The Environmental Impact and Policy Implications of Supercommuting in the Northern California Megaregion

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract The long distances some commuters travel to work, 50 miles or more for each trip, means that despite the small share of so-called supercommuters, their contribution to total vehicle miles traveled (VMT) and greenhouse gas emissions is significant. This study provides a detailed overview of supercommuting in the Northern California Megaregion, home to some of the counties with the highest numbers and rates of long-distance commuting. The empirical focus of the research is to estimate the incidence of supercommuting to better understand what factors may contribute to people commuting long distances and to assess the environmental impact of supercommuting. We use data from several public and proprietary data sources to develop a picture of supercommuting that includes geographic patterns, trends over time, demographics, and insights into why people supercommute. We estimate that supercommuting accounts for as much as 4-5% of total VMT and that while some supercommuting is more common in the exurban edge of the San Francisco Bay Area, many supercommuters live close to the major regional employment centers, emphasizing the heterogeneity of causes for long-distance commutes. We use worker miles traveled estimates to assess three emissions reduction strategies: clean vehicle adoption, remote work, and residential relocation, and find that while clean vehicles have the smallest initial impact, they have the greatest long-term potential to reduce emissions.

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Pacific Southwest Region UTC
University Transportation Center

About the Pacific Southwest Region University Transportation Center

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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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Disclosure

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Abstract

The long distances some commuters travel to work, 50 miles or more for each trip, means that despite the small share of so-called supercommuters, their contribution to total vehicle miles traveled (VMT) and greenhouse gas emissions is significant. This study provides a detailed overview of supercommuting in the Northern California Megaregion, home to some of the counties with the highest numbers and rates of long-distance commuting. The empirical focus of the research is to estimate the incidence of supercommuting to better understand what factors may contribute to people commuting long distances and to assess the environmental impact of supercommuting. We use data from several public and proprietary data sources to develop a picture of supercommuting that includes geographic patterns, trends over time, demographics, and insights into why people supercommute. We estimate that supercommuting accounts for as much as 4-5% of total VMT and that while some supercommuting is more common in the exurban edge of the San Francisco Bay Area, many supercommuters live close to the major regional employment centers, emphasizing the heterogeneity of causes for long-distance commutes. We use worker miles traveled estimates to assess three emissions reduction strategies: clean vehicle adoption, remote work, and residential relocation, and find that while clean vehicles have the smallest initial impact, they have the greatest long-term potential to reduce emissions.

Executive Summary

Supercommutes are commute trips longer than 50 miles or 90 minutes. This report focuses on long-distance commutes by car as the obvious contributor to greenhouse gas emissions. We use data from public and proprietary sources to establish a baseline for supercommuting in the Northern California Megaregion, a 29-county region home to 14 million people and some of the highest supercommuting rates in the United States. The first part of the report provides an overview of supercommuting in terms of its geographic incidence and changes over time, as well as information on who supercommutes in different parts of the megaregion. The overview supports a set of exploratory scenarios that highlight mitigation strategies to reduce supercommute-related emissions.

Supercommuting trends and pattern

Supercommutes account for up to 9% of commute trips and 36% of commute-related worker miles traveled. This is likely an overestimate, but corroboration from other data sources suggests that the share of supercommutes among all commutes is no less than 4% in the Northern California Megaregion. Based on these figures, we estimate that supercommuting plausibly accounts for between 3.6% and 4.5% of total person miles traveled.

Supercommuting peaked in 2019 and decreased during the COVID-19 pandemic without dipping below 2000 levels. The trend since 2022 has been sharply upward. The longer-term shift toward remote work appears to offset some supercommuting, as an estimated 18% of workers who previously supercommuted were working remotely in 2023.

Supercommutes are most prevalent in counties directly east of the San Francisco-Oakland Metropolitan Area and San Jose Metropolitan Area (the Bay Area). Depending on the data source, supercommuting rates in these counties range from 20% to 30% of all commutes. These areas have direct transportation links into the Bay Area and the top destinations out of these counties are primarily within the Bay Area.

Despite making up a much smaller share of commuters in the Bay Area, the much larger number of workers there means that many supercommuters live and work within the Bay Area. Many supercommuters live in core urbanized areas and affluent suburbs where housing costs are elevated, suggesting that housing affordability is not the sole driver of supercommuting. However, the areas within the Bay Area with the highest rate of supercommuting are suburban areas where housing costs were historically lower than the core Bay Area (e.g., the Concord-Antioch area) and have grown rapidly. These areas resemble the San Joaquin Valley counties more than the rest of the Bay Area.

Supercommuters' socioeconomic characteristics

Research on supercommuters suggests two main types. Workers in lower-wage occupations who travel long distances to live in areas with lower housing costs and higher-wage workers who travel long distances to live in areas that match their preferences. The descriptive

overview shows that supercommuters are likelier in high-wage employment than the general working population, especially in exurban counties. In contrast, they are no more likely to belong to higher-income households, suggesting a differentiation within households with higher wage members more likely to travel longer distances. This is supported by a regression analysis that shows higher-wage workers have significantly higher odds of supercommuting.

The relationship between wages and supercommuting does not map onto a clear pattern by occupation. The only occupations that exhibit significantly higher rates of supercommuting are construction, healthcare, and installation, with office, production, transportation, and management all showing higher, though more subdued, odds of supercommuting.

Emissions scenarios

The scenarios cover three strategies that we apply to four focal counties. We chose the counties where supercommuting is most common to show how differing context leads to significantly different outcomes for each scenario.

Clean vehicle adoption: The transition from gas-powered vehicles to clean-fuel vehicles is a direct method of reducing emissions. It is, however, a longer-term strategy. The complete turnover of the vehicle fleet will likely take decades. Without complementary strategies to incentivize shared mobility, the number of vehicles on roads is likely to increase and continue polluting through non-fuel-related emissions. We estimate a plausible increase in the number of clean vehicles that supercommuters might switch to in a typical year and show that the rate of change would result in small reductions in emissions of up to 0.6%. The reduction is smaller in most counties we examined (as low as 0.15%) and lower for PM2.5 than for CO_2.

Remote work: Remote work has the benefit of immediately cutting vehicle miles traveled without the need for investments in infrastructure or subsidies and reducing congestion. It is unclear if remote work necessarily translates to such reductions if people simply replace commute travel with other travel purposes. We suggest, based on results from the 2023 METRANS Remote Work and Migration Survey, that there is little evidence of induced travel from working remotely and that, therefore, reductions in commute should translate into cuts in overall driving. We estimate that emissions can decrease between 3% and 7% depending on the workforce composition of the focal counties.

Residential location: This scenario compares travel for residents who live within their workplace's catchment area to that of supercommuters. This comparison produces a measure of excess driving that we use to estimate reductions in emissions associated with living closer to where people work. Reductions under this scenario range from 1% to 2%. Changing residential location is a challenging approach and does not eliminate driving altogether but has potential benefits if it leads to a mode shift toward transit.

Introduction

Commuting is a relatively small part of people's daily driving. According to the 2022 National Household Travel Study (NHTS), travel to and from work accounted for an average of 30% of household miles traveled.[1] Despite being less than a third of all miles driven, commuting is the leading source of vehicle miles traveled (VMT) and, therefore, a priority for reducing overall driving and associated greenhouse gas (GHG) emissions. The trend, however, has been in the opposite direction, and commute vehicle miles driven have been increasing over time. The average commute distance based on the NHTS increased from 11.8 miles in 2017 to 13.6 in 2022 for people driving to work. Hybrid work arrangement, which allows people to commute to their workplace only some days, contributes to the trend toward longer commutes as people trade off fewer commute days for longer one-way commutes (Asmussen et al., 2024; Boarnet et al., 2024; Bloom & Finan, 2024).

At the extremes of these trends are people who commute very long distances on a regular basis. Supercommuters are generally defined as people who travel to work more than 50 miles one-way (FHWA, 2018), with some variations in terminology as extreme commutes (longer than 100 miles) become more common (Andersson et al., 2018). The share of supercommuters is small, with estimates usually between 2-3% of all commuters (see Salviati, 2023), but the amount they drive means they contribute a disproportionate amount of commute-related VMT.

