county, but LODES does not. Over time, LODES reports that the share of supercommuters increased by 5 percentage points in the Central Valley region, growing from 18% in 2002 to 23% in 2018. The highest percentage point growth from 2002 to 2018 according to LODES was in Merced, followed by El Dorado and Placer counties.

Table 6. Proportion commuting to Bay Area from the Central Valley (LODES)

Region	Counties	Total Employed			Proportion Commuting to Bay Area			Supercommuter % (50+ miles)		
		2002	2018	2018 minus 2002	2002	2018	2018 minus 2002	2002	2018	2018 minus 2002
Central Valley	**Central Valley**	**1,352,257**	**1,795,281**	**443,024**	**16.40%**	**16.60%**	**0.30%**	**18%**	**23%**	**5%**
	El Dorado	60,866	76,335	15,469	10.10%	11.40%	1.30%	21%	28%	7%
	Merced	76,404	98,140	21,736	11.40%	13.00%	1.60%	23%	32%	9%
	Placer	104,964	160,558	55,594	9.50%	10.70%	1.30%	17%	24%	7%
	Sacramento	480,259	662,007	181,748	11.90%	10.50%	-1.50%	17%	20%	3%
	San Joaquin	232,538	296,147	63,609	23.10%	26.40%	3.30%	18%	24%	6%
	Solano	147,507	199,831	52,324	34.30%	34.60%	0.40%	12%	15%	3%
	Stanislaus	182,595	217,126	34,531	16.10%	16.30%	0.20%	24%	28%	4%
	Yolo	67,424	85,137	17,713	7.90%	8.80%	1.00%	12%	17%	5%

Data source: LODES (2002, 2008)

Table 7 shows the outbound commuters for the 8 largest incorporated cities in the Central Valley that are not part of the Sacramento metropolitan area. The largest Central Valley communities have grown in terms of the number of employed residences over the past two decades, some by over 40%. However, the proportion of commuters to the Bay Area has not grown by more than 3 percentage points in any of them since 2002. The largest share growth has been in the city of Lodi, from 12% going to Bay Area in 2002 to 15% in 2018. This largely trends with the results at the county level above and means that the economic connectivity of these places with the Bay Area grows via population growth rather than massive shifts in employment trends.

Table 7. Proportion commuting to Bay Area from the Central Valley (LODES) for the 8 largest incorporated cities in Central Valley, that are not part of the Sacramento metropolitan area

Residence City	# of Employed Residents in 2018	Growth in # of Employed Residents (2018 – 2002)	Proportion Commuting to 5-County Bay Area		
			2002	2010	2018
Lodi city, CA	75,489	13%	12%	13%	15%
Los Baños city, CA	29,709	49%	19%	16%	19%
Manteca city, CA	80,036	47%	35%	34%	34%
Merced city, CA	77,172	30%	10%	11%	12%
Modesto city, CA	233,199	7%	16%	15%	16%
Stockton city, CA	309,836	20%	18%	18%	21%
Tracy city, CA	86,349	59%	48%	48%	46%
Turlock city, CA	80,258	28%	12%	11%	12%

A further analysis looks at flows from region to region and within region by distance using the travel diaries and Streetlight. Table 8 shows the results from NHTS (2017). A total of 6,395 commute trips are generated in our study region. A commute trip is a home-based work trip, meaning that a trip starts from home (trip origin=home), ends at the workplace (trip destination=workplace), and has a trip purpose of “work”. We find for example, that even though overall supercommute share by distance is low (2.4% of all 6,395 commute trips in the 2017 NHTS for example), 48% of these are Central Valley to Bay Area trips. In the 2012 CHTS, this level is 36% of the 2.5% of trips that are supercommutes, and in Streetlight it is 33% of the 1.5% of trips that are supercommutes. Moreover, Table 8 highlights the uneven flow of commuters between regions: 2.3% of commuters travel from the Central Valley to the Bay Area for work, while only 0.2% of commuters travel from Bay Area to Central Valley for work (2017 NHTS). The Central Valley also has more supercommuters (1.1%) as a whole than the Bay Area (0.1%). Data from 2012 CHTS and 2020 StreetLight also show similar results.

Table 8. Region to region commute trips by distance (CHTS, NHTS, and SL(Streetlight))

Trip distance	Bay – Bay			Bay – Central Valley			Central Valley - Bay			Central Valley – Central Valley			Total		
Data Source	2012 CHTS (%)	2017 NHTS (%)	2020 SL (%)	2012 CHTS (%)	2017 NHTS (%)	2020 SL (%)	2012 CHTS (%)	2017 NHTS (%)	2020 SL (%)	2012 CHTS (%)	2017 NHTS (%)	2020 SL (%)	2012 CHTS (%)	2017 NHTS (%)	2020 SL (%)
0	0.1	0.1	-	0.0	0.0	-	0.0	0.0	-	0.1	0.1	-	0.2	0.2	-
<1	3.4	2.4	0.03	0.0	0.0	0	0.0	0.0	0	1.7	3.2	0	5.1	5.6	0.03
1-14	41.5	25.6	48.2	0.2	0.0	0.0	0.3	0.0	0.0	21.1	38.4	32.0	63.0	64.0	80.3
15-24	11.7	6.5	6.1	0.2	0.0	0.1	0.6	0.4	0.1	4.8	10.4	4.8	17.2	17.3	11.1
25-49	7.5	5.1	4.2	0.2	0.0	0.2	1.3	0.8	0.4	3.0	4.6	2.4	12.0	10.5	7.1
>=50	0.8	0.5	0.4	0.1	0.1	0.2	0.9	1.1	0.5	0.7	0.7	0.4	2.5	2.4	1.5
Total	64.9	40.2	58.9	0.7	0.2	0.5	3.0	2.3	1.0	31.4	57.3	39.6	100	100	100

Data source: NHTS, 2017 - Total commute trips: sample size = 6,395; CHTS, 2012 - Total commute trips: sample size = 5,540; Streetlight: sample size: 6,319,612 - time period: 01/01/2020-03/10/2020; daytype: Tuesday (Tu-Tu); daypart: Early AM (12am-6am); Peak AM (6am-10am)

Demographic Characteristics of Supercommute

The previous sections summarize supercommute trends and flows. This section aims to answer the question of who bears the burden of supercommuting? What type of household is more likely to supercommute: lower or higher income, young or old? Which industries are more likely to produce more supercommuters? To address this, we analyze a set of demographic factors of supercommuters, including income distribution, age distribution, choice of transit modes, and occupation with cross-source datasets.

Income

Two data sources provide information on commuters' income: travel diaries and LODES. Travel diaries divide household income is divided into 5 categories: <$25k, $25-50k, $50-100k, $100-150k, and >$150k, while LODES has three, albeit less useful, categories: <$1250 / month (<$15k per year), $1250 - $3333 / month ($15-40k per year), and >$3333 / month (>$40k per year). Tables 9 and 10 show travel diary results by income, table 11 shows LODES results.

The higher-income group is more likely to supercommute than the lower-income group both in the Central Valley and in Bay Area. In the Bay Area, the highest income group (>$150k) make up 62% of supercommute trips while the lowest income group (<$25k) make up 2% of supercommute trips. In Central Valley, the highest income group (>$150k) make up 17% of supercommute trips while the lowest income group (<$25k) makeup 7% of supercommute trips.

Combining the two highest income groups ($100-150k and >$150K) accounts for 90% of supercommute in the Bay Area and 57% in the Central Valley. In contrast, the lower-income group in the Central Valley are more likely to supercommute than the same group living in the Bay Area. The lower-income group (<25kand $25-50k) made up 18% of all supercommutes in the Central Valley, but only 2% of all supercommutes in the Bay Area.

Differences in income groups preclude direct comparisons to LODES, in addition to the fact that LODES likely overestimates supercommute levels, as discussed earlier. Nevertheless, LODES is consistent for comparisons within the dataset and hence useful to compare across counties and regions. As such, table 11 using LODES tells a different story by income than the travel diaries. Namely, the lowest income group (below $15k per year) has higher supercommute rates in Bay Area counties than the higher income group (above $40k per year). This pattern reverses in most Central Valley counties, where commuters with income above $40k per year generally have higher supercommute rates than those with income below $15k per year.

It is not entirely clear how to reconcile the conflicting data on supercommuters by income in the Bay Area. Given the small samples in the travel diaries, preference may go toward LODES. However, known issues with LODES provide a relative rather than absolute estimate of the supercommute phenomenon. This is an area where better data collection by demographic characteristics is needed.

Table 9. Commute trips produced in the Bay Area counties (household income)

Trip distance	<$25k	$25-50k	$50-100k	$100-150k	>$150k	Total
0	0.04%	0.00%	0.04%	0.00%	0.16%	0.23%
<1	0.31%	1.29%	1.17%	1.25%	1.91%	5.92%
1-14	2.41%	5.18%	13.47%	14.88%	26.40%	62.34%
15-24	0.62%	0.55%	3.39%	3.39%	8.45%	16.39%
25-49	0.74%	0.62%	2.96%	3.08%	5.76%	13.16%
>=50	0.04%	0.00%	0.16%	0.55%	1.21%	**1.95%**
Total	4.17%	7.63%	21.18%	23.13%	43.89%	100.00%

Data source: NHTS, 2017; Total commute trips: sample size = 2,562

Table 10. Commute trips produced in the Central Valley counties (household income)

Trip distance	<$25k	$25-50k	$50-100k	$100-150k	>$150k	Total
0	0.00%	0.00%	0.05%	0.05%	0.05%	0.16%
<1	0.60%	1.51%	1.57%	1.04%	0.52%	5.25%
1-14	5.19%	11.30%	21.79%	15.81%	9.47%	63.57%
15-24	0.97%	2.09%	5.79%	5.40%	3.78%	18.03%
25-49	0.37%	1.38%	2.95%	2.53%	2.64%	9.86%
>=50	0.23%	0.34%	1.07%	0.94%	0.55%	**3.13%**
Total	7.36%	16.62%	33.22%	25.78%	17.01%	100.00%

Data source: NHTS, 2017; Total commute trips: sample size = 3,832

Table 11. Share of Supercommuters (>= 50 miles) by income group (LODES)

Region	County	All Incomes (>=50 mile)	<$15k (>=50 mile)	$15 – 40k (>=50 mile)	>$40k (>=50 mile)	All Jobs for All Incomes	low wage minus high wage
Bay Area	Alameda	9%	12.13%	11.69%	7.67%	805,131	4.45%
	Contra Costa	11%	13.39%	12.98%	9.78%	515,000	3.61%
	San Francisco	7%	9.25%	8.78%	6.32%	473,702	2.93%
	San Mateo	9%	11.94%	11.66%	6.70%	385,644	5.24%
	Santa Clara	9%	12.92%	12.80%	7.43%	945,648	5.49%
Central Valley	El Dorado	28%	23.31%	24.08%	30.86%	76,335	-7.54%
	Merced	32%	32.48%	29.37%	34.29%	98,140	-1.81%
	Placer	24%	21.56%	21.77%	25.19%	160,558	-3.63%
	Sacramento	20%	19.72%	19.82%	19.57%	662,007	0.15%
	San Joaquin	24%	23.38%	23.13%	25.97%	296,147	-2.58%
	Solano	15%	16.49%	16.75%	14.42%	199,831	2.07%
	Stanislaus	28%	27.23%	26.42%	29.68%	217,126	-2.45%
	Yolo	17%	18.17%	18.02%	16.19%	85,137	1.97%

Data source: Lodes, 2018

Age

The following analysis on age and supercommute used data from LODES (2018). Age is divided into 3 categories: <30, 30-54, and >55. Table 12 shows the results of the share of supercommuters by age group in the study region. The youngest group has the highest share of supercommuters in all counties in both the Bay Area and Central Valley, and the share of supercommuters in the youngest group is almost three times larger in the Central Valley than in Bay Area. Central Valley Counties with the highest share of younger (<30) supercommuters are Merced (35.9%) and Stanislaus (30.9%). Central Valley counties with the lowest share of older supercommuters (>55) are Solano (14.1%) and Yolo (15.6%).

Table 12. Share of Supercommuters (>= 50 miles) by age group (LODES)

Region	County	All Ages	Age < 30	Age 30-54	Age 55+	young minus old age
Bay Area	Alameda	9%	11.60%	8.71%	8.89%	2.71%
	Contra Costa	11%	13.66%	10.61%	10.49%	3.16%
	San Francisco	7%	8.61%	6.91%	6.67%	1.95%
	San Mateo	9%	10.86%	7.89%	8.11%	2.74%
	Santa Clara	9%	12.31%	8.59%	8.66%	3.65%
Central Valley	El Dorado	28%	28.44%	28.16%	25.71%	2.72%
	Merced	32%	35.88%	31.33%	29.08%	6.80%
	Placer	24%	24.69%	23.60%	23.05%	1.64%
	Sacramento	20%	22.13%	19.38%	17.90%	4.23%
	San Joaquin	24%	26.26%	24.51%	22.47%	3.78%
	Solano	15%	18.08%	15.05%	14.16%	3.92%
	Stanislaus	28%	30.87%	27.72%	25.65%	5.22%
	Yolo	17%	20.30%	16.39%	15.66%	4.64%

Data source: Lodes, 2018

Industry

Table 13 shows the results of the share of supercommuters by 3 overarching industry types using data from LODES (2018). While the total employment in Goods Production and in Trade & Transport contribute only 10-20% each to all commutes, results show that they have the highest share of supercommuters in both the Bay Area and Central Valley, compared to all other industries. The top three counties that produce the highest share of supercommuters working in the trade and & transport industry are: Merced (43.3%), El Dorado (39%), and Stanislaus (35.1%). The top three counties that produce the highest share of supercommuters working in the good producing industry are: El Dorado (29.9%), Placer (27.4%), Sacramento (25.7%), and Merced (25.5%).

Table 13. Share of supercommute trips among different industries

Region	County	Industry Proportion of Total Commuters			Supercommute: % going 50+ miles		
		Goods Producing	Trade & Transport	All Other	Goods Producing	Trade & Transport	All Other
Bay Area	Alameda	14%	16%	70%	10.8%	13.0%	8.2%
	Contra Costa	13%	17%	71%	14.9%	15.2%	9.5%
	San Francisco	7%	13%	79%	14.1%	10.4%	6.1%
	San Mateo	11%	16%	73%	11.9%	12.9%	7.0%
	Santa Clara	20%	13%	67%	8.0%	16.3%	8.4%
Central Valley	El Dorado	13%	15%	71%	29.9%	39.3%	24.6%
	Merced	29%	19%	52%	25.5%	43.3%	31.5%
	Placer	12%	17%	71%	27.4%	31.0%	21.2%
	Sacramento	11%	17%	72%	25.7%	27.9%	16.8%
	San Joaquin	19%	23%	58%	23.2%	28.4%	23.4%
	Solano	16%	18%	66%	17.7%	21.4%	13.3%
	Stanislaus	24%	21%	55%	23.9%	35.1%	27.1%
	Yolo	14%	16%	69%	19.8%	26.4%	14.4%

Source: LODES, 2018

Mode of transit

The following analysis on transit modes and supercommute uses data from NHTS (2017) and ACS (2015-2019). The transit modes are divided into 8 categories: Walk / bicycle, private vehicle, bus, rail, car-share (Taxi/Uber/Lyft/Rental car/Zipcar...), airplane, boat/ferry/water taxi, and something else. Results from both travel distance and travel duration analysis are similar.

By Distance:

Tables 14 and 15 show the results of commute trips produced in the Bay Area and Central Valley counties by mode of transit and travel distance using data from NHTS (2017). More commuters (18%) in the Bay Area travel to work by public transit (bus and rail). 92% of commuters in the Central Valley travel to work by private vehicle. Among supercommuters, 26% use transit in the Bay Area, but only 7% in the Central Valley.

By Duration:

Tables 16 and 17 show the results of commute trips produced in the Bay Area and Central Valley counties by mode of transit and travel duration using data from NHTS (2017). The result is similar to the “by distance” analysis. More commuters (18.4%) in the Bay Area travel to work by public transit (bus and rail). 92% of commuters in the Central Valley travel to work by private vehicle. Among supercommuters by duration, 59% use transit in the Bay Area, and 19% in the Central Valley. This means that the duration measurement of supercommuting likely captures a larger proportion of commuters living in areas with poor transit service, rather than the distance measure which captures those living much further out (though there is some clear overlap between the measures).

Table 14. Commute trips produced in the Bay Area counties by transit modes (NHTS - distance)

Trip distance	0	<1	1-14	15-24	25-49	>=50	Total
Walk/bicycle	0.3%	3.3%	4.4%	0.0%	0.0%		8.0%
Private vehicle		2.4%	48.1%	12.7%	8.4%	1.4%	73.0%
Bus		0.1%	4.0%	0.8%	0.9%	0.1%	5.9%
Rail		0.04%	5.3%	2.7%	3.7%	0.4%	12.2%
Car-share		0.04%	0.5%	0.04%	0.04%		0.6%
Airplane							0.0%
Boat/ferry/water taxi				0.1%			0.1%
Something Else			0.3%				0.3%
Total	0.3%	5.9%	62.5%	16.4%	13.0%	1.9%	100.0%

Data Source: NHTS, 2017; Total commute trips: sample size = 2,580

Table 15. Commute trips produced in the Central Valley counties by transit modes (NHTS - distance)

Trip distance	0	<1	1-14	15-24	25-49	>=50	Total
Walk/bicycle	0.1%	1.5%	2.5%				4.1%
Private vehicle	0.1%	3.6%	59.0%	17.0%	9.1%	2.9%	91.7%
Bus			0.9%	0.6%	0.2%	0.0%	1.7%
Rail			0.6%	0.4%	0.4%	0.2%	1.7%
Car-share			0.4%				0.4%
Airplane							0.0%
Boat/ferry/water taxi							0.0%
Something Else		0.1%	0.2%		0.1%		0.4%
Total	0.2%	5.3%	63.6%	18.0%	9.8%	3.1%	100.0%

Data source: NHTS, 2017; Total commute trips: sample size = 3,814

Table 16. Commute trips produced in the Bay Area counties by transit modes (NHTS - duration)

Trip duration	1-29	30-59	60-90	>=90	Total
Walk/bicycle	5.9%	1.9%	0.3%	0.04%	8.1%
Private vehicle	36.6%	27.6%	6.5%	1.9%	72.5%
Bus	0.5%	3.1%	1.6%	0.7%	6.0%
Rail	0.5%	5.0%	4.7%	2.2%	12.4%
Car-share	0.4%	0.2%	0.04%	0.04%	0.7%
Boat/ferry/water taxi			0.04%	0.04%	0.1%
Something Else		0.2%	0.04%		0.3%
Total	43.8%	37.9%	13.3%	4.9%	100.0%

Source: NHTS, 2017; Total commute trips: sample size = 2,580

Table 17. Commute trips produced in the Central Valley counties by transit modes (NHTS - duration)

Trip duration	1-29	30-59	60-90	>=90	Total
Walk/bicycle	3.3%	0.6%	0.2%	0.1%	4.1%
Private vehicle	54.8%	29.5%	4.9%	2.4%	91.6%
Bus	0.2%	0.7%	0.7%	0.1%	1.8%
Rail	0.1%	0.4%	0.7%	0.5%	1.8%
Car-share	0.3%	0.1%			0.4%
Something Else	0.2%	0.1%			0.3%
Total	58.9%	31.5%	6.5%	3.1%	100.0%

Source: NHTS, 2017; Total commute trips: sample size = 3,814

Duration analysis by mode is also possible using the ACS. Table 18 shows the transit mode of commute trips in the Central Valley by county from ACS. Unfortunately, this variable is only available for commutes above 60 minutes, rather than our preferred over 90-minute definition. More than 80% of commuters drive alone, 10-15% use carpool, and less than 5% take public transit (and frequently even fewer). Supercommuting using the duration measure is most pronounced among public transit users in the Central Valley – over 20% in each county and as high as 70% in Solano and San Joaquin counties. Carpool commuters also report relatively high supercommute rates, as high as 25-30% in the top 4 overall supercommute counties (Merced, San Joaquin, Solano, Stanislaus). In contrast, less than 20% of drivers in these counties report supercommuting, and in some counties this is below 10%.

These results point to a broader difference in transit service between the well-served Bay Area and relatively less well-served Central Valley. Figure 3 below presents the public transit mode share by city in both regions on the x-axis and the share commuting over 60 minutes in one direction on public transit on the y-axis, using the ACS data. We see that in the Bay Area, transit mode shares are generally higher (with over 20% in some cases), and localities with higher mode shares see lower transit supercommute shares. This is indicated by the negative slope of the trendline on the Bay Area chart. In contrast, Central Valley localities tend to have much lower transit mode shares, with no cities having greater than 10% transit mode use. Moreover, supercommute shares are high and higher mode shares do not indicate lower supercommute shares, as shown by the positive slope of the trendline in the Central Valley chart.

Service and ridership are likely related, especially in the Central Valley. Low service provision breeds low ridership which in turn breeds low service provision. The result: users of transit in the Central Valley report very high shares of commuting for over an hour in one direction, leading likely to undoubted social costs.

Table 18. Commute trips produced in the Central Valley counties by transit modes (ACS - duration)

Region	County	Total Commuters	Mode Split			Supercommute by Time: share of commuters with a greater than 60-minute commute		
		All Modes	Drove Alone	Carpool	Public Transit	Drove Alone	Carpool	Public Transit
Central Valley	El Dorado	75,549	85%	10%	2%	13%	10%	44%
	Merced	97,330	82%	10%	1%	13%	28%	24%
	Placer	158,348	88%	8%	1%	8%	12%	38%
	Sacramento	646,569	82%	11%	3%	7%	11%	35%
	San Joaquin	290,719	82%	13%	2%	18%	33%	75%
	Solano	196,052	80%	14%	3%	16%	27%	77%
	Stanislaus	210,559	86%	11%	1%	12%	25%	51%
	Yolo	91,410	74%	10%	5%	7%	9%	23%

Source: ACS (2015-2019)

Figure 3. Public Transit commute mode share versus duration (ACS - duration)

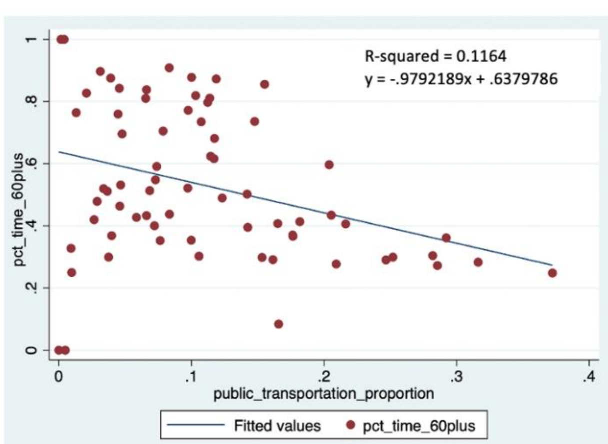


Figure 5: Bay Area Place 2017

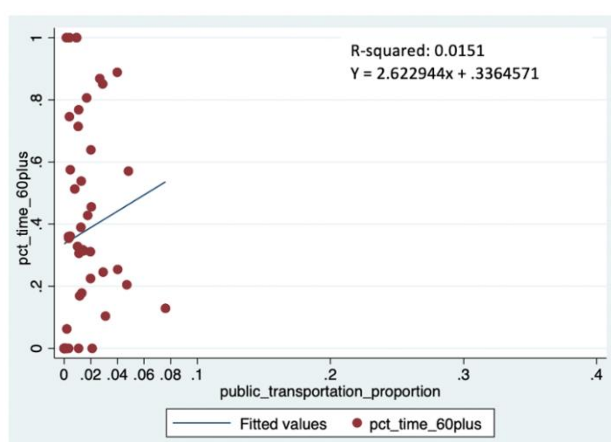
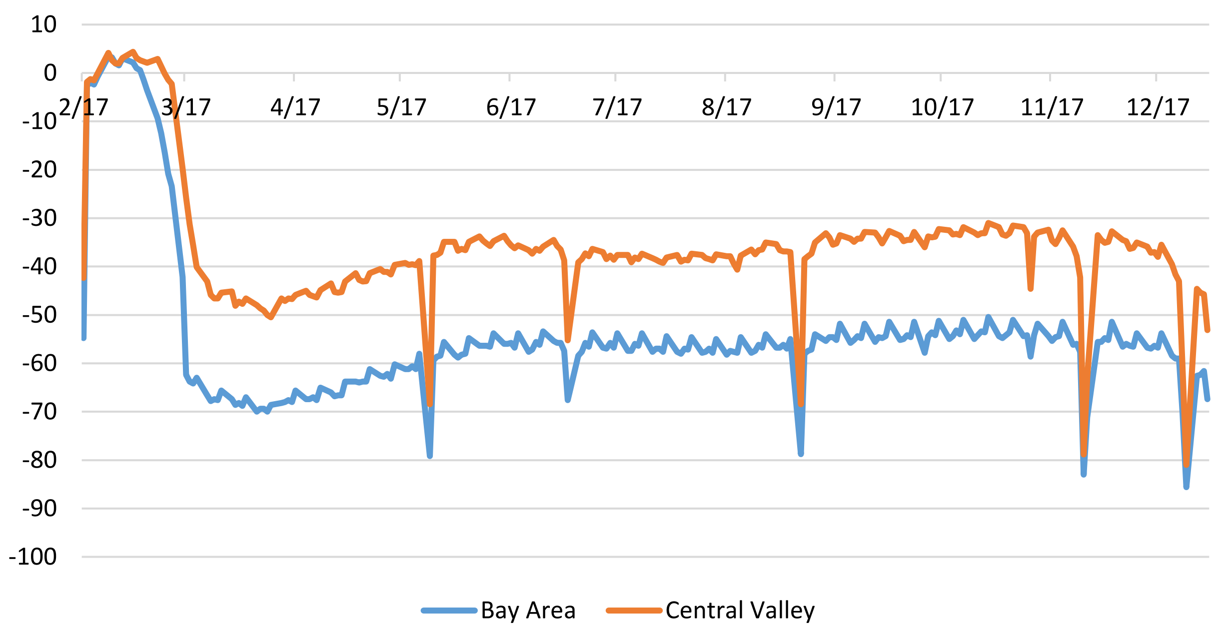


Figure 6: Study Area Place 2017

Effect of COVID-19 on Supercommute

The spread of COVID-19 to California in early 2020 led in March 2020 to a series of policies such as social distancing, work from home, retail closures or limited hours, and quarantines. These policies curbed the spread of the disease but reduced economic activity and travel. According to Google's COVID-19 Community Mobility Reports, the mobility trends for places of work dropped 54% in Bay Area and 42% in Central Valley from the pre-pandemic baseline (Jan 3 – Feb 6, 2020) (Figure 4). These mobility trends provide a reasonable estimate for commuting behavior at a very fine temporal scale (per day). The downward spikes seen in Figure 4 correspond to federal holidays (Memorial Day, Independence Day, Labor Day, Thanksgiving, and Christmas).