This report provides an overview of trends in supercommuting in the Northern California Megaregion, one of the urbanized megaregions where supercommuting is most common. We focus on the megaregional scale because one of the defining characteristics of supercommutes is that they extend beyond the boundaries of Census-defined metropolitan areas and even Combined Statistical Areas (CSA). Figure 1 shows the extent of the megaregion, which includes 29 counties spanning the San Francisco Bay Area, Greater Sacramento, Northern San Joaquin Valley, Fresno, and Sierra Foothills.

The purpose of documenting supercommuting is to provide estimates for the environmental impact excessive driving causes. While 50 miles has become a common cutoff to define supercommuters, commutes over 30 miles already represent more than double the average commute distance. The report focuses on the 50-mile definition but includes commutes longer than 30 miles at various points to emphasize the magnitude of emissions long commutes generate.

Following a review of existing research on supercommuting and strategies to mitigate emissions linked to commuting, the report provides a detailed overview of supercommuting trends and patterns, including an analysis of supercommuters' socioeconomic characteristics. This overview, in addition to providing estimates for how supercommuting has changed and

[1] Bureau of Transportation Statistics. Average Annual PMT, VMT Person Trips and Trip Length by Trip Purpose. https://www.bts.gov/content/average-annual-pmt-vmt-person-trips-and-trip-length-trip-purpose

information on the places and people driving the most, provides important background for understanding drivers of environmental impacts and policy challenges in targeting this group.

The environmental impact analysis focuses on emissions linked to driving and possible strategies to mitigate those emissions. The first is transitioning to clean vehicles as a direct way to reduce emissions without changing the underlying travel behavior. The second is remote work, which eliminates some commuting altogether but requires changes to work arrangements and is limited to some occupations. Finally, we examine the role of residential location as the likely cause of supercommuting (i.e., people choose to live farther from work for housing). The policy implications of each strategy range in terms of feasible options and effectiveness, and the report concludes with a discussion of policy obstacles and benefits rather than recommendations.

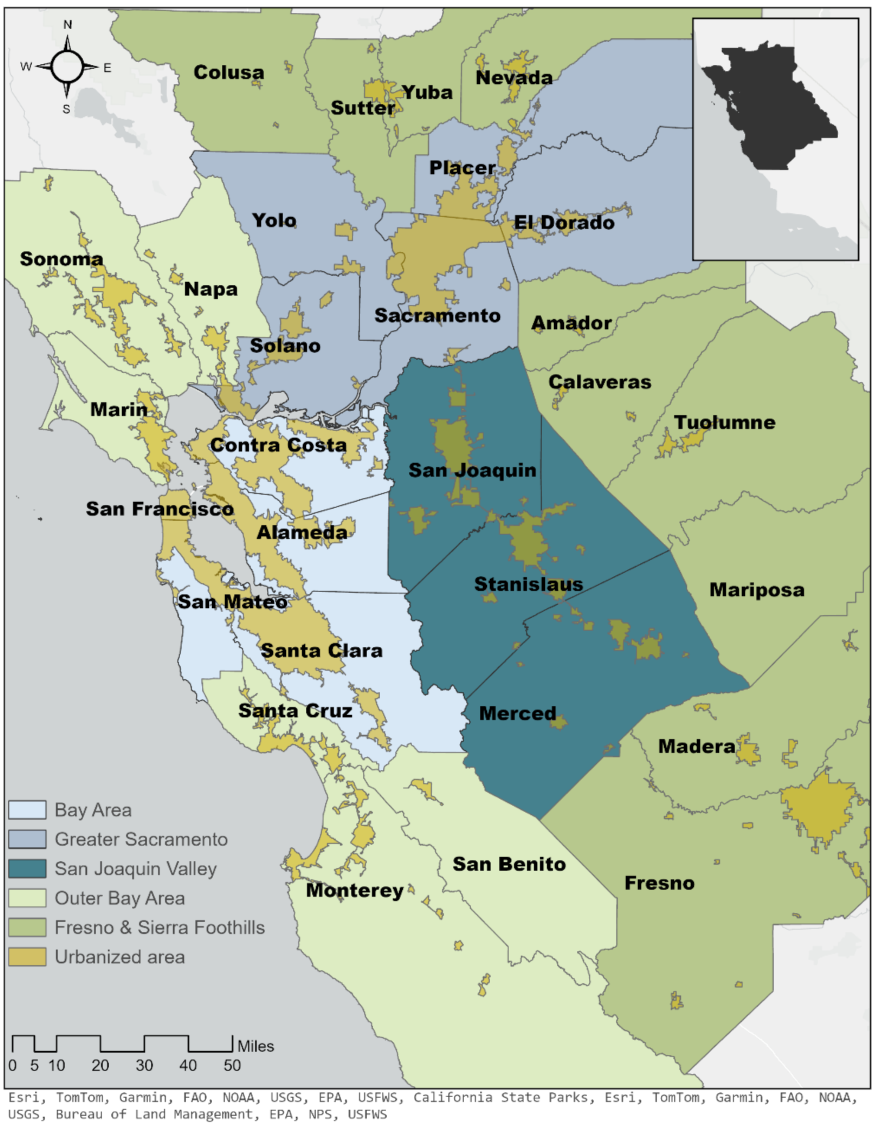


Figure 1. Map of the Northern California Megaregion showing the main urban center.

Literature Review

Supercommuting, generally defined as commutes greater than time or distance thresholds of 90 minutes or 50 miles one way, has become entrenched in the United States. Based on the commute time definition, the number of supercommuters decreased to 3.1 million in 2023 from a high of 4.2 million in 2019 (Salviati, 2023). The decrease is significant but not as large as we might expect. The 2023 data is at the tail end of a dramatic uptick in remote working, and the decrease may be reversed if remote work rates trend downward. The number of supercommuters remains as high as in 2010 and is especially elevated in the counties surrounding the largest, most expensive metropolitan areas like the San Francisco Bay Area, Los Angeles, Washington D.C., and New York City (Salviati, 2023). This concentration of the phenomenon in high housing cost metropolitan areas has spun a narrative explaining that the rise of supercommuting has been driven by people unable to afford living closer to their place of work (e.g., Castleman, 2023). This narrative has shifted with the rise in remote working.

Remote work can eliminate commuting altogether, but for the many workers on a hybrid schedule that includes some visits to the office, commuting is still a regular occurrence. Many hybrid workers, however, have traded the lower frequency of commuting for longer commutes (Bloom & Finan, 2024). Supercommuting, in short, encompasses a great deal of variation in frequency, length, and causes.

The variability in patterns of supercommuting makes the environmental impact of very long commutes unclear. Boarnet et al. (2024), for example, find that hybrid workers, as a group, produce fewer commute-related emissions despite their longer commute distance. Despite the balance of frequency and distance favoring lower emissions, the impact on non-commute-related emissions is unaccounted for. It may be that people who elect to live farther from their work location reside in places that require additional driving to reach schools, stores, and entertainment.

In this review, we first cover the definitions, data sources, and trends of supercommuting. We then briefly discuss the causes of supercommuting in the United States, a field that has received little attention. Next, we address the environmental impacts of driving and possible mitigation strategies researchers have explored. While all forms of supercommuting have environmental impacts, we focus this review on driving and long-distance (rather than time) commuting. In addition, in line with the focus of this research project, we emphasize research relevant to the Northern California Megaregion.

Supercommuting: Definitions and prevalence

The concept of supercommuting is referred to by several other terms including “extreme commuting” or “long-distance” commuting. Usually, it refers to commuting trips of over 50 miles or 90 minutes one-way. For example, Marion and Horner (2007) use the term “extreme commuting” to describe commutes over 90 minutes. A series of research reports use “supercommuting” to refer to both commutes of over 50 miles and 90 minutes (Boarnet et al.

2021, 2022, 2023). Kures and Deller (2023) use "stretch commuting" for the same distance threshold.

While these thresholds are the norm, they are not always used. Moss and Qing (2012a, 2012b) define supercommuting as working in the core county of a metropolitan area but living outside of it. Particularly outside of the United States, some authors use lower distance thresholds (e.g., 30 kilometers in Limtanakool et al., 2006 and in Sandow and Westin, 2010), but the determinants of supercommuting do not appear very sensitive to the distance threshold (Andersson et al., 2018). The general definition is not mode-specific and may also refer to commuting by transit (e.g., Wang and Hu, 2017) or even aero-commuters who commute by plane (e.g., Bissel et al., 2017).