Figure 4. Percent change of workplace traffic volume from pre-COVID (weekday only)



Source: Google Mobility, 2021 https://www.google.com/covid19/mobility/

StreetLight provides real-time, up-to-date, ZCTA-to-ZCTA trip flows, which allows us to compare the months prior to the pandemic to the early months of the pandemic. We compare commuting flow in 01/01/2020-03/10/2020 (Pre-COVID) to 03/11/2020-05/19/2020 (during-COVID). The number of trips over 50 miles is estimated from a sample of phone locations collected and averaged over the entire period. We focus on Tuesdays during Peak AM hours (6AM – 10AM) as proxies for commute trips on a typical weekday. We compare these changes in supercommute from Streetlight to overall mobility changes from Google (Table 19).

The average daily trip volume for morning commutes among the two regions before the COVID-19 outbreak was 8,158,828. The trip volume of the first two months of COVID-19 was 3,975,590, a 51% drop. The regional share of supercommute trips remained constant before

(2%) and after (3%) COVID-19 started (Table 19). In some counties, supercommute shares even increased in the first two months of the pandemic (San Joaquin and Yolo).

Did the spatial distribution of supercommutes also change as a result of the pandemic? Figures 3 and 4 map supercommute counts and shares at the ZCTA level during the two observation periods. Before COVID-19, the spatial distribution of supercommuting was uneven, with highest concentrations in ZCTAs in San Joaquin County, Merced County, and southern Santa Clara County. Though, pockets of higher supercommuting existed in ZCTAs throughout the Central Valley and even in the outer reaches of the Bay Area. In the first two months of the pandemic, ZCTAs in the Bay area display much lower supercommute shares, as do many of those in the Central Valley. Yet, the highest supercommute ZCTAs remain in San Joaquin County, Merced County, and southern Santa Clara County, likely reflecting those locations as residences for essential workers.

While supercommuting decreased everywhere, high volumes persisted in many areas with the highest pre-pandemic volume. The workplace mobility dropped by over 60% in the Bay Area, indicating that higher-income households might have more flexibility on working remotely. In contrast, the workplace mobility in the Central Valley only dropped by 40%, which is 20 percentage points less than Bay Area, indicating that lower-income households could be less flexible in their work arrangements. This contrasts the control of mobility between workers in high-wage industries that would have enabled remote working and workers who cannot afford to stop commuting the long distance.

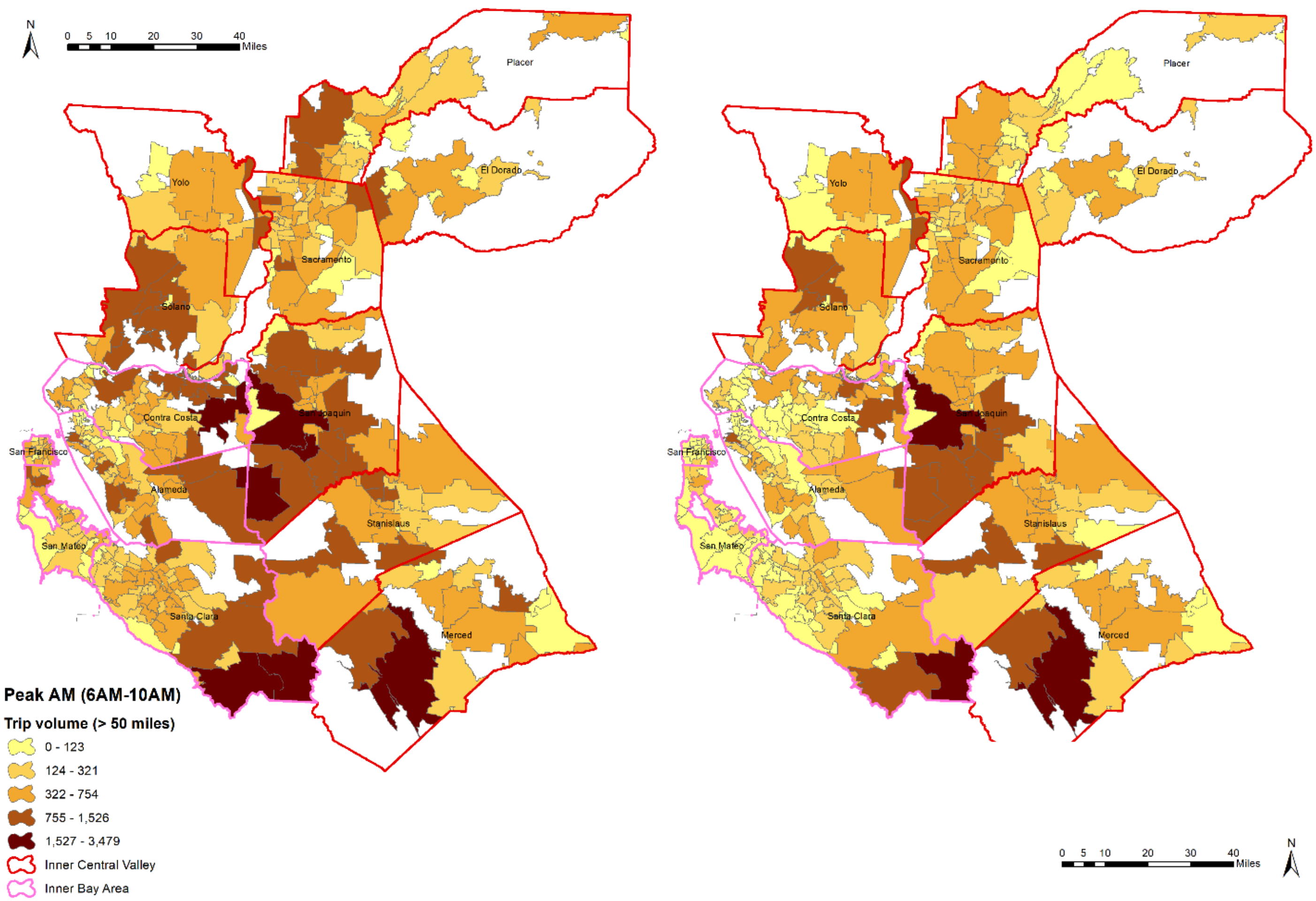
Table 19. Change in mobility by County before and after COVID-19

Region	County	% change in workplace mobility 3/11 - 5/19 (Google Mobility)	% supercommute (StreetLight)			Median household income (2015-2019)
			Pre-COVID (1/1 - 3/10)	COVID (3/11 - 5/19)	change	
Bay Area	Alameda	-59.1	1.8	2.3	0.5	$99,406
	Contra Costa	-51.1	2.3	3.0	0.7	$99,716
	San Francisco	-72.0	1.5	1.2	-0.4	$112,449
	San Mateo	-63.4	1.4	1.4	0.0	$122,641
	Santa Clara	-67.5	1.6	1.8	0.2	$124,055
Central Valley	El Dorado	-45.9	2.5	2.5	0.1	$83,377
	Merced	-33.1	6.2	6.9	0.7	$53,672
	Placer	-46.3	1.9	2.2	0.3	$89,691
	Sacramento	-44.7	1.9	2.6	0.8	$67,151
	San Joaquin	-36.8	4.9	6.4	1.5	$64,432
	Solano	-39.2	3.5	4.1	0.7	$81,472
	Stanislaus	-34.3	3.2	3.9	0.7	$60,704
	Yolo	-46.7	2.3	3.7	1.4	$70,228

Data Source: Google Mobility, 2021 https://www.google.com/covid19/mobility/ ; StreetLight, 2021; ACS, 2015-2019

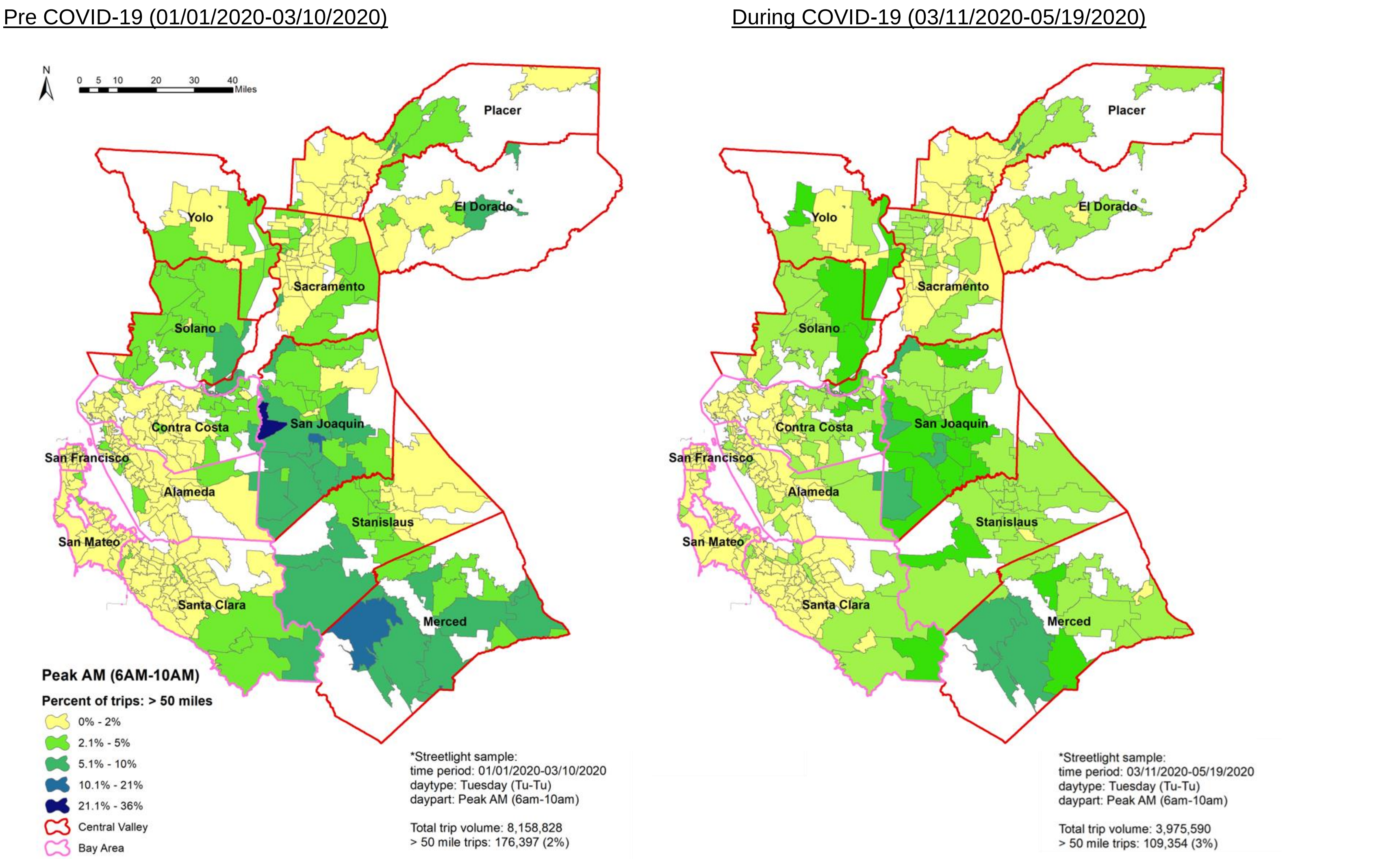
Figure 3. Daily supercommute volume before and after COVID-19

Pre COVID-19 (01/01/2020-03/10/2020)   During COVID-19 (03/11/2020-05/19/2020)



Data Source: StreetLight, 2021

Figure 4. Percent of supercommute before and after COVID-19



Data Source: StreetLight, 2021

Chapter 5: Regression Analysis

Despite evidence of high housing costs in the Bay Area and migration to the Central Valley and increasing commuting from the Central Valley to the Bay Area, there is a lack of evidence connecting these two phenomena. We formulate two main hypotheses that focus on households and places. First, do lower-income persons have longer commutes? This is explored in the Household Level analyses below. Second, do zip codes that received more migrants from the Bay Area generate more supercommuting trips?

We rely on zip code level analysis of migration flows to draw inferences about the impact of residential migration, Bay Area to Central Valley, on supercommuting. These are explored in the Neighborhood Level analyses below.

Household Level:
Association Between Demographics and Supercommute

For the household level regression analysis, we use the 2017 NHTS and 2012 CHTS travel surveys. We test two dependent variables: commute distance (miles) and duration (minutes). We also test a logit model where the dependent variable is 1 if commute distance is above 50 miles and 0 otherwise, and likewise a dependent variable equal to 1 if commute time is greater than 90 minutes, 0 otherwise. We include three broad categories of explanatory variables that could influence supercommuting: directional commute flow categories, household characteristics, and neighborhood characteristics. A wide range of control variables associated with individual, household, and neighborhood characteristics such as age, sex, ethnicity, employment status, household size, persons, and workers per block group, is defined directly from the travel diary or from census data.

Each regression analysis includes 5 models: models 1,2,3, and 4 are estimated using OLS regression with the commute distance (mile) as the dependent variable and model 5 is estimated using logistic regression with supercommute dummy (1=yes, 0=no) as the binary dependent variable. In Models 2 and 4, an interaction term between income and location of trip production is included in the estimation. Results for the duration model using the 2017 NHTS are presented in table 20 and discussed below, focusing on statistically significant results. Since results are largely similar for the 2017 NHTS duration model and the 2012 CHTS distance and duration models, we omit results here for brevity. Please see the Appendix for detailed regression results of these additional models.

The first category of explanatory variables is commute flow. The 2017 NHTS regression results indicate that Central Valley to Bay Area commuters take longer commutes than Bay Area to Central Valley commuters. Comparing with Bay Area to Bay Area commuters, Bay Area to Central Valley commuters travel approximately 35 miles more, and Central Valley to Bay Area commuters travel approximately 43 miles more. This underscores the prevalence of supercommuting in cross-regional commutes, even when controlling for demographic, socioeconomic, and employment characteristics.

According to the 2017 NHTS, households with higher annual income tend to commute longer to work. When compared with households with income below $25,000: in model 1, households with income above $150,000 commute the longest (+ 2 miles) to work. However, in models 2, 3, and 4, this is no longer a statistically significant difference. In contrast, in Models 2, 3, and 4, the commute distance of lower-income households ($25-50k) is the shortest among all income groups. Model 5 also shows that households with income between $25-50k are least likely to be supercommuters. Both Models 3 and 4 indicate that households with more vehicles (+ 0.6 miles per vehicle) and more children between 0-4 years old (+2.5 miles per child) commute further to work.

Next, we look at the association between occupation and commute distance. Commuters with jobs in manufacturing, construction, maintenance, and farming travel farther (+ 4 miles) to work, as do commuters in professional, managerial, and technical fields (+2 miles), compared with commuters with jobs in sales or service. We also looked at whether neighborhood composition is associated with commute distance. We found that commuters travel shorter distances to work if living in a block group with a higher share of renter-occupied housing.

Table 20. Regression results

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
y=		trip distance (mile)	trip distance (mile)	trip distance (mile)	trip distance (mile)	supercommute (0,1)
Commute flow (baseline = Bay Area to Bay Area)	Bay Area to Central Valley	35.834*** (3.67)	35.886*** (3.68)	35.202*** (3.63)	35.151*** (3.63)	5.198*** (0.78)
	Central Valley to Bay Area	44.133*** (1.03)	43.697*** (1.13)	41.844*** (1.05)	41.284*** (1.14)	3.897*** (0.28)
	Central Valley to Central Valley	-0.536 (0.33)	-1.018 (0.61)	-1.807*** (0.37)	-2.437*** (0.62)	-0.484 (0.26)
Household income (baseline = <$25k)	$25-50k	-1.375 (0.75)	-3.925** (1.48)	-1.953** (0.75)	-4.213** (1.48)	-1.023* (0.49)
	$50-100k	1.093 (0.68)	0.319 (1.30)	-0.159 (0.70)	-0.467 (1.31)	-0.751 (0.42)
	$100-150k	1.633* (0.69)	0.226 (1.29)	-0.251 (0.74)	-0.979 (1.31)	-0.328 (0.44)
	>$150k	2.251** (0.70)	1.342 (1.25)	0.104 (0.76)	-0.207 (1.27)	-0.547 (0.46)
Income * trip production (baseline = Bay Area trip origin and >$150k)	<$25k: Central Valley		-1.003 (1.52)		-0.114 (1.53)	
	$25-50k: Central Valley		2.406* (1.17)		2.867* (1.16)	
	$50-100k: Central Valley		0.038 (0.87)		0.279 (0.87)	
	$100-150k: Central Valley		0.997 (0.88)		0.917 (0.87)	
Education (baseline = less than high school graduate)	High school graduate or GED			1.138 (1.11)	1.253 (1.11)	0.387 (0.70)
	Some college or associates degree			0.896 (1.08)	1.013 (1.08)	0.342 (0.69)
	Bachelor's degree			1.675 (1.11)	1.795 (1.11)	-0.039 (0.72)
	Graduate degree or professional degree			0.468 (1.13)	0.545 (1.13)	-0.042 (0.73)
Job category (baseline = sales or service job)	Clerical / administrative support			0.896 (0.58)	0.884 (0.58)	-0.825 (0.55)
	Manufacturing/ construction/ maintenance/ farming			3.870*** (0.59)	3.886*** (0.59)	1.093*** (0.32)
	Professional/ managerial/ technical			1.953*** (0.46)	1.951*** (0.46)	0.179 (0.32)
	Something else			-0.468 (2.78)	-0.072 (2.78)	

Table 20. Regression results (continued)

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
y=		trip distance (mile)	trip distance (mile)	trip distance (mile)	trip distance (mile)	supercommute (0,1)
Housing tenure (baseline = homeowner)	Home ownership: Rent			-0.442 (0.37)	-0.436 (0.37)	-0.483 (0.26)
	Home ownership: Some other arrangement			-1.993 (3.02)	-1.879 (3.02)	
	# vehicles (household)			0.628*** (0.14)	0.626*** (0.14)	-0.014 (0.09)
Household size	# persons (household)			-0.276 (0.14)	-0.277 (0.14)	-0.155 (0.09)
	# children between 0-4 (household)			2.509*** (0.42)	2.515*** (0.42)	0.649** (0.20)
Neighborhood characteristics	% renter-occupied housing (block group)			-0.024** (0.01)	-0.024** (0.01)	0.003 (0.01)
	persons per sq mi (block group)			-0.00004 (0.00)	-0.00004 (0.00)	0.0001* (0.00)
	housing units per sq mi (block group)			-0.00007 (0.00)	-0.00007 (0.00)	-0.0002 (0.00)
	Workers per sq mi (census tract)			-0.00005 (0.00)	-0.00005 (0.00)	-0.0001 (0.00)
Constant		10.839*** (0.66)	11.923*** (1.19)	11.291*** (1.37)	11.738*** (1.70)	-3.394*** (0.89)
Observations		6276	6276	6237	6237	6202
R-squared		0.251	0.252	0.275	0.275	
Adjusted R-squared		**0.250**	**0.250**	**0.272**	**0.272**	

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

Neighborhood Level: Association Between Migration and Supercommute

For the neighborhood level regression analysis, we use three datasets to measure supercommuting via distance and duration at the ZCTA level: LODES, ACS, and StreetLight, for ZCTAs in the Central Valley. The dependent variables are the ZCTA share of commuters who travel at least 50 miles in one direction (LODES and StreetLight) or at least 60 or 90 minutes in one direction (ACS and StreetLight). We exclude ZCTAs with population under 500 because the small denominator creates outliers in the share of supercommuters that distort the results. Of the 210 ZCTAs in the area, up to 189 are used in the analyses.

Table 21 shows descriptive statistics for supercommuting variables. Time periods for descriptive statistics reflect data availability LODES data is available from 2002 to 2018, ACS from 2007 to 2017, StreetLight in 2017, and migration data from 1993 to 2015. Similar to the discussion in Chapter 4, different datasets yield different means, medians, and decile differences.

The focal explanatory variable is the level of inter-regional migration into these ZCTAs from Bay Area counties. Table 21 presents mean, median, and decile differences in two migration measures: annual and cumulative. The annual migration measure is the annual average number of moves in a ZCTA normalized by the ZCTA population in the closest year available (see regression notes). The cumulative measure sums the annual moves and normalizes by the population in 2015. The average number of migrants from the Bay Area to the Central Valley is about 24,000 per year, peaking at 30,000 in 2002 and reaching a floor of 21,000 in 2011. The average annual ZCTA in-migrant rate is 0.64 moves per hundred residents. The average cumulative in-migration rate is 7.48 moves per hundred residents (see Table 21).

Table 21. Summary Statistics for Neighborhood analysis

	Supercommute share (share of all ZCTA commutes that are supercommutes)					In-migration into ZCTA	
Data	ACS – all years		LODES – all years	StreetLight - 2017		Migration per 100 residents	
	90 min	60 min	50 miles	90 min	50 miles	Annual	Cumulative
mean	4.56%	10.92%	22.44%	2.93%	1.49%	0.64	7.48
median	3.71%	8.67%	20.79%	2.8%	1.1%	0.45	6.16
Decile [10-90]	[1.01 - 8.73]	[3.86-21.72]	[11.28-33.97]	[2.3-3.7]	[0.6-2.86]	[0.18-1.3]	[2.97-15.25]