One reason for the multiplicity of definitions is that few data sources offer consistent identification of very long commutes, and each source uses a specific measure. Common data sources for supercommuting research in the United States include Longitudinal Household-Employer Dynamics (LODES) data, American Community Survey (ACS) data, third-party, GPS-based sources such as Streetlight Insight Inc, and travel surveys including the National Household Travel Survey (NHTS). LODES data can provide an origin-destination matrix of places of work and residence at the census block level. This has allowed researchers to estimate the typical commute distance from every block. ACS data is based on a survey question asking the respondent's commute duration in minutes. ACS data is available both in aggregate form down to the census tract level and as microdata.

The ACS and LODES data are illustrative of the tradeoffs involved in choosing data sources. LODES data gives higher spatial resolution, but it often assigns every employee to a firm's main branch and may not accurately reflect where the work was performed (see next section for details). In addition, LODES does not include self-employed individuals, who are 12% of the workforce in California. Several researchers note this problem (Boarnet et al., 2021, 2022, and 2023; Dash et al., 2016; Kures & Deller, 2023), and a common strategy is to use the two sources together (e.g., Blumenberg & Siddiq, 2023; Blumenberg & Wander, 2023; Boarnet et al., 2021) since they are intended as complements of one another (Graham et al., 2014).

Data derived from Global Positioning System-enabled services like mobile applications provide added flexibility by aggregating (and sometimes extrapolating from) observed trips. Streetlight Insight data, for example, estimates from a sample of location-based services data points the average vehicle miles traveled from any geography (if the sample is large enough), origin-destination matrix, distance, and time traveled. However, such data are not publicly available, and estimates may be inaccurate in low-volume scenarios (Yang et al., 2020). Further, since this data relies on GPS data, it may be spatially inaccurate, and it is unclear which drivers are left out of the data. More studies comparing the accuracy of Streetlight to reference data may be necessary (Yang et al., 2020; Racca, 2022).

Trip survey data tends to be limited in coverage and may not be suitable to represent the overall levels of supercommuting. However, since this data is directly reported and usually variable-rich, it is well-suited to identify the characteristics of supercommuters. For example, Bai et al. (2020) use the Puget Sound Travel Survey to investigate the socioeconomic determinants of supercommuting in the greater Seattle region, and Boarnet et al. (2021) use NHTS and California Household Travel Survey data to compare estimates of supercommuting in the Bay Area with other data sources.

We focus on driving commutes for two reasons: First, experiences are likely to differ heavily between modes on commutes with similar times or distances. Second, when identifying supercommuters based on a distance threshold, times are likely to vary heavily between modes and vice versa. A sizable literature compares the differences in commuting experience between transit and driving. For example, Brutus et al. (2017) found that car commuters arrived at work with worse moods and higher stress levels than transit or bike commuters. Werner and Evans (2011) also found that car commuters in New York had both higher stress and lower moods than transit commuters. The commuting experience of different groups is also not likely to be equal, even on similar modes, due to differences in perceived safety, gender, and accessibility needs (see Litman, 2014; Hsu et al., 2019; Bezyak et al., 2017). Supercommuting time or distance thresholds are central to its definition, and it would be difficult to devise a comparable set of thresholds for different modes due to these different experiences. As Bai et al. (2020) note, supercommuters of different modes may be doing so for different reasons, and so relationships with explanatory factors are likely to differ among these groups. Marion and Horner (2007) note that transit commuting times are also subject to service provision, and they leave these commuters out of their analysis as well.

Causes of supercommuting

Researchers often examine supercommuting behavior within a framework that sees commuting distance and housing as a tradeoff (e.g., Mitra and Saphores, 2019). The traditional urban model based on the bid-rent theory states that individuals will trade greater travel costs for cheaper rents as they locate farther from the city center (Alonso, 1964; Mills, 1967; Muth, 1969). As housing costs rise, supercommuting will increase as well. Indeed, a study based in Australia found that as housing costs increased, so did commute duration and that households, where possible, reallocated some of their budgets toward public transit (Khammo et al., 2024). From a different perspective, the spatial mismatch hypothesis (Kain, 1968) states that some workers face constraints on their locational choices (e.g., housing segregation). For these individuals, longer commutes would also be an outcome.

More recently, job accessibility studies have begun to focus on the difference in job access by modes, as transit mode explains job accessibility differences by race/ethnicity or income more consistently than residential location (see Taylor & Ong, 1995; Grengs, 2010). In places where jobs have been decentralized, cars can offer access to multiple job centers, and a person may have higher access to the total number of jobs by living in an area that has few jobs nearby. Many authors have relatedly found much higher levels of jobs accessible by car than transit in the same commute times (e.g., Kawabata and Shen, 2007). Despite the relevance of car ownership to job accessibility, households who own a car have no significantly higher odds of supercommuting (Mitra & Saphores, 2019). This result, however, is based on a distance-based definition of supercommuting (commutes greater than 50 miles). Most people traveling more than 50 miles to work are likely to live outside areas with dense transit services and, therefore, most own a car.

The COVID-19-related increase in telework (particularly for occasional commuters) may have also contributed to changes in supercommuting behavior. While the exact impact of COVID-19 on travel behavior is still under discussion, telecommuting has seen a marked increase and seems to have increased distances from housing to city centers (Zhu & Wang, 2024). A study of the decisions to change jobs, residential location, and remote work shows that most people increased telework without changing residential location, but an estimated one in five moved in response to being able to telework (Asmussen et al., 2024).

Consistent with the bid-rent explanation, evidence points to the jobs/housing mismatch as a determinant of longer commute distances (Blumenberg & Siddiq, 2023; Blumenberg & Wander, 2023). That is, when areas with low-wage jobs, for instance, do not have enough housing affordable to low-wage workers, commute distances increase. High housing costs may preclude workers from moving if they are unable to find housing that matches their preferences for commuting distance. Mitra and Saphores (2019), using the 2012 California Household Survey long-distance travel module, found that the odds of supercommuting were higher for people living in high-median-home value neighborhoods and higher for people working in locations with high median home values. A longitudinal study of commuters in China shows that workers with long commuters are more likely to change jobs, but commuting time does not significantly affect the propensity toward residential mobility (Ma et al., 2024). While the researchers find a relationship between commute length and changing jobs, they note that job changes are not associated with a consistent decrease in commute length.

Research shows that distance to work is not the primary factor in deciding where to live. Giuliano and Small (1993) speculate that the difference may be explained by individuals optimizing for future work locations, non-work travel, or two-person households, personal factors including a preference for longer commutes, and external constraints such as racial segregation. In a study of the Greater Toronto region, Berry (2022) finds that, on average, supercommuters pay more toward housing and transportation than commuters closer to central Toronto, suggesting that factors other than housing and transportation costs are leading to the decision to supercommute. O'Kelly and Lee (2005) find different levels of imbalances in different metropolitan areas. They disaggregate excess commuting models by occupation, indicating that different types of work locations and housing may not be interchangeable. Among Shanghai Metro riders, Zhang et al. (2021) note that the frequency of commuting is often overlooked, and model prediction increases when frequency is considered. This supports the idea that supercommuting has increased in tandem with telecommuting.

Supercommuting has been on the rise in the past few decades and has increased more quickly between the Bay Area and the Central Valley than in the United States overall (Boarnet et al., 2021). While commute flows between Bay Area and Central Valley counties have increased with the population, the rate of supercommuting has increased more quickly. Rates of supercommuting from the Central Valley are nearly 3 percent via NHTS and Streetlight estimates but as high as 22 percent via LODES (Boarnet et al., 2021). This is consistent with the view that rising housing costs have driven people to relocate from the Bay Area to the Central Valley, but they have not changed their place of employment.

The majority of supercommuting appears to be rural-to-urban. In the Midwest (Kures & Deller, 2023) and Sweden (Andersson et al., 2018), supercommuting has increased in rural areas, and the size of commuting sheds seems to have increased. Andersson et al. (2018) found that the most common type of new supercommuters in Sweden were those who remained at a rural residential location but changed jobs to a city center. Most of these new commuters were male, high-income, young, highly educated, and working in knowledge-intensive jobs. In the Bay Area and Central Valley, manufacturing, maintenance, construction, and farm workers; households with more children; zip codes with high shares of renters, transit users, and migration from the Bay Area associated positively with supercommuting, while income, age, education, and housing characteristics appeared to be insignificant (Boarnet et al., 2021). Kures and Deller (2023) identify those under 29 and low-income as most likely to supercommute. Accordingly, Bucholz (2022) finds that most out-migrants from regions with high housing costs are of lower socioeconomic status but notes that some remain in exchange for more crowded housing and/or longer commutes. However, Bai et al. (2020) find that the relationships between sociodemographic variables and supercommuting varies by geographic area, so it appears that extreme commuting is a function of land use characteristics rather than a constrained choice based on sociodemographic characteristics. However, the relationship between land use and supercommuting may not be entirely straightforward. Hipp et al. (2022) find that employment deconcentration results in shorter commutes in large metropolitan areas but longer commutes in small metropolitan areas.