Mapping Supercommuting and Migration

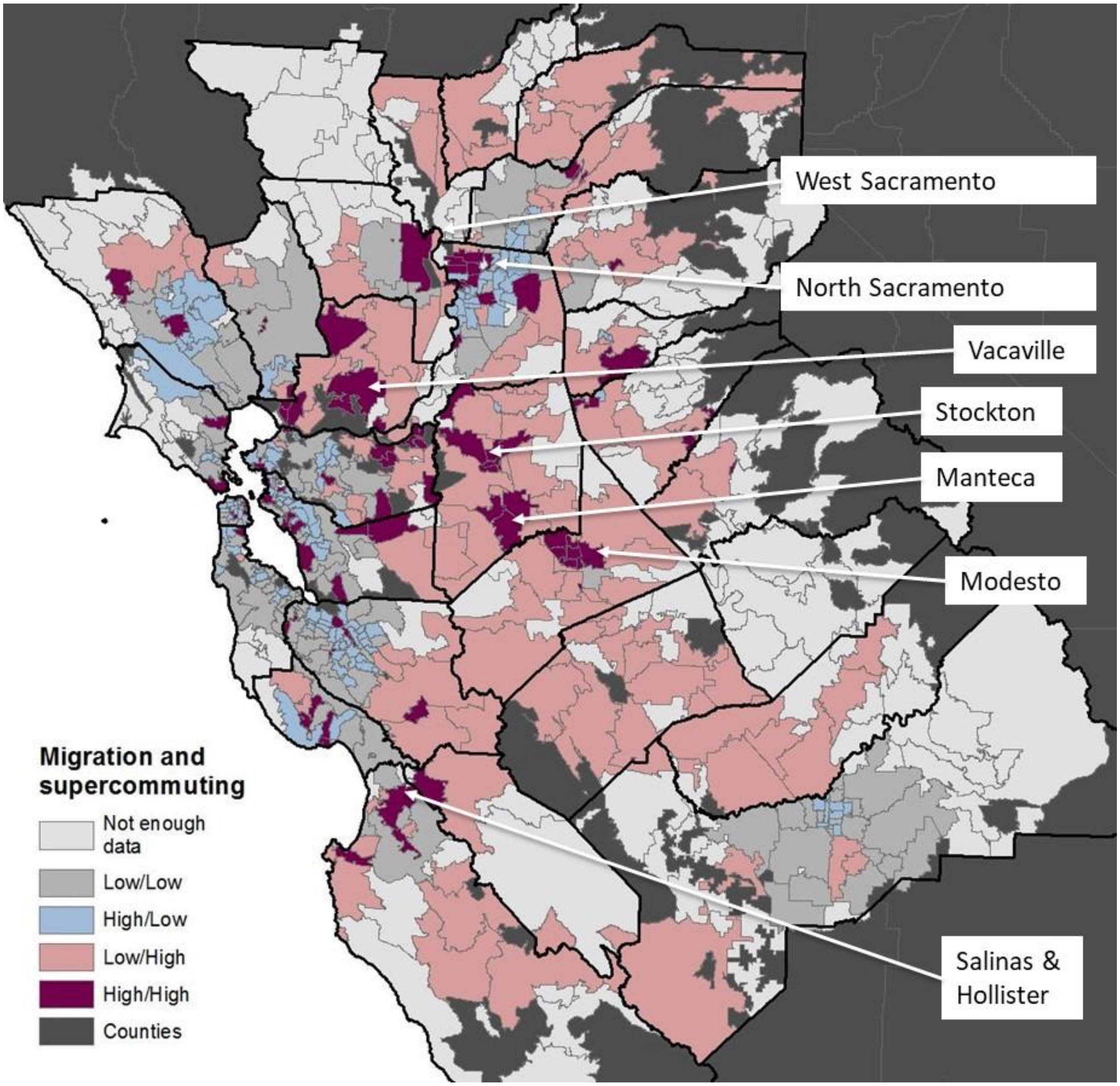
We map ZCTAs to better visualize the spatial context of supercommuting and migration together. Figure 4 displays each ZCTA based on whether it has above or below median supercommuting rate (using 2017 Streetlight) and above or below median migration rate (using the cumulative measure). The map legend shows the four possible options:

- Low / Low: below median supercommuting and below median migration
- High / Low: **above** median supercommuting and below median migration
- Low / High: below median supercommuting and **above** median migration
- High / High: **above** median supercommuting and **above** median migration

Note that certain ZCTAs do not have enough data to be displayed on the map.

This research is most interested in the High / High category, based on our hypothesis of the relationship between migration and supercommuting. Figure 4 reveals multiple clusters of ZCTAs in the High / High category. Many of them are in the Central Valley counties adjoining the Bay Area and include the areas in and around the cities of Modesto, Manteca, and Stockton. Several others are in and around Sacramento, including the neighborhoods directly North of the city and in the city of West Sacramento. Solano County has several clusters including Vacaville and Vallejo. Other notable clusters are in the Outer Bay counties, including Salinas and Hollister in Monterey and San Benito counties and parts of Sonoma county. It is notable also that certain ZCTAs within the Bay Area itself are in the High / High category, including portions of Eastern Contra Costa and Alameda counties. This map helps provide geographic context for understanding the neighborhood level regression analysis below.

Figure 4. Supercommuting and Migration (Streetlight and FTB): below and above median values by ZCTA



Source: Author Calculations on FTB data, Streetlight, Inc

Regression Analysis

We estimate linear models of supercommute share controlling for migration, age and occupation of the workforce (LODES), and for neighborhood income, racial/ethnic composition, transit use, educational attainment, and housing tenure (ACS). We also include year fixed effects and ZCTA fixed effects. LODES data is available from 2002 to 2018, ACS from 2007 to 2017, StreetLight in 2017, and migration data from 1993 to 2015. Our primary analysis pools ZCTA data from 2007 through 2015, controlling for year and ZCTA fixed effects (table 22). A secondary analysis compares single years 2009 versus 2015 (table 22). Our analysis of cumulative migration uses 2015 LODES and ACS data and 2017 StreetLight data (table 24).

We find that the share of Bay Area in-migration is positively correlated with supercommuting in nearly all specifications and highly statistically significant in many. However, the magnitude of the effect varies quite a bit. ZCTAs with substantial annual in-migration (say 10% of the population) are correlated with often large supercommute shares (table 22). The effects of migration on duration supercommuting seems to have grown from 2009 to 2015 (table 23). The cumulative effect of migration over more than two decades on supercommuting is likewise positive and statistically significant (table 24). An increase from no migration to the median cumulative in-migration rate (6 moves per 100 people) increases rate of commuting over 90 minutes by about 1.38 percentage points or by almost a third of the mean value.

Other variables correlated with high shares of supercommuters include housing tenure, transit usage, and industry composition. Across most specifications, the proportion of renters in a ZCTA is statistically significantly negatively correlated with supercommute share. Potentially, ZCTAs with higher renter proportions are more likely to be closer to job centers (i.e., within larger urban areas) and therefore associated with less supercommuting. Transit share is slightly positively correlated with supercommuting in several specifications, though generally only for the durations above 60 minutes. It is possible that transit is not viable or not available for commutes over 90 minutes in this region. A ZCTA’s higher share of workers in trade or manufacturing also correlates positively with supercommute share.

Table 22. Pooled analysis of ZCTA supercommute share

Dependent Variable:	% of jobs further than 50 miles from home block (LODES)				% of commuters who travel more than 60 minutes (ACS)				% of commuters who travel more than 90 minutes (ACS)			
Model:	Year FE		ZCTA/Year FE		Year FE		ZCTA/Year FE		Year FE		ZCTA/Year FE	
Migration	0.54		0.94		6.36	***	1.16		2.38	***	-0.08	
age (30-55)	-1.17	***	-0.34		0.033	*	-0.07		0.07		-0.06	
age (55+)	-1.44	***	-1.25	***	0.52	***	-0.27	*	0.04		0.02	
% mfg jobs	0.36	***	0.26		0.06		-0.31	*	0.04		-0.15	**
% trade jobs	2.1	***	2.87	***	0.36	*	-0.05		0.21	***	-0.1	*
log med. income	-0.16	***	-0.005		0.05	*	0.008		0.006		-0.0006	
% nonwhite	-0.15	***	0.24	**	0.02		-0.12	*	0.02	**	-0.05	+
% who use transit	0.97	**	0.45	+	0.59	+	0.38	+	0.15		0.1	
% college degrees	0.39	***	0.02		-0.24	***	0.01		-0.05	*	-0.08	
% renter	-0.26	***	-0.15	+	-0.15	***	-0.06		-0.09	***	0.04	
Adjusted R^2	0.39		0.8		0.8		0.89		0.4		0.89	
Unique ZCTAs	189		189		189		189		189		189	
Years	7		7		7		7		7		7	
Sample Size	1267		1267		1267		1267		1267		1267	

Notes: Migration is number of moves from Bay Area divided by ZCTA population in 2000 for years up to 2006, population in 2009 for years 2007-2009 and ACS yearly estimates for 2010 onward.
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1, based on clustered standard errors*

Table 23. Single year comparison of ZCTA supercommute share: 2009 vs 2015

Dependent Variable	% of jobs further than 50 miles from home block				StreetLight (2017) - Distance > 50 miles		% of commuters who travel more than 60 minutes				% of commuters who travel more than 90 minutes				StreetLight (2017) - Duration > 90	
Analysis Year	2009		2015		2017		2009		2015		2009		2015		2017	
Migration in prev. year	1.38	+	-0.24		0.87	***	4.72	***	9.43	***	1.73	***	3.89	***	0.53	***
age (30-55)	-1.25	***	-0.81	**	-0.12	+	0.76	***	0.21		0.23	*	-0.01		-0.06	
age (55+)	-0.66	*	-1.09	***	-0.02		0.66	**	0.41	+	0.1		-0.1		-0.07	*
% jobs in manufacturing	0.22	*	0.39	***	0.06	***	0.08		0.009		0.06		0.06		0.02	**
% jobs in trade	0.69	*	0.95	***	-0.013		0.27		0.05		-0.07		0.11		-0.02	
median income (log)	-0.08	*	-0.15	***	0.001		-0.02		0.06	**	-0.03	+	0.008		-0.001	
%nonwhite	-0.1	**	-0.14	***	0.01	+	-0.009		0.03		0.01		0.03	+	0.003	
% who use transit	-0.5		0.6		-0.11		0.86	*	0.38		0.55	**	0.01		-0.04	
% college educated	11		0.3	***	0.009		-0.21	**	-0.28	***	-0.08	*	-0.05		-0.002	
% renter	-0.04		-0.26	***	-0.02		-0.23	***	-0.1	**	-0.13	***	-0.09	***	-0.02	*
Adjusted R^2	0.29		0.33		0.26		0.44		0.57		0.43		0.43		0.23	
Unique ZCTAs	169		169		134		169		169		169		169		134	

Notes: Migration is number of moves from Bay Area divided by ZCTA population in the respective year. For the StreetLight specifications we use 2014/2015 migration – the most recent available data.
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1, based on clustered standard errors*

Table 24. Single year analysis (2015) of the effect of cumulative migration on supercommute share

Dependent Variable:	% of jobs further than 50 miles from home block		StreetLight (2017) - Distance > 50 miles		% of commuters who travel more than 60 minutes		% of commuters who travel more than 90 minutes		StreetLight (2017) - Duration > 90	
Cumulative migration	0.1		0.06	**	0.59	***	0.23	***	0.04	**
age (30-55)	-0.83	**	-0.09		0.5	*	0.11		-0.04	
age (55+)	-1.1	***	-0.007		0.62	*	-0.01		-0.07	+
% mfg jobs	0.37	***	0.05	**	-0.02		0.04		0.02	*
% trade jobs	0.78	**	0.009		0.27		0.23	+	-0.006	
log med. income	-0.14	***	0.001		0.07	**	0.01		-0.001	
% nonwhite	-0.14	***	0.01		0.04		0.03	*	0.002	
% who use transit	0.47		-0.09		0.75	*	0.19		-0.02	
% college degrees	0.26	***	0.008		-0.29	***	-0.05		-0.003	
% renter	-0.25	***	-0.02		-0.07		-0.08	**	-0.01	+
Adjusted R^2	0.33		0.25		0.45		0.34		0.21	
Unique ZCTAs	169		134		169		169		134	

Notes: Migration is the total number of moves from Bay Area between 2002 and 2015, divided by the 2015 ZCTA population.
**** p<0.001, ** p<0.01, * p<0.05, + p<0.1, based on clustered standard errors*

Chapter 6: Conclusion

The evidence indicates that supercommuting is a growing phenomenon, especially in the Central Valley, and that it clusters spatially. By both distance and time, the share of supercommuters has grown in many Central Valley counties since 2012 (earliest travel survey data available) and up through 2020 Q1 (StreetLight data). For example, the data show San Joaquin County had a supercommute share of 3.3 percent in 2012 (CHTS data), 3.8 percent in 2017 (NHTS data), and 7.71 percent in the first quarter of 2020 (from StreetLight data for early morning and a.m. peak periods). These different data sources collect their data in different ways, but the CHTS and NHTS, in particular, have very similar survey and sampling methodologies. San Joaquin County is not alone in the trend toward increasing rates of supercommuting. While there is no data source that tracks supercommuting in a consistent method over time, the evidence suggests that supercommuting is growing more common.

Supercommutes cluster in geographic locations and on particular flows. We note that some ZCTAs, often but not exclusively in San Joaquin and Merced Counties, have particularly large flows of commuters longer than 50 miles (StreetLight). We find also that the total share of Central Valley commuters to Bay Area counties has stayed remarkably consistent from 2002 to 2018, though this grew in absolute terms due to population growth in the Central Valley. However, the share of supercommuters among those commuting from Central Valley to Bay Area counties has increased by 3 to 9 percentage points by county (LODES).

Of the four data sets that can track supercommuting, the LEHD LODES has a clear "level shift" – the incidence of supercommuting is notably larger in that dataset. The methodology of the LODES, which relies on matching commuters to workplaces by joining data from residential surveys with data on business establishment locations, differs from the methodology of the CHTS, NHTS, and StreetLight, each of which observes commutes either through survey or GPS tracking methods. Yet the LODES shows similar patterns of spatial concentration of supercommuting in Central Valley counties and of growth rates over time, similar in pattern if not level to the other three data sources.

The regression analysis gives little evidence of income patterns in supercommuting after controlling for a range of household and regional characteristics. Persons who work in manufacturing, construction, maintenance, and farm jobs are more likely to supercommute, controlling for other factors. Households with larger numbers of children were also more likely to supercommute. Income, age, education, and housing characteristics have no statistically significant effect on the decision to supercommute. Additionally, transit users are more likely to supercommute than other commuters, and this is especially pronounced in the Central Valley, where transit service is less frequent and more limited and where ridership is lower than the Bay Area.