Environmental impacts of supercommuting

While greenhouse gas emissions (GHG) are the main focus of the literature, there are several other externalities to driving. As Button (1990) notes, CO2 emissions have been a focus since the 1970s, but other indicators, including nitrogen oxides (NOx), volatile organic compounds (VOC), carbon monoxide (CO), sulfur dioxide (SO2), hydrocarbons (HC), and suspended particulate matter (e.g., PM2.5) are used to measure environmental impacts directly. Additionally, higher levels of driving increase noise pollution, traffic congestion, and accidents (Button, 1990; Joumard & Gudmundsson, 2010; Profidillis et al., 2014).

In practice, the impact of driving can be represented by measures of overall travel, such as vehicle miles traveled (VMT) or energy consumption (e.g., gasoline consumption). For example, using survey results on driving reduction by COVID-19-induced telework, Sutton-Parker (2021) uses a region-specific multiplier to convert VMT reductions into estimated reductions in CO2 emissions. As Gainza and Livert (2013) note, VMT or energy consumption is most often used to characterize the impact of driving, but Camagni et al. (2002) developed a method of applying specific conversion factors to the total number of commuters in each mode and duration within a geographical area. Governments have developed methods for quantifying emissions linked to driving. The California Air Pollution Control Officers Association, for example, developed a methodology for quantifying GHG emissions mitigation (Lee, 2010).

However, since supercommuting is a small, emerging topic, few studies have directly assessed its environmental impact. In this section, we focus on research pertaining to the three factors affecting driving-related emissions that we examine in the scenario.

Clean vehicles

Transitioning to clean vehicles results in a direct and immediate decrease in emissions. Benefits from reduced emissions from cars are significant for air quality and related health impacts (Garcia et al., 2023; Yu et al., 2023). The magnitude of the decrease in emissions, however, depends on several factors. If looking at overall emissions (e.g., at the state level), the source of electricity is a critical factor that can nullify much of the benefit of vehicle electrification (Nordelöf, 2014). Electricity generation in California is conducive to significant decreases in emissions thanks to a mix of sources that is 60% from renewables or clean (US DOE, 2024). In this context, vehicle electrification results in significant declines in overall emissions. Yet, even with complete electrification, some emissions associated with brake and tire wear will remain significant (Skipper et al., 2023).

Emissions associated with the production of electric vehicles tend to be accounted for at the highest level of aggregation because the supply chain is global. As such, the impact of emissions associated with vehicle production may not be reflected locally at the state or even national level. However, vehicle production in states like California, with relatively clean electricity sources, can account for up to two-thirds of life cycle greenhouse gas emissions (Ambrose et al., 2020). The trend toward larger, more resource-intensive vehicles exacerbates the significant environmental impact of production. For such vehicles, usage is important, and a shift toward shared mobility and high-mileage driving (as is the case with supercommuting) can mitigate large production impacts (Ambrose et al., 2020).

While the benefits of vehicle electrification in terms of pollution far outweigh the costs, an important limitation is that the electrification of a large car fleet like that of California will take time and will reflect socioeconomic divides. Electric vehicles as a share of new vehicles have increased rapidly, but the concentration of clean vehicles is most visible in more affluent neighborhoods with education as the main predictor of adoption (Garcia et al., 2023). If supercommuters match these characteristics, there is a possibility of a more rapid transition to clean vehicles among the population that drives the most.

California has mandated an aggressive timeline for electrifying its car fleet. The Advanced Clean Cars II regulations require that all cars sold in 2035 be electric. Yet, even with this requirement, the number of gas-powered cars still on the roads will be significant and there are no provisions in the regulations to reduce the number of cars on the road. This can lead to increased environmental impact from land-use conversion for roads (and the lack of incentives to rein in sprawling urban development) and increased congestion, which carries significant emissions and other pollution burdens where congestion happens (Xu et al., 2024).

The consequences of keeping a car-centric approach to decarbonization are particularly relevant for supercommuting. Supercommuting relies on the ability to drive long distances at a relatively low cost. Under a regime where individual mobility, albeit clean mobility, is prioritized, environmental impacts are likely to be higher than they need to be if transit and other forms of shared mobility are under-invested (Shen et al., 2024; Xu et al., 2024).

Remote work

Remote work, alternatively known as teleworking and work-from-home, is another strategy that promises to significantly reduce the environmental impact of driving. The impact should be simple to quantify. If people work from home, they do not need to commute, therefore, reducing their vehicle miles traveled. However, a burgeoning literature is disputing this simple association. The impact of remote work is complicated by the fact that it affects all aspects of people's lives and the entire economic structure, from residential and commercial power usage to driving patterns (Tao et al., 2024). In this review, we focus on the transportation aspect.

A pilot study closely tracking 11 participants in the Ottawa region found a decrease in miles driven when people switched to hybrid or fully remote working (Simon & O'Brien, 2023). The authors, however, point out that there is evidence that a reduction in driving by one member of the household often is associated with increased driving by another. The magnitude of the decrease also depends on lifestyle and routines. For households whose commute was a smaller-than-average part of their daily driving or who did not drive to work, the impact can be minimal. Another study based on data from England and Wales takes a scenario approach to estimate the change in emissions associated with increasing shares of remote workers. They find a modest decrease in the transportation sector and still smaller decreases overall (Santos & Azhari, 2021). As Simon and O'Brien (2023) and Santos and Azhari (2021) warn, these decreases can quickly become increases when assumptions about rebound effects in the transportation sector and building usage are relaxed.

As with electrification, remote work's effect on transportation works through the entire system and can affect congestion. Remote work should reduce congestion by removing cars from the road, especially at peak hours. However, the effect may simply shift when traffic happens and still create significant congestion if people follow routines such as school pickups (Speroni et al., 2024). A set of simulations working under the assumption that half of all workers work remotely shows the limited impact of removing commute trips, finding VMT reductions of only 0.69% in the Chicago Metropolitan Area (Shabanpour et al., 2018).

Residential location

In contrast to remote working and clean vehicles that grew in significance in the last few years, the effect of residential location on driving is a well-established research area. A possible cause of supercommuting is a lack of jobs-housing balance. If there is not enough housing within the

Bay Area, people working jobs in the Bay Area must find housing outside of the area. The Bay Area has grown more imbalanced, resulting in a severe housing shortage that may push people to live much farther from their jobs than they would otherwise (Boarnet et al., 2023; Schaffran, 2018). The imbalance is worsened by the lack of housing affordable to people working in lower-wage occupations (Benner & Karner, 2016).

Geography exacerbates the case of the Bay Area as there is little room for large-scale development of new housing, and densification faces high land and construction costs. The bay's geography also means that there are large gaps between the core urbanized area and the next set of urban areas (often separated by 20 or more miles of land that cannot be developed, see Figure 1). These factors constrain where people can live within the Bay Area and, in turn, how much they must drive (see, e.g., Long et al., 2023 for a discussion of the similarly geographically constrained Boston Metropolitan Area). As noted above, however, the jobs-housing imbalance is not enough to explain where people live and how much they commute. There is a large element of choice.

Where people choose to live is consequential because areas that have low accessibility to jobs, essential services, and amenities require much more driving than areas where most destinations are close by. The threshold for accessibility, however, is not near the extreme. People are not required to live in the dense urban core to cut emissions and some researchers suggest that the difference between people living in central cities as opposed to their suburbs is insignificant when taking all sources of household emissions into account (Wilson et al., 2013).

Data and Methodology

Supercommuters are a small population with no single source of data that can appropriately document their place of residence, work location, and demographic characteristics. This section provides an overview of the different data sources we rely on to triangulate information about supercommuters and the method used to create emission mitigation scenarios.