Given our unique migration flow data, which can track household moves from the Bay Area into ZCTAs in the Central Valley, we have an opportunity to make a new contribution. We find evidence that ZCTAs with larger amounts of in-migration from the Bay Area have higher rates of super-commuting. That evidence supports the idea that the Bay Area and the Central Valley are linked, and that high housing costs in the Bay Area contribute to longer commutes among residents of the Central Valley.

In terms of COVID-19, we document a large drop in overall traffic volume immediately after the start of the pandemic in California (March 15, 2020), relative to pre-pandemic baselines, using GPS-derived data from StreetLight. This is in line with other estimates such as Google Community Mobility reports. We find, however, that supercommute shares remained resilient during the same time period. In fact, supercommute shares decreased only in San Francisco County, but increased in all other Bay Area and Central Valley counties under study and went up by as much as 1.5 percentage points (20-25% increase) in San Joaquin and Yolo counties. These possibly reflect different policy reactions to the pandemic, the distribution of essential employees and job sites, and shifting migration patterns during the pandemic.

Studies of supercommuting are inherently limited by the lack of longitudinal data. One contribution of our research is to compare the results from different data sources. Yet for a phenomenon like supercommuting in high housing cost areas, for which we seek to understand time trends, better longitudinal data would be helpful.

Overall, the evidence shows that some Central Valley counties have supercommuting rates that approach 10 percent of all commute trips, and that the incidence of supercommuting is increasing over time. Those supercommutes are linked, in part, to migration of households from the Bay Area into the Central Valley. This suggests an increasing need for planning that spans regions and that can address link points between housing costs, household migration patterns, and commuting.

References

1. Bennet, S. (2018). Rise of the Super Commuters. Apartment List. https://www.apartmentlist.com/rentonomics/increase-in-long-super-commutes/
2. Moss, M.L., and Qing, C.Y. (2012). The Emergence of the Super-Commuter. *NYU Wagner Rudin Center for Transportation Policy and Management.*
3. Moss, M.L., Qing, C.Y., and Kaufman, S. (2012). Commuting to Manhattan A study of residence location trends for Manhattan workers from 2002 to 2009. *NYU Wagner Rudin Center for Transportation Policy and Management*.
4. U.S. Department of Transportation Federal Highway Administration (FHWA) (2018). Summary of Travel Trends: 2017 National Household Travel Survey. Report: FHWA-PL-18-019.
5. San Joaquin Council of Governments. (2011). I-580 Interregional multi-modal corridor study.
6. San Joaquin Council of Governments. (2013). Interregional multi-modal commute trip planning study.
7. Kakar, V., & Grossman, A. (2018). Jobs and Housing (Im) balance in the San Francisco Bay Area. *Center for Applied Housing Research*, Working Paper, 3.
8. Elmendorf, C. S., Elkind, E., Lens, M., Manville, M., Marantz, N., Monkkonen, P., O'Neill, M., & Trounstine, J. (2020). Regional Housing Need in California: The San Francisco Bay Area.
9. Alonso, William. (1964). "Location and land use. Toward a general theory of land rent." *Location and land use.* Toward a general theory of land rent.
10. Muth, R. F. (1969). *Cities and Housing*. *The spatial pattern of urban residential land use*.
11. Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review*, 57(2), 197-210.
12. Brueckner, J. K. (1987). The structure of urban equilibria: A unified treatment of the Muth-Mills model. *Handbook of regional and urban economics*, 2(20), 821-845.
13. Kain, J. F., & Meyer, J. R. (1961). *A first approximation to a Rand model for study of urban transportation.* RAND CORP Santa Monica California.
14. Mills, E. S., & Tan, J. P. (1980). A comparison of urban population density functions in developed and developing countries. *Urban studies*, 17(3), 313-321.
15. Oliveira, R., Moura, K., Viana, J., Tigre, R., & Sampaio, B. (2015). Commute duration and health: Empirical evidence from Brazil. *Transportation Research Part A: Policy and Practice*, *80*, 62-75.
16. Hansson, E., Mattisson, K., Björk, J. *et al.* Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. *BMC Public Health* 11, 834 (2011). https://doi.org/10.1186/1471-2458-11-834
17. Walsleben, J. A., Norman, R. G., Novak, R. D., O'Malley, E. B., Rapoport, D. M., & Strohl, K. P. (1999). Sleep habits of Long Island rail road commuters. *Sleep*, *22*(6), 728-734.
18. Van Ommeren, J. N., & Gutiérrez-i-Puigarnau, E. (2011). Are workers with a long commute less productive? An empirical analysis of absenteeism. *Regional Science and Urban Economics*, *41*(1), 1-8.
19. Hilbrecht, M., Smale, B., & Mock, S. E. (2014). Highway to health? Commute time and well-being among Canadian adults. *World Leisure Journal*, *56*(2), 151-163.

20. Lyons, G., & Chatterjee, K. (2008). A human perspective on the daily commute: costs, benefits and trade-offs. *Transport reviews*, 28(2), 181-198.
21. LeBeau, P. (Feb. 12, 2019). Traffic jams cost US $87 billion in lost productivity in 2018, and Boston and DC have the nation's worst. CNBC.
22. Cervero, R., Round, A., Goldman, T., & Wu, K. L. (1995). Rail access modes and catchment areas for the BART system.
23. Giuliano, G., & Small, K. A. (1993). Is the journey to work explained by urban structure?. *Urban studies*, *30*(9), 1485-1500.
24. Brueckner, J. K., Thisse, J. F., & Zenou, Y. (1999). Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. *European economic review*, 43(1), 91-107.
25. Cropper, M. L., & Gordon, P. L. (1991). Wasteful commuting: a re-examination. *Journal of urban economics*, *29*(1), 2-13.
26. Hamilton, B. W., & Röell, A. (1982). Wasteful commuting. *Journal of political economy*, *90*(5), 1035-1053.
27. Hamilton, B. W. (1989). Wasteful commuting again. *Journal of political economy*, *97*(6), 1497-1504.
28. Hamburg, J. R., Guinn, C. R., Lathrop, G. T., & Hemmens, G. C. (1968). *Linear programming test of journey-to-work minimization*. Planning and Research Bureau, Planning Division, New York State Department of Transportation.
29. Small, K. A., & Song, S. (1992). " Wasteful" commuting: a resolution. *Journal of political economy*, *100*(4), 888-898.
30. White, M. J. (1988). Urban commuting journeys are not" wasteful". *Journal of Political economy*, *96*(5), 1097-1110.
31. Ha, J., Lee, S., & Kwon, S. M. (2018). Revisiting the relationship between urban form and excess commuting in US metropolitan areas. *Journal of Planning Education and Research*, 0739456X18787886.
32. Bay Area Council Economic Institute and McKinsey and Co. (2018). Continuing Growth and Unparalleled Innovation: Bay Area Economic Profile. Tenth in a Series.
33. Shoag, D., & Muehlegger, E. (2015). Commuting times and land use regulations. *Procedia Engineering*, *107*, 488-493.
34. Holder, S., (2018). Where Commuting is Out of Control, CityLab, April 25, https://www.citylab.com/transportation/2018/04/where-commuting-is-the-worst/558671/
35. Golan, M. S., L. H. Jernegan, and I. Linkov. Trends and Applications of Resilience Analytics in Supply Chain Modeling: Systematic Literature Review in the Context of the COVID-19 Pandemic. Environment Systems & Decisions, 2020, p. 1.
36. Gray, R. S. (2020). Agriculture, transportation, and the COVID-19 crisis. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 68(2), 239-243.
37. Guan, D., Wang, D., Hallegatte, S., Huo, J., Li, S., Bai, Y., ... & Gong, P. (2020). Global economic footprint of the COVID-19 pandemic.
38. Seto, C., Khademi, A., Graif, C., & Honavar, V. G. (2020). Commuting Network Spillovers and COVID-19 Deaths Across US Counties. *arXiv preprint arXiv:2010.01101*. https://arxiv.org/ftp/arxiv/papers/2010/2010.01101.pdf

39. Ando, H., Ikegami, K., Nagata, T., Tateishi, S., Eguchi, H., Tsuji, M., ... & Ogami, A. (2021). Effect of commuting on the risk of COVID-19 and COVID-19-induced anxiety in Japan, December 2020. *Archives of Public Health*, *79*(1), 1-10.
40. Engle, S., J. Stromme, and A. Zhou. Staying at Home: Mobility Effects of COVID-19. Publication ID 3565703. Social Science Research Network, Rochester, NY, 2020.
41. De Vos, J. The Effect of COVID-19 and Subsequent Social Distancing on Travel Behavior. Transportation Research Interdisciplinary Perspectives, Vol. 5, 2020, p. 100121. https://doi.org/10.1016/j.trip.2020.100121.
42. Thomas, F. M., Charlton, S. G., Lewis, I., & Nandavar, S. (2021). Commuting before and after COVID-19. *Transportation Research Interdisciplinary Perspectives*, *11*, 100423.
43. Harrington, D. M., & Hadjiconstantinou, M. (2021). Changes in commuting behaviours in response to the COVID-19 pandemic in the UK. *Journal of transport & health*, 101313.
44. Currie, G., Jain, T., & Aston, L. (2021). Evidence of a post-COVID change in travel behaviour–Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice*, *153*, 218-234.
45. Shibayama, T., Sandholzer, F., Laa, B., & Brezina, T. (2021). Impact of COVID-19 lockdown on commuting: a multi-country perspective. *European Journal of Transport and Infrastructure Research*, *21*(1), 70-93.
46. Hensher, D. A., Beck, M. J., & Balbontin, C. (2021). What does the quantum of working from home do to the value of commuting time used in transport appraisal?. *Transportation Research Part A: Policy and Practice*, *153*, 35-51.
47. Hensher, D. A., Beck, M. J., & Wei, E. (2021). Working from home and its implications for strategic transport modelling based on the early days of the COVID-19 pandemic. *Transportation Research Part A: Policy and Practice*, *148*, 64-78.
48. Balbontin, C., Hensher, D. A., Beck, M. J., Giesen, R., Basnak, P., Vallejo-Borda, J. A., & Venter, C. (2021). Impact of COVID-19 on the number of days working from home and commuting travel: A cross-cultural comparison between Australia, South America and South Africa. *Journal of Transport Geography*, *96*, 103188.
49. Riggs, W., Appleyard, B., & Johnson, M. (2020). A design framework for livable streets in the era of autonomous vehicles. Urban, Planning and Transport Research, 8(1), 125-137.
50. Kar, A., Le, H. T., & Miller, H. J. (2021). What Is Essential Travel? Socioeconomic Differences in Travel Demand in Columbus, Ohio, during the COVID-19 Lockdown. *Annals of the American Association of Geographers*, 1-24.
51. Liu, L., Miller, H. J., & Scheff, J. (2020). The impacts of COVID-19 pandemic on public transit demand in the United States. *Plos one*, *15*(11), e0242476.
52. Abraham, K. G., Haltiwanger, J., Sandusky, K., & Spletzer, J. R. (2013). Exploring differences in employment between household and establishment data. *Journal of Labor Economics*, 31(S1), S129-S172.
53. Graham, M. R., Kutzbach, M. J., & McKenzie, B. (2014). Design comparison of LODES and ACS commuting data products. Working paper. https://www.census.gov/library/working-papers/2014/adrm/ces-wp-14-38.html
54. https://www.cnbc.com/2019/02/11/americas-87-billion-traffic-jam-ranks-boston-and-dc-as-worst-in-us.html

55. Schafran, A., (2018). *The Road to Resegregation: Northern California and the Failure of Politics.* Oakland, CA: University of California Press.
56. StreetLight Insight. Traffic Volume Methodology and Validation White Paper. 2021. Accessed: https://learn.streetlightdata.com/methodology-data-sources-white-paper
57. Steven Manson, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 16.0 [dataset]. Minneapolis, MN: IPUMS. 2021. http://doi.org/10.18128/D050.V16.0
58. Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., & TuYe, H. Y. (2020). COVID-19 and remote work: An early look at US data (No. w27344). National Bureau of Economic Research.
59. Bick, A., Blandin, A., & Mertens, K. (2020). Work from home after the COVID-19 Outbreak.

Data Management Plan

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.

Public data sources:
Census American Community Survey, 2015-2019 (commute data for counties)
Census LODES (commute data for counties)

Public data source with restrictions on data release
2012 California Household Travel Survey (CHTS) and 2017 National Household Travel Survey (NHTS) (we can only release the publicly available version, which is only available at county aggregates shown in the tables; the confidential geocoded data used to obtain commute distance cannot be released)

Data that cannot be released:
California Franchise Tax Board
StreetLight

Data Format and Content
We deposited in the Dataverse data repository files with the Census ACS and LODES data used in this study. Those are county level descriptions of commute patterns. The files contain information about the data and variables.

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

Reuse and Redistribution
Data from the California Franchise Tax Board and StreetLight were made available to the research team through agreements that require that those data not be released publicly, to protect subject confidentiality. Similarly, the geocoded version of the CHTS and NHTS cannot be released. All CHTS and NHTS data used in this study rely on the geocoded version to obtain commute distances and times, and hence the CHTS and NHTS data are not released to the public.

Appendix

Detail Analysis and Results

Equation: NHTS (2017)

Model 1: Linear regression: income & location

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs)$$

Model 2: Linear regression: income & + interaction terms

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, household\ incomegroup \times trip\ production\ location)$$

Model 3: Linear regression: all variables (no interactions)

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \#\ of\ vehicles\ in\ household, \#\ of\ children\ between\ 0-4\ in\ household, neighborhood\ characteristics\ (share\ of\ renter - occupied\ housing\ , population\ density, housing\ density, worker\ density\ ))$$

Model 4: Linear regression: all variables (with interactions)

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, household\ incomegroup \times trip\ production\ location, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \#\ of\ vehicles\ in\ household, \#\ of\ children\ between\ 0 - 4\ in\ household, neighborhood\ characteristics\ (share\ of\ renter - occupied\ housing\ , population\ density, housing\ density, worker\ density\ ))$$

Model 5: Logistic regression: all variables (no interaction)

$$Supercommute\ (Trip\ Distance\ or\ Duration) = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \#\ of\ vehicles\ in\ household, \#\ of\ children\ between\ 0-4\ in\ household, neighborhood\ characteristics\ (share\ of\ renter - occupied\ housing\ , population\ density, housing\ density, worker\ density\ ))$$

Findings: NHTS (2017) – Travel distance

1. **Household characteristics:**
    - Household income: Comparing with households with income <$25k,
        - Households with income >$150k commute furthest to work.

    - Households with income between $25-50k commute shortest to work.
- Households with more vehicles and more children between 0-4 years old commute further to work.
- Households with more people commute shorter to work.
- Within the same household income category ($25-50k): Central Valley households commute longer to work than Bay Area households

2. Trip production and attraction:

CV – Bay workers take longer commutes than Bay – CV workers

a. Bay - CV commuters travel approximately 35 miles more than Bay – Bay commuters.
b. CV – Bay commuters travel approximately 43 miles more than Bay – Bay commuters.

3. Occupation:

- Comparing with commuters with job in sales or service:
    - Commuters with job in Manufacturing / construction / maintenance / farming travel furthest (4 miles longer) to work.
    - Commuters with job in Professional / managerial / technical travel 2 miles longer to work

4. Neighborhood characteristics:

- Commuters travel shorter if living in the block group with higher share of renter-occupied housing.

Table A1. Regression results (NHTS 2017): travel distance

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
Y=		trip distance (mile)	trip distance (mile)	trip distance (mile)	trip distance (mile)	supercommute (0,1)
Household income	<$25k	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	$25-50k	-1.375	-3.925**	-1.953**	-4.213**	-1.023*
		(0.75)	(1.48)	(0.75)	(1.48)	(0.49)
	$50-100k	1.093	0.319	-0.159	-0.467	-0.751
		(0.68)	(1.30)	(0.70)	(1.31)	(0.42)

	$100-150k	1.633*	0.226	-0.251	-0.979	-0.328
		(0.69)	(1.29)	(0.74)	(1.31)	(0.44)
	>$150k	2.251**	1.342	0.104	-0.207	-0.547
		(0.70)	(1.25)	(0.76)	(1.27)	(0.46)
PA pairs	Bay-Bay	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	Bay-CV	35.834***	35.886***	35.202***	35.151***	5.198***
		(3.67)	(3.68)	(3.63)	(3.63)	(0.78)
	CV-Bay	44.133***	43.697***	41.844***	41.284***	3.897***
		(1.03)	(1.13)	(1.05)	(1.14)	(0.28)
	CV-CV	-0.536	-1.018	-1.807***	-2.437***	-0.484
		(0.33)	(0.61)	(0.37)	(0.62)	(0.26)
Income * trip production	<$25k: Bay Area		0.000		0.000	
			(.)		(.)	
	<$25k: Central Valley		-1.003		-0.114	
			(1.52)		(1.53)	
	$25-50k: Bay Area		0.000		0.000	
			(.)		(.)	
	$25-50k: Central Valley		2.406*		2.867*	
			(1.17)		(1.16)	
	$50-100k: Bay Area		0.000		0.000	
			(.)		(.)	
	$50-100k: Central Valley		0.038		0.279	
			(0.87)		(0.87)	
	$100-150k: Bay Area		0.000		0.000	
			(.)		(.)	
	$100-150k: Central Valley		0.997		0.917	
			(0.88)		(0.87)	
	>$150k: Bay Area		0.000		0.000	
			(.)		(.)	

	>$150k: Central Valley		0.000		0.000	
			(.)		(.)	
Education	Education: Less than a high school graduate			0.000	0.000	0.000
				(.)	(.)	(.)
	Education: High school graduate or GED			1.138	1.253	0.387
				(1.11)	(1.11)	(0.70)
	Education:S ome college or associates degree			0.896	1.013	0.342
				(1.08)	(1.08)	(0.69)
	Education: Bachelor's degree			1.675	1.795	-0.039
				(1.11)	(1.11)	(0.72)
	Education: Graduate degree or professional degree			0.468	0.545	-0.042
				(1.13)	(1.13)	(0.73)
Job category	Sales or service			0.000	0.000	0.000
				(.)	(.)	(.)
	Clerical/administrative support			0.896	0.884	-0.825
				(0.58)	(0.58)	(0.55)
	Manufacturing/construction/maintenance/farming			3.870***	3.886***	1.093***
				(0.59)	(0.59)	(0.32)
	Professional/managerial/technical			1.953***	1.951***	0.179
				(0.46)	(0.46)	(0.32)
	Something else			-0.468	-0.072	0.000
				(2.78)	(2.78)	(.)
Household characteristics	Home ownership: Own			0.000	0.000	0.000
				(.)	(.)	(.)
	Home ownership: Rent			-0.442	-0.436	-0.483
				(0.37)	(0.37)	(0.26)
	Home ownership: Some other arrangement			-1.993	-1.879	0.000
				(3.02)	(3.02)	(.)
	# persons (household)			-0.276	-0.277	-0.155
				(0.14)	(0.14)	(0.09)

Pacific Southwest Region UTC
University Transportation Center

	# vehicles (household)			0.628***	0.626***	-0.014
				(0.14)	(0.14)	(0.09)
	# children between 0-4 (household)			2.509***	2.515***	0.649**
				(0.42)	(0.42)	(0.20)
Neighborhood characteristics	% renter-occupied housing (block group)			-0.024**	-0.024**	0.003
				(0.01)	(0.01)	(0.01)
	persons per sq mi (block group)			-0.000	-0.000	0.000*
				(0.00)	(0.00)	(0.00)
	housing units per sq mi (block group)			-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)
	Workers per sq mi (census tract)			-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)
Constant		10.839***	11.923***	11.291***	11.738***	-3.394***
		(0.66)	(1.19)	(1.37)	(1.70)	(0.89)
Observations		6276	6276	6237	6237	6202
R-squared		0.251	0.252	0.275	0.275	
Adjusted R-squared		**0.250**	**0.250**	**0.272**	**0.272**	

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

Findings: NHTS (2017) – Travel duration

1. **Household characteristics:**
   - Household income: Comparing with households with income <$25k,
     - Households with income between $25-50k spend least time commute to work.
   - Households with more children between 0-4 years old spend more time commute to work.
   - Within the same household income category ($100-150k): Central Valley households spend more time commute to work than Bay Area households

2. **Trip production and attraction:**
   CV – Bay workers spend more time commuting than Bay – CV workers.
   - Bay - CV commuters spend approximately 22 minutes more than Bay – Bay commuters.
   - CV – Bay commuters spend approximately 55 minutes more than Bay – Bay commuters.

3. **Occupation:**
   - Comparing with commuters with job in sales or service:
     - Commuters with job in Manufacturing / construction / maintenance / farming spend the most time travel to work.
     - Commuters with job in Clerical /administrative support and Professional / managerial / technical spend more time travel to work

Table A2. Regression results (NHTS 2017): travel duration

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
Y=		trip duration (minute)	trip duration (minute)	trip duration (minute)	trip duration (minute)	supercommute (0,1)
Independent variables						
Household income	<$25k	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	$25-50k	-3.968**	-3.005	-4.393**	-3.301	-0.889**
		(1.40)	(2.76)	(1.42)	(2.80)	(0.32)
	$50-100k	-1.901	-0.175	-3.091*	-1.048	-1.129***
		(1.27)	(2.44)	(1.33)	(2.47)	(0.29)
	$100-150k	-0.915	-0.429	-2.535	-1.570	-0.969**
		(1.29)	(2.42)	(1.39)	(2.47)	(0.30)

	>$150k	-0.392	2.212	-2.325	0.704	-0.815**
		(1.30)	(2.33)	(1.44)	(2.41)	(0.30)
PA pairs	Bay-Bay	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	Bay-CV	22.078**	22.134**	22.641***	22.586***	1.377
		(6.85)	(6.85)	(6.84)	(6.84)	(0.80)
	CV-Bay	54.826***	52.574***	54.116***	51.778***	2.908***
		(1.92)	(2.11)	(1.97)	(2.15)	(0.21)
	CV-CV	-9.163***	-11.679***	-8.934***	-11.550***	-1.508***
		(0.62)	(1.14)	(0.69)	(1.18)	(0.19)
Income * trip production	<$25k: Bay Area		0.000		0.000	
			(.)		(.)	
	<$25k: Central Valley		4.832		5.426	
			(2.84)		(2.89)	
	$25-50k: Bay Area		0.000		0.000	
			(.)		(.)	
	$25-50k: Central Valley		3.472		3.873	
			(2.18)		(2.19)	
	$50-100k: Bay Area		0.000		0.000	
			(.)		(.)	
	$50-100k: Central Valley		2.464		2.628	
			(1.63)		(1.63)	
	$100-150k: Bay Area		0.000		0.000	
			(.)		(.)	
	$100-150k: Central Valley		4.438**		4.358**	
			(1.64)		(1.65)	
	>$150k: Bay Area		0.000		0.000	
			(.)		(.)	
	>$150k: Central Valley		0.000		0.000	
			(.)		(.)	

Education	Education: Less than a high school graduate			0.000	0.000	0.000
				(.)	(.)	(.)
	Education: High school graduate or GED			-1.651	-1.544	-0.310
				(2.09)	(2.09)	(0.46)
	Education:Some college or associates degree			-1.889	-1.701	-0.441
				(2.04)	(2.04)	(0.45)
	Education: Bachelor's degree			1.377	1.570	-0.312
				(2.09)	(2.09)	(0.45)
	Education: Graduate degree or professional degree			-1.344	-1.243	-0.572
				(2.13)	(2.13)	(0.47)
Job category	Sales or service			0.000	0.000	0.000
				(.)	(.)	(.)
	Clerical/administrative support			2.756*	2.754*	-0.129
				(1.09)	(1.08)	(0.29)
	Manufacturing/construction/maintenance/farming			3.965***	4.035***	0.292
				(1.11)	(1.11)	(0.25)
	Professional/managerial/technical			2.588**	2.560**	-0.141
				(0.86)	(0.86)	(0.22)
	Something else			-7.442	-7.019	0.000
				(5.23)	(5.24)	(.)
Household characteristics	Home ownership: Own			0.000	0.000	0.000
				(.)	(.)	(.)
	Home ownership: Rent			0.060	0.058	-0.112
				(0.70)	(0.70)	(0.17)
	Home ownership: Some other arrangement			3.109	3.297	0.878
				(5.69)	(5.69)	(1.06)
	# persons (household)			-0.203	-0.198	-0.079
				(0.27)	(0.27)	(0.07)
	# vehicles (household)			0.035	0.038	-0.090
				(0.27)	(0.27)	(0.07)