Data sources

We use several data sources to establish patterns of supercommuting. Our primary data source for identifying supercommuting levels is the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). These data are provided by the Census Bureau and summarize the number of workers within each home and work census block in California, and a full origin-destination matrix showing the number of workers traveling between home and work locations. Using the 2019 origin-destination matrix version of the file, we can calculate the proportion of workers in each block who supercommute based on distance.

We estimate commute distance based on the shortest route between two block centroids (converted to coordinate pairs) on the road network. This distance was calculated for every pair with at least one worker traveling using an Open Source Routing Machine based on the distance between the origin and destination's centroid coordinates (see Blumenberg & Siddiq, 2023). The California topography means that many places that are close as the crow flies can be far more distant by road. Figure 2 shows how someone traveling from Patterson to San Jose, just 40 miles away, would have to drive more than double that distance because of the Diablo Mountain range separating the two cities.

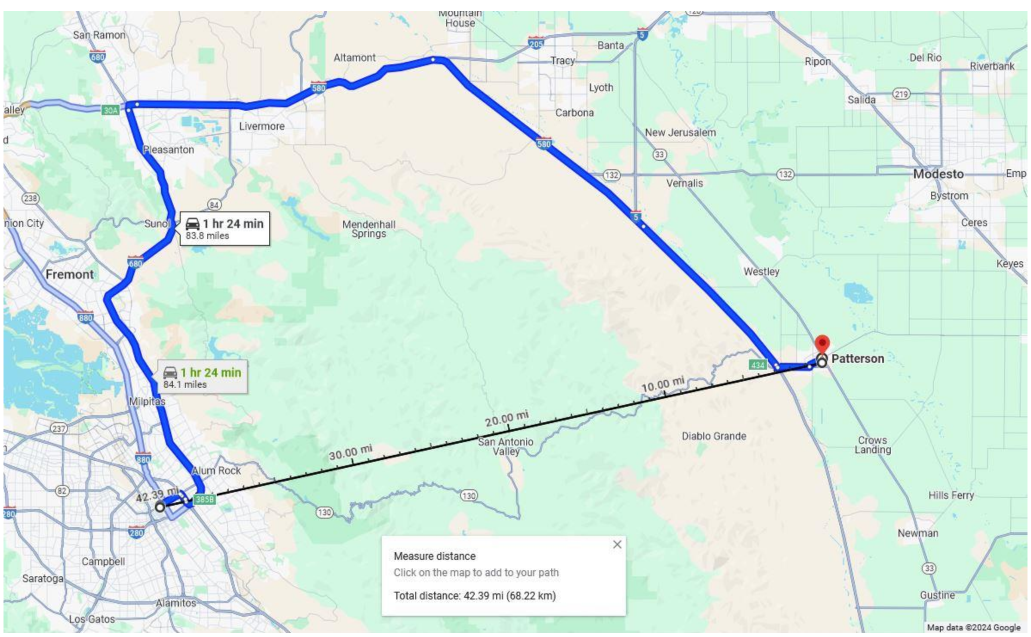


Figure 2. Map showing the distance between Patterson and San Jose using straight line distance (42.4 miles) and distance over the road network (83.8 miles).

The LODES data has several known limitations. It only captures workers that are part of the unemployment insurance program and, therefore, excludes self-employed people, unregistered workers, and workers in certain industries, notably in the defense sector. Still, the underlying data is administrative and covers much of the population (~88% of people in the labor force, Manduca, 2018), but much of the information is inputted with sophisticated models. The resulting data on workers are accurate (Kinney et al., 2020), but the data are limited in the information they provide on the workers, especially for the origin-destination data. An important characteristic that is not included is the commuting mode. However, most long-distance commuters are likely to drive. Based on the 2017 NHTS data, Californians drove 95% of all trips longer than 50 miles when excluding flights.

In addition, LODES is not always able to match workers to their actual work location. In cases where someone works for an employer with multiple locations (e.g., a school district or a corporation with many outlets), LODES is not always able to match the worker to the place where the worker commutes most often (either because of the timing of the data collection or incomplete information from the employer). This leads to an overestimation of cross-county and longer commutes (Green et al., 2017). While the comparison of LODES data and data from the American Community Survey on the share of workers working in a different county than where they reside shows a high correlation of 0.93, some counties deviate substantially. A comparison shows that LODES data for cross-county commutes is often 10 to 20 percentage points higher than the levels reported in the American Community Survey (see Table A1 in the appendix).

This issue is likely compounded by the inability to account for commute behavior. Workers may commute only some days and work remotely the rest of the time. Alternatively, some workers may shift work locations regularly (e.g., construction sites) and have variable work locations. In either case, the data will report a likely commute rather than an actual commute. For this reason, LODES is the distance from the work location rather than a commute. We use the term commute in relation to LODES to mean the distance between work and residential location. Despite these limitations, LODES has been used extensively to study commuting patterns and workforce characteristics.

LODES offers unmatched coverage and geographic granularity, but it only captures commute trips. Therefore, we complement LODES with Streetlight data, which uses Location-Based Services, GPS, and land-use data to provide estimates of trip distribution by length, time, and speed. StreetLight has the advantage of providing data on all trips, which is essential for understanding the environmental effects of supercommuting. The most recent data, however, do not differentiate between trip purposes, meaning we cannot separate commute trips from all trips in the data. We, therefore, use StreetLight to estimate non-work related driving, but limit the use of the data for other purposes.

Neither LODES nor StreetLight can provide detailed information on supercommuters. LODES includes information on wages, age, and industry, but each measure is coarse and provides limited insights. We turn to the American Community Survey (ACS) and the National Household

Travel Study (NHTS) 2017 California add-on to develop a broader overview of supercommuters. Each data source provides a detailed set of demographic and socioeconomic information about individual respondents, meaning that we know whether the respondent is a supercommuter and, to some extent, where they reside. The strength of surveys in terms of individual information is counterbalanced by limited information about location, which comes from limited sample sizes.

The ACS 1-year samples are available for units where the population is above 65,000. These units are the Public Use Microdata Areas (PUMA) and tend to be large in geographic scale, especially in sparsely populated areas. While the PUMA provides a sample large enough to study the entire population, a sub-population like supercommuter is far too small to reliably analyze at that scale. We, therefore, rely on aggregations of PUMAs and of sample years (i.e., multiple 1-year samples) to define different areas for analysis. We use 5 years of data consistent with the ACS 5-year samples used in many products the Census Bureau releases. All ACS data were extracted through the IPUMS service (Ruggles et al., 2024).

The NHTS provides the exact location of respondents in its restricted version. The sample size is the main limitation in using these data (see Appendix Table A2). There are only a few hundred supercommuters in the NHTS data and even if grouping them by county, the sample size would be too small to reliably estimate characteristics. We, therefore, rely on NHTS largely for analysis at the megaregional scale.

We use the California Air Resource Board 2023 fleet data to estimate the share of clean vehicles at the ZCTA level. The fleet data is based on vehicle registration data from the California Department of Motor Vehicles. The database reports the number of vehicles in different use classes (e.g., passenger vehicles or light-duty trucks), the fuel type, and the year of the model. Using these data we can reliably calculate how many vehicles are considered clean (zero-emissions and partial zero-emissions) and the year in which they were bought.

Lastly, we rely on the METRANS Remote Work and Migration Survey for specific questions about the relationship between remote work and commuting. The survey was designed by a team of researchers from the University of Southern California and Occidental College to better understand how remote work changed how and where people moved (Boarnet et al., 2024). The survey is nationally representative (N = 2,104) and was fielded in September 2023 by the firm IPSOS.

Units of analysis

We chose to aggregate most data at the Zip Code Tabulation Area (ZCTA) level because two data sources are only available to us at the ZCTA level. The StreetLight license makes zone activity data available for a maximum of 500 zones. If we include all ZCTA that intersect urbanized areas or have a population of at least 3,000, the Northern California Megaregion includes 498 ZCTA. Smaller units like the Census Tract would quickly surpass the zone limit and require adjustment to coverage.

The vehicle fleet database is the other data source only available at the zip code level. The data are collected from the Department of Motor Vehicle and the zip code used is, therefore, the postal zip code. The postal zip code is different from the ZCTA in that it has no geographic boundaries. The US Census Bureau created the ZCTA to approximate the extent of postal zip codes while conforming to other census geographies. A comparison of the best estimates of postal zip code extent (i.e. how far delivery routes extend) and ZCTA in the megaregion shows that 85% have nearly identical boundaries that nearly all people fall within the same zip code and ZCTA (see Comandon et al., 2024 for more detail). In short, we are confident vehicle fleet data can be joined to ZCTA data without significant bias.

The ZCTA is a large and variable unit. It can range from virtually empty to having tens of thousands of residents. An important drawback of using a larger unit is that supercommuters may be clustered within one part of the ZCTA that is different from the average of the unit. We evaluated this possibility with a cluster analysis for supercommuting rates within ZCTA (i.e., how evenly the percent of supercommuting at the block level is distributed within ZCTA). The analysis resulted in an average Moran's I index close to zero.[2] The low value indicates that in most ZCTA there is no spatial clustering of high supercommuting rate blocks. In other words, the average supercommuting rate tends to be representative of the entire ZCTA rather than a small part of it where most supercommuters co-locate. If that were not the case (had we found evidence of clustering) there would be a stronger case for using a smaller unit.

In addition to the ZCTA, we rely on a set of 'hotspots' to provide a unit of analysis for the scenarios and for a deeper analysis of who supercommutes. The demographic analysis relies on microdata (PUMS and NHTS). Microdata are unavailable at scales smaller than the county or Public Use Microdata Areas (PUMA). The hotspots address this limitation by grouping areas with a high incidence of supercommuting into units large enough to provide usable samples of supercommuters to analyze. The scale of hotspots means that we lose most geographic information, but it nonetheless reflects the diversity of circumstances that give rise to supercommuting (e.g., central cities vs exurb). In addition to requirements for microdata, we are limited to the county scale for the scenarios (more details below). The county is the unit available in the 2021 EMission FACtor (EMFAC) scenario modeling we use to estimate changes in emissions that is most consistent with the scale of the hotspots.

Scenario approach

The scenarios aim to provide estimates for changes in GHG emissions associated with varying levels of clean vehicles (zero-emission and partial zero-emission vehicles), remote work (hybrid and full-time remote), and changes in residential location. For each scenario, we first provide an analysis of the mitigation strategy to determine plausible levels of change. The scenario analyses reviewed above often use a pre-determined level (e.g., a 20% increase in remote workers). This approach does not reflect the context on the ground and constraints on change. Our approach aims to provide a level of change within what is reasonable to expect without major changes in policy and to highlight the different impacts change will have based on local

[2] We used inverse-distance weight matrix.

constraints. That is, we account for the differences in economic structure and population in the counties for which we produce estimates.

Once we have established parameters for change, we use them to estimate changes in total VMT driven by different kinds of vehicles. The EMFAC models include functionalities to generate baseline emissions based on total VMT by vehicle type for counties.[3] Total VMT can then be updated to reflect the estimated change and generate new emissions data. For each scenario, we report the change in emissions linked to changes in driving alone. These estimates are meant to be focused on commute changes and do not take into account possible rebound effects and other sources of emissions associated with changes in household and workplace behavior.

Clean vehicle adoption

The rate at which people buy clean vehicles has increased in recent years, but the overall share of clean vehicles remains low at around 5% of all vehicles. We estimate the potential for a clean vehicle adoption based on the analysis of vehicle composition from the 2023 California Air Resource Board (CARB) fleet composition data. We use two estimates for the number of additional clean vehicles likely to be driven by supercommuters.

The first is based on a regression of the share of clean vehicles in the fleet as the dependent variable and a set of socioeconomic indicators as the independent variables. For every ZCTA within a hotspot, we compare the predicted share of clean vehicles to the observed share. Where the predicted share is higher than observed, we classify the ZCTA as having the potential for increased clean vehicle use and use the difference between the observed and predicted values as the estimated number of clean vehicles that could be added without major policy changes (because the ZCTA is underperforming and can be expected to converge to the mean over time). Where the predicted value is lower than the observed value, we classify the ZCTA as aligned with macro-trends and exclude the observation from the overall estimate of potential new clean vehicles (i.e., no change). We then sum the number of additional clean vehicles to get a county-level estimate.

The second approach is based on a simple linear interpolation of the annual growth rate in clean vehicles in the county. For example, if the number of clean vehicles increased at an annual rate of 20% from 2019 to 2023, and there were 1000 clean vehicles in the county, we estimate that an additional 200 vehicles could be added to the fleet within a year. Each approach is based on a one-time increase so that estimates reflect change based on a one-year equivalent increase in the number of electric vehicles.

Based on the share of supercommuters who drive clean vehicles, we allocate a proportional share of these clean vehicles to supercommuters and multiply the number of supercommuting clean vehicles by the average commute-based VMT for the county. Workers are likely to use their clean vehicles for more than commuting and we assume that they shift all their VMT to

[3] The online platform can be accessed at https://arb.ca.gov/emfac/. Last accessed 12/28/2024.

the clean vehicle. We add average non-work related VMT to the estimate based on the adjusted average VMT for the county from StreetLight Data. We adjust the average VMT figures, which include all trips, based on the share of total VMT that comes from commuting and the average number of trips per person. We estimate non-commute VMT for supercommuters by calculating the total VMT in the ZCTA that account for most supercommuter (ZCTA where 90% of supercommuters reside based on LODES). We then subtract the share of VMT that supercommuters account for. This is based on the assumption that 30% of VMT comes from commuting and the share of commute VMT in each county supercommuters account for. Finally, we multiply the estimate by the average number of non-work trips. Based on the 2017 NHTS, the average number of trips per person was 2.78 (Bricka et a., 2024).

Finally, we re-allocate the clean vehicle commute-based VMT in the EMFAC model from conventional vehicles to ZEV and PZEV. That is, we add the estimated VMT driven by supercommuters who are likely to drive clean vehicles to the light-duty full electric and partial electric vehicle categories (based on their proportion of VMT in the database) and subtract the VMT from the conventional fuel light-vehicle categories.[4] Equation 1 below shows the operation for adding VMT to the clean vehicle classification. The opposite applies to removing VMT from the conventional fuel categories. Equation 2 shows how we estimate non-work VMT as outlined above.

$$\text{New\_EMFAC}_{CVVMT} = EMFAC_{CVVMT} + Clean_{new} \times SC_{CV} \times SC_{VMT} \times 0.68 + Nonwork_{VMT} \quad (1)$$

$$Nonwork_{VMT} = \frac{tot_{VMT} - SC_{VMT} \times 0.68 \times 0.3}{trips \times 2.8} \quad (2)$$

$\text{New\_EMFAC}_{\text{CVMT}}$: Estimated clean vehicle miles to input in EMFAC model
$\text{EMFAC}_{\text{CVVMT}}$: Baseline EMFAC clean vehicle VMT
$\text{Clean}_{\text{new}}$: Estimate of number of new ZEV in the county
SC_{cv} : Share of commuters who supercommute and drive clean vehicles
SC_{vmt} : Average commute VMT for supercommuters in the county
Tot_{vmt} : Total County VMT from StreetLight
Trips : Total number of trips from StreetLight

[4] Light duty includes passenger (LDA) vehicles and the two classes of light-duty trucks (LDT1 and LDT2).

Remote work

There is a lack of data that can be used for location-specific analyses of remote work arrangements. For this scenario, we use an approach that compares the occupational distribution within hotspots based on the 2023 American Community Survey to the share of jobs in each occupational category that can be performed remotely. We use data from Hansen et al. (2023) based on the number of job ads that include the option to work remotely to determine the share of jobs within each occupational category that can be done remotely. These data provide an up-to-date view of the remote work landscape but do not indicate whether jobs can be done remotely full-time or partially.

For each hotspot, we calculate the number of workers that could be remote if current norms in different occupational categories were applied uniformly. This number is an upper-bound estimate based on the assumption that all workers within an occupation can and choose to work remotely at the same rate as what is currently advertised.[5]

We then use the share of supercommuters in each occupational category to estimate the VMT associated with changes in the number of days of remote work based on Equation 3. For this scenario, changes to conditions only affect commute-related VMT (i.e., we keep non-work VMT constant), and there are no reasons to assume that one class of vehicle would be affected differently. We, therefore, allocate the change in VMT to all light-duty classes proportionally to their share of total VMT in the EMFAC database.

$$\text{New\_EMFAC}_{VMT} = EMFAC_{VMT} - SC_{VMT} \times \sum Occ_i \times SC_i \times WFH_i \tag{3}$$

$\text{New\_EMFAC}_{\text{VMT}}$: Estimated total vehicle miles traveled to input in EMFAC model
$\text{EMFAC}_{\text{VMT}}$: Baseline EMFAC total VMT
SC_{vmt}: Average commute VMT for supercommuters in the county
Occ_{i}: number of workers in occupation *i*
SC_{i}: Share of workers in occupation *i* who supercommute
WFH_{i}: Share of workers in occupation *i* who can work remotely

Change in residential location

This scenario compares what would happen if people who supercommute were to live within the catchment area of their work location. The catchment area is based on the set of origins that account for the closest 50% of workers working at that location. For example, if the work location is central Oakland, we arrange all blocks sending workers to that location by distance, from closest to farthest, and keep the distance of the origin block containing the median

[5] The estimate is the upper-bound in that we assign all workers to remote work arrangements. However, the estimate may be an underestimate if the current rates at which remote work is offered is lower than the current rate of people working remotely, a possible legacy of pandemic policies.

worker. All blocks within that median distance are considered part of the catchment area. We then calculate the average commute distance for the location's catchment area to determine the distance people generally commute to that work location. We also calculate the total VMT of people who live within the catchment area using StreetLight data and adjust as we did for the clean vehicles scenario to estimate non-work-related driving. Non-work-related VMT is important in this scenario as people living close to employment centers (many of them in dense urban areas) are likely to drive less on average, thanks to higher accessibility to all kinds of destinations. Many catchment areas have high-quality transit access, and people living within their catchment area are likely to use transit rather than drive. We, therefore, adjust VMT to reflect the average transit use in the Bay Area (12.8%).

Once we have the average commute VMT and non-work-related VMT for every destination, we can calculate the average catchment area VMT for all destinations with origins in the hotspots. The difference between the supercommuters' VMT from each origin and the average of all catchment areas to which they travel gives us a measure of excess VMT. Excess VMT is the amount by which supercommuters exceed the VMT they would drive if they were to work at the edge of the catchment area where they commute to.

In this scenario, change in VMT happens at two points: the county of origin (Equation 4) and the county of destination (Equation 5). We assume that 5% of supercommuters move to within a catchment area. The total VMT associated with 5% of supercommuters is subtracted from their origin county's total and the total VMT associated with the county in which the catchment areas are added to that county. There is little variation in the average VMT of catchment areas, so to simplify the inputs, we use Alameda as the county of destination (adding total catchment area VMT to Alameda). Alameda, in addition to having large employment centers many supercommuters travel to, has a higher than average transit use without being uncharacteristically high for the region (as San Francisco would be).

$$\text{New\_EMFAC}_{VMT\_O} = EMFAC_{VMT\_O} - SC_{VMT} \times SC \times 0.05 \tag{4}$$

$$\text{New\_EMFAC}_{VMT\_D} = EMFAC_{VMT\_D} + CA_{VMT} \times SC \times 0.05 \tag{5}$$

New_EMFAC_{VMT_O}: Estimated total vehicle miles traveled at origin to input in EMFAC model
New_EMFAC_{VMT_D}: Estimated total vehicle miles traveled at destination to input in EMFAC model
EMFAC_{VMT_O} : Baseline EMFAC total VMT at origin
EMFAC_{VMT_D}: Baseline EMFAC total VMT at destination
SC_{vmt}: Average VMT for supercommuter in origin county
SC: Total number of supercommuters in origin county

CA_{vmt}: Average catchment area VMT in destination county

Results

Supercommuting trends and patterns

In this section, we examine how supercommuting has changed over time and how it varies within the megaregion. It is difficult to pinpoint a consistent estimate of how common supercommuting is. The share of people commuting very long distances varies with data sources and the methodologies they use to measure commuting. Our best estimate is that at least 4% of commutes in the Northern California Megaregion were over 50 miles at the peak in 2019, with the share going as high as 9%, based on LODES data. The 9% estimate, while on the high side compared to other sources (see Boarnet et al., 2021), is plausible given what we know about the relationship between commute time and distance. The lowest estimate of supercommutes, at 2.6%, comes from Streetlight, which does not distinguish trip purpose. This is likely an underestimate. The average commute distance is significantly higher than that of non-commute trips, and commute trips represent about 30% of all trips (US DOT, 2023).

The best way to estimate the share of supercommute person miles traveled as a share of total commute miles traveled is the LODES data. It is the only data source that provides a reasonably comprehensive record of commute patterns by distance for recent years. Based on the LODES data, supercommutes greater than 50 miles are 9% of all commutes and 36% of total commute miles traveled. The unit in LODES is the worker, so the distance traveled is for workers rather than vehicles. A conservative estimate of total worker miles traveled supercommuting accounts for between 3.6% and 4.5%. This is based on assuming that LODES overestimates long commutes by a factor of two and commutes account for 20% to 25% of trips in the megaregion. This would make supercommuting closely equivalent to all VMT attributed to school and church travel (US DOT, 2023).

Trends over time

The year 2019 provides a high mark for supercommuting as the pandemic resulted in significant shifts to remote working as well as longer commute distances for some workers who work remotely part-time (Bloom & Finan, 2024). Figures 3 and 4 show the supercommuters as a share of all commutes based on the American Community Survey 1-year samples for the years 2005 through 2023 and long-form Census for the years 1990 and 2000. The trend lines show the rapid increase in supercommuting in the megaregion after 2009, reaching a peak in 2019 at 12.5% of all driving commutes. Throughout the period covered, supercommutes that lasted longer than 90 minutes were about a third of supercommutes, with the rest being between 60 and 90 minutes. The ACS figures match closely with the results from the 2017 NHTS (Boarnet et al., 2021).

The ACS data is based on commute time, which may over or underestimate distance. We assessed the relationship between commute time and commute distance in the megaregion using the 2017 NHTS data, which provides measures by both time and distance. Table 1 shows the relationship between commute time, speed, and distance for three urban counties and three exurban counties in the megaregion. The data show that in urban counties where congestion is more pronounced, a 60-minute commute is, on average, between 30-40 miles, but 60 minutes is associated with commutes of at least 40 miles in exurban counties. In all cases, 90 minutes indicates commutes longer than 50 miles. Based on these data, we assume that commute times longer than 60 minutes are likely to result in distances of at least 40 miles.

Table 1. Average Speed and Travel Times, Outbound Private-Vehicle Trips from Home, NHTS 2017

County	30-40 miles		40-50 miles		50-100 miles		All	
	Avg. MPH	Avg. Minutes	Avg. MPH	Avg. Minutes	Avg. MPH	Avg. Minutes	Avg. MPH	Avg. Minutes
San Francisco	34.0	68.2	45.5	64.5	41.4	99.1	16.2	26.9
Santa Clara	39.4	59.1	40.0	73.8	41.0	99.9	19.1	20.0
San Joaquin	36.6	61.7	42.2	66.0	45.8	94.8	21.8	19.3
Solano	37.4	62.3	38.0	75.8	42.6	110.7	22.4	21.5
Stanislaus	42.1	49.1	58.3	48.8	49.0	110.1	21.8	23.8
Merced	43.0	53.8	44.9	62.5	48.8	93.2	24.1	21.0

The notable increase in the share of supercommutes post-2008 can be linked to the 2007 financial crisis. In the Northern California context, the years leading up to the crisis (especially 2001-2006) corresponded to the widest gap between outward migration from the core Bay Area counties toward the San Joaquin Valley and Sacramento Metro areas and the reverse inward flow into the Bay Area counties (Comandon et al., 2024). These were years during which housing prices rose extremely rapidly, leading to many people seeking cheaper housing outside the Bay Area. This imbalance, when linked with the high rate of supercommute in areas that received many migrants, suggests that the increase is correlated with the flow of migration and people commuting back into the Bay Area (Boarnet et al., 2023).

Figure 4 shows that the decrease in 2020 is accompanied by an explosion in remote work. Remote work has decreased since the peak in 2020 but has not decreased back to pre-pandemic levels, just as supercommuting has not reached the high levels from 2019.

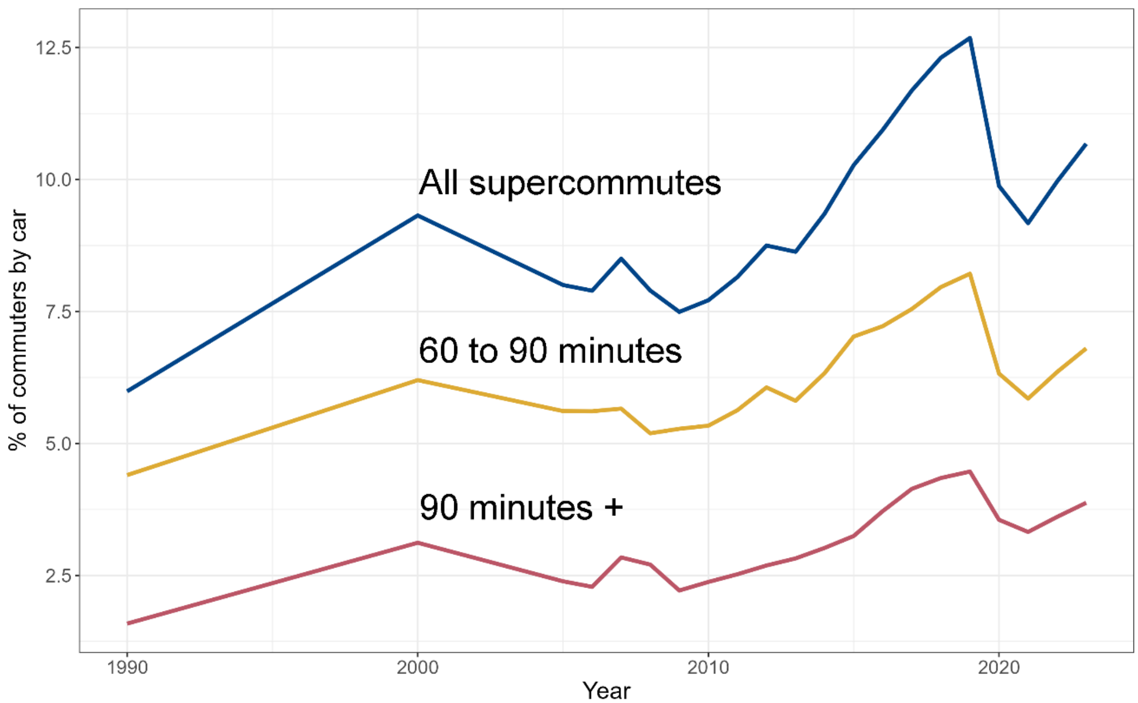


Figure 3. Trends over time in the share of supercommuters in the Northern California Megaregion

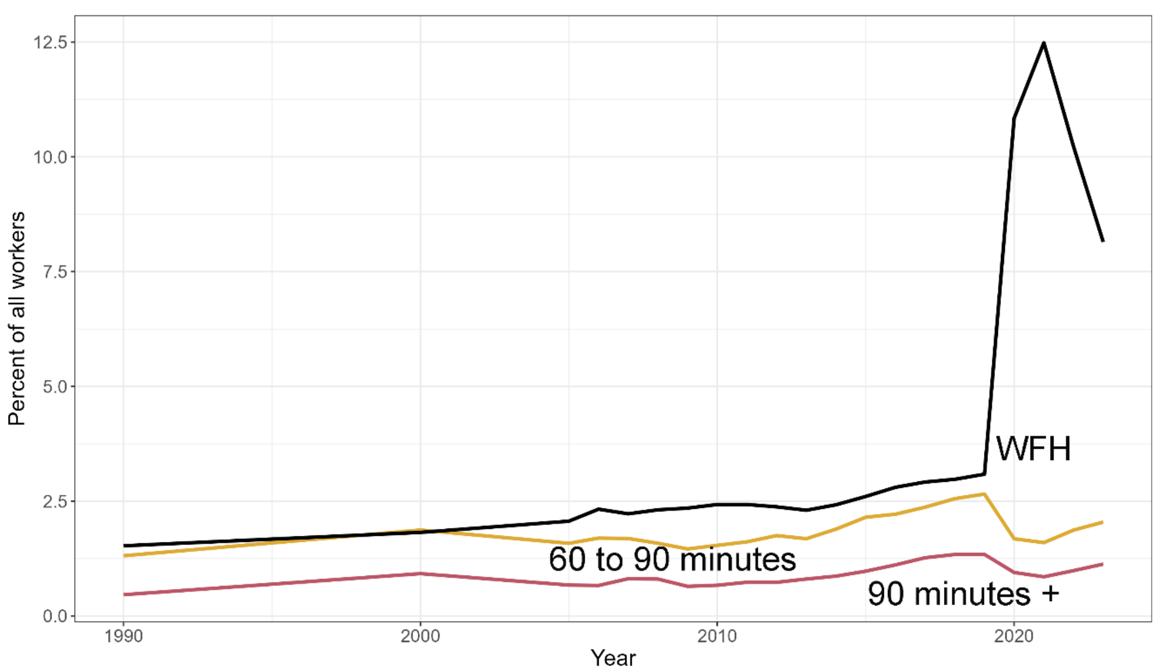


Figure 4. Trends over time in the share of supercommuters and telecommuters (WFH)

It is unclear how many of the people who supercommute post-pandemic already did so before the pandemic. That is, the workers who increased their commute distance the most may have already been accustomed to driving long distances, reflecting a preference for living outside the urban core. The METRANS Remote Work and Migration Survey offers some insights into this scenario by asking people about their residential and work locations before and after the pandemic.[6] About two-thirds of people who supercommuted before the pandemic still did after the pandemic (excluding people who worked remotely full-time before or after the pandemic). Put another way, only 30% of people who supercommuted after the pandemic did not do so before the pandemic, highlighting that long-distance commuting after the pandemic is correlated with pre-pandemic habits. This correlation also helps explain the lower supercommuting rate in the ACS post-2020. If most supercommuters have already done so, and a share of them have switched to remote work, the overall share should decrease. Indeed, the share of supercommuters in the METRANS survey decreased from 8.9% pre-pandemic to 7.7% in September 2023. At the same time, 18% of people who formerly supercommuted (at least once a week) were working remotely full-time in 2023, more than offsetting the number of people who increased their commute distance to more than 50 miles.

Figure 3 shows a reversal of the downward trend in the rate of supercommuting in 2023. As work-from-home policies continue to fluctuate, the increase could continue or stabilize the upward trend of the pre-pandemic. However, even in the case of a stabilization, data from the American Community Survey and the METRANS Remote Work and Migration Survey point to supercommuting representing up to 8% of commutes nationally and close to 11% in the Northern California Megaregion. In short, supercommuting remains significantly higher than at its low points in 1990 and 2009.

Geographic patterns

We use LODES data to compare the incidence of supercommuting across the region. The results are for the year 2019, the last year before the onset of the COVID-19 pandemic, and the peak year for supercommuting in the region. LODES, as noted in the previous section, overstates the share of supercommutes, but when excluding extreme commutes over 100 miles long, the share of commutes at different distance bands mirrors the results based on commute time.[7] Table 2 shows the number and share of supercommuters based on the 2019 LODES data. The 40-100 mile band, which would capture commutes longer than 60 minutes, is 14% of all commutes compared to 12.5%, according to the ACS 2019. The share of commutes over 50 miles is double the rate for commutes longer than 90 minutes, reflecting, in part, the fact that many commutes longer than 50 miles take less than 90 minutes to drive.

[6] The survey is nationally representative and, therefore, not necessarily reflective of the Northern California Megaregion. Respondents were asked about their work and home zip codes in March 2020 and September 2023. The distance was then calculated between zip code centroids on the road network.

[7] The choice of a 100-mile cutoff marks the difference with what are sometimes called extreme commutes. These commutes should constitute a very small share of all trips, but LODES counts shares in excess of 5% for some locations, a number that is not only implausible but also large enough to distort summary measures.

Long-distance commutes are a small share of commutes but account for a majority of commute-related WMT (CWMT). The median CWMT in the Northern California Megaregion in 2019 was 12.7 miles. The shorter distance most people drive means that their relative contribution to miles driven and emissions is small compared to the 20% of commuters who drive more than 30 miles to work.

Table 2. Workers by Distance, N CA Megaregion, LODES 2019

	30-100 Miles	40-100 Miles	50-100 Miles	All
Number (1,000s)	1,282	863	588	6,293
% of all commutes	20	14	9	100
% of total CVMT	59	46	36	100

San Joaquin County has the highest share of supercommuters in the nation, according to the American Community Survey. San Joaquin County stands out not only for the high share of people who supercommute but also for the number of supercommuters this share represents. Table 3 shows that some rural counties have higher shares of supercommuters. The