	# children between 0-4 (household)			2.228**	2.228**	0.140
				(0.80)	(0.80)	(0.17)
Neighborhood characteristics	% renter-occupied housing (block group)			-0.027	-0.027	-0.005
				(0.01)	(0.01)	(0.00)
	persons per sq mi (block group)			-0.000	-0.000	-0.000
				(0.00)	(0.00)	(0.00)
	housing units per sq mi (block group)			-0.000	-0.000	0.000
				(0.00)	(0.00)	(0.00)
	Workers per sq mi (census tract)			0.000*	0.000*	0.000
				(0.00)	(0.00)	(0.00)
Constant		36.552***	34.854***	37.371***	35.145***	-0.838
		(1.24)	(2.23)	(2.57)	(3.21)	(0.57)
Observations		6274	6274	6235	6235	6218
R-squared		0.174	0.175	0.182	0.183	
Adjusted R-squared		**0.173**	**0.174**	**0.179**	**0.180**	

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

Equation: CHTS (2012)

Model 1: Linear regression: income & location

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs)$$

Model 2: Linear regression: income & + interaction terms

$$Trip\ Distance\ or\ Duration = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, household\ incomegroup \times\ trip\ production\ location)$$

Model 3: Linear regression: all variables (no interactions)

$$\begin{aligned} &Trip\ Distance\ or\ Duration \\ &\quad = F(household\ income\ group, trip\ production\ and\ attraction\ pairs, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \\ &\quad \#\ of\ vehicles\ in\ household, \#\ of\ students\ in\ household) \end{aligned}$$

Model 4: Linear regression: all variables (with interactions)

$$\begin{aligned} &Trip\ Distance\ or\ Duration \\ &= F(household\ income\ group, trip\ production\ and\ attraction\ pairs, household\ incomegroup \\ &\times\ trip\ production\ location, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \#\ of\ vehicles\ in\ household, \#\ of\ students\ in\ household\ ) \end{aligned}$$

Model 5: Logistic regression: all variables (no interaction)

$$\begin{aligned} &Supercommute\ (Trip\ Distance\ or\ Duration) = \\ &F(household\ income\ group, trip\ production\ and\ attraction\ pairs, education, occupation, home\ ownership, \#\ of\ persons\ in\ household, \\ &\#\ of\ vehicles\ in\ household, \#\ of\ students\ in\ household) \end{aligned}$$

Findings: CHTS (2012) – Travel distance

1. **Household characteristics:**
   - Household with higher income and more vehicles tend to commute longer to work
     - Household income: Comparing with households with income <$25k, households with income >$150k commute furthest to work, following by household with $100-150k and household with $50-100k.

2. **Trip production and attraction:**
   CV – Bay workers take longer commutes than Bay – CV workers
   - Bay - CV commuters travel approximately 21 miles more than Bay – Bay commuters.
   - CV – Bay commuters travel approximately 28 miles more than Bay – Bay commuters.

3. **Education:**
   - Comparing with commuters with no high school diploma:
     - Commuters with associate or technical school degree commute furthest to work, following by those with bachelor's or undergraduate degree.

4. **Occupation:**
    - Comparing with commuters with job in sales or service:
        - Commuters with job in Manufacturing / construction / maintenance / farming travel furthest (4 miles longer) to work.
        - Commuters with job in Professional / managerial / technical travel 2 miles longer to work

Table A3. Regression results: CHTS (2012) – Travel distance

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
Y=		trip distance (mile)	trip distance (mile)	trip distance (mile)	trip distance (mile)	supercommute (0,1)
Household income	<$25k		0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	$25-50k	0.423	0.267	-0.647	-0.582	-0.640
		(0.93)	(1.34)	(0.98)	(1.41)	(0.50)
	$50-100k	1.958*	1.943	0.236	0.558	-0.761
		(0.84)	(1.21)	(0.94)	(1.32)	(0.45)
	$100-150k	3.080***	3.895**	1.131	2.287	-1.220*
		(0.85)	(1.22)	(0.98)	(1.34)	(0.49)
	>$150k	3.520***	3.951***	1.471	2.166	-0.814
		(0.85)	(1.19)	(1.01)	(1.34)	(0.50)
PA Pairs	Bay-Bay	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	Bay-CV	21.643***	21.677***	21.472***	21.477***	3.047***
		(2.04)	(2.04)	(2.09)	(2.09)	(0.47)
	CV-Bay	28.049***	27.671***	27.011***	26.793***	3.440***
		(1.02)	(1.24)	(1.03)	(1.24)	(0.27)
	CV-CV	0.214	-0.357	-0.180	-0.597	0.497
		(0.39)	(0.88)	(0.40)	(0.88)	(0.26)
	<$25k: Bay Area		0.000		0.000	

			(.)		(.)	
	<$25k: Central Valley		1.184		1.550	
			(1.78)		(1.84)	
	$25-50k: Bay Area		0.000		0.000	
			(.)		(.)	
	$25-50k: Central Valley		1.574		1.559	
			(1.34)		(1.35)	
	$50-100k: Bay Area		0.000		0.000	
Income * trip production			(.)		(.)	
	$50-100k: Central Valley		1.360		1.101	
			(1.07)		(1.07)	
	$100-150k: Bay Area		0.000		0.000	
			(.)		(.)	
	$100-150k: Central Valley		-0.867		-1.149	
			(1.14)		(1.14)	
	>$150k: Bay Area		0.000		0.000	
			(.)		(.)	
	>$150k: Central Valley		0.000		0.000	
			(.)		(.)	
Education	Not a high school graduate: 12 grade or less			0.000	0.000	0.000
				(.)	(.)	(.)
	High school graduate: high school diploma or GED			1.454	1.482	-0.141
				(1.08)	(1.08)	(0.54)
	Some college credit but no degree			2.085	2.112	-0.741
				(1.11)	(1.11)	(0.59)
	Associate or technical school degree			2.930*	2.922*	-0.536
				(1.15)	(1.15)	(0.60)
	Bachelors or undergraduate degree			2.585*	2.604*	-0.313
				(1.10)	(1.10)	(0.56)
	Graduate degree (includes MD/DDs/JD)			2.077	2.111	-0.075

				(1.13)	(1.13)	(0.58)
	Other: Specify			1.840	1.915	0.000
				(5.37)	(5.37)	(.)
Job category	Sales or service			0.000	0.000	0.000
				(.)	(.)	(.)
	Clerical/administrative support			0.668	0.649	0.178
				(0.78)	(0.78)	(0.54)
	Manufacturing/construction/maintenance/farming			3.913***	3.885***	0.274
				(0.66)	(0.66)	(0.42)
	Professional/managerial/technical			2.088***	2.052***	0.690
				(0.52)	(0.52)	(0.36)
	Something else			5.204***	5.281***	1.472**
				(1.13)	(1.13)	(0.55)
Home ownership	Own/Buying (Paying off Mortgage)			0.000	0.000	0.000
				(.)	(.)	(.)
	Rent			-0.711	-0.671	0.176
				(0.51)	(0.51)	(0.29)
	Other: Specify			-6.694	-6.988	0.000
				(6.80)	(6.80)	(.)
Household characteristics	# persons (household)			-0.293	-0.306	-0.037
				(0.23)	(0.23)	(0.13)
	# vehicles (household)			0.754***	0.781***	0.253*
				(0.22)	(0.22)	(0.12)
	# students (household)			0.591*	0.600*	0.085
				(0.27)	(0.27)	(0.15)
Constant		9.276***	8.943***	5.883***	5.225**	-4.388***
		(0.80)	(1.14)	(1.39)	(1.64)	(0.75)
Observations		4635	4635	4489	4489	4511
R-squared		0.164	0.166	0.176	0.177	
Adjusted R-squared		**0.163**	**0.164**	**0.172**	**0.173**	

Pacific Southwest Region UTC
University Transportation Center

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

Findings: CHTS (2012) – Travel duration

1. **Trip production and attraction:**
   CV – Bay workers spend more time commuting than Bay – CV workers.
   - Bay - CV commuters spend approximately 15 minutes more than Bay – Bay commuters.
   - CV – Bay commuters spend approximately 30 minutes more than Bay – Bay commuters.
   - CV – CV commuters spend approximately 3 minutes less than Bay – Bay commuters.

2. **Occupation:**
   - Comparing with commuters with job in sales or service:
     - Commuters with job in Manufacturing / construction / maintenance / spend the most time commute to work, following by commuters with job in Professional / managerial / technical industry.

Table A4. Regression results: CHTS (2012) – Travel duration

Model		(1) Income & location	(2) Income * location	(3) All – Linear (No interaction)	(4) All – Linear (with interaction)	(5) All – Logit (No interaction)
Y=		trip duration (minute)	trip duration (minute)	trip duration (minute)	trip duration (minute)	supercommute (0,1)
Household income	<$25k	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	$25-50k	-1.685	-2.620	-2.832	-3.454	-1.130
		(1.60)	(2.31)	(1.73)	(2.48)	(0.70)
	$50-100k	0.221	0.254	-1.341	-0.906	-0.732
		(1.44)	(2.09)	(1.66)	(2.31)	(0.57)
	$100-150k	1.548	1.601	-0.282	0.077	-0.479
		(1.48)	(2.10)	(1.73)	(2.35)	(0.59)
	>$150k	1.736	2.106	-0.176	0.486	-0.762
		(1.48)	(2.06)	(1.77)	(2.35)	(0.63)

PA Pairs	Bay-Bay	0.000	0.000	0.000	0.000	0.000
		(.)	(.)	(.)	(.)	(.)
	Bay-CV	15.223***	15.257***	15.007***	15.026***	2.368***
		(3.56)	(3.56)	(3.70)	(3.70)	(0.65)
	CV-Bay	29.599***	28.139***	28.920***	27.660***	3.041***
		(1.77)	(2.16)	(1.81)	(2.19)	(0.31)
	CV-CV	-3.130***	-4.861**	-3.242***	-4.744**	-0.152
		(0.67)	(1.52)	(0.71)	(1.55)	(0.35)
Income * trip production	<$25k: Bay Area		0.000		0.000	
			(.)		(.)	
	<$25k: Central Valley		1.835		2.142	
			(3.08)		(3.24)	
	$25-50k: Bay Area		0.000		0.000	
			(.)		(.)	
	$25-50k: Central Valley		3.780		3.518	
			(2.33)		(2.37)	
	$50-100k: Bay Area		0.000		0.000	
			(.)		(.)	
	$50-100k: Central Valley		1.778		1.352	
			(1.86)		(1.89)	
	$100-150k: Bay Area		0.000		0.000	
			(.)		(.)	
	$100-150k: Central Valley		1.733		1.556	
			(1.98)		(2.01)	
	>$150k: Bay Area		0.000		0.000	
			(.)		(.)	
	>$150k: Central Valley		0.000		0.000	
			(.)		(.)	
Education	Not a high school graduate: 12 grade or less			0.000	0.000	0.000
				(.)	(.)	(.)
	High school graduate: high school diploma or GED			2.698	2.703	0.417

				(1.89)	(1.89)	(0.71)
	Some college credit but no degree			2.814	2.855	-0.415
				(1.94)	(1.95)	(0.79)
	Associate or technical school degree			3.011	3.006	0.350
				(2.02)	(2.02)	(0.75)
	Bachelors or undergraduate degree			3.560	3.540	0.186
				(1.92)	(1.92)	(0.73)
	Graduate degree (includes MD/DDs/JD)			2.808	2.782	-0.367
				(1.98)	(1.98)	(0.78)
	Other: Specify			-0.807	-0.896	0.000
				(9.48)	(9.49)	(.)
Job category	Sales or service			0.000	0.000	0.000
				(.)	(.)	(.)
	Clerical/administrative support			0.854	0.828	-1.405
				(1.38)	(1.38)	(1.08)
	Manufacturing/construction/maintenance/farming			4.231***	4.245***	0.602
				(1.17)	(1.17)	(0.48)
	Professional/managerial/technical			2.968**	2.972**	0.535
				(0.92)	(0.92)	(0.42)
	Something else			5.284**	5.302**	0.666
				(1.98)	(1.99)	(0.83)
Home ownership	Own/Buying (Paying off Mortgage)			0.000	0.000	0.000
				(.)	(.)	(.)
	Rent			-0.509	-0.464	-0.250
				(0.89)	(0.89)	(0.39)
	Other: Specify			-12.877	-12.930	0.000
				(12.01)	(12.02)	(.)
Household characteristics	# persons (household)			0.000	-0.017	0.156
				(0.40)	(0.40)	(0.16)
	# vehicles (household)			0.109	0.118	-0.014

Pacific Southwest Region UTC
University Transportation Center

				(0.38)	(0.38)	(0.15)
	# students (household)			0.397	0.418	0.040
				(0.47)	(0.47)	(0.18)
Constant		26.624***	26.561***	22.361***	21.987***	-4.860***
		(1.38)	(1.96)	(2.44)	(2.88)	(0.95)
Observations		4667	4667	4519	4519	4511
R-squared		0.073	0.074	0.077	0.077	
Adjusted R-squared		**0.072**	**0.072**	**0.073**	**0.072**	

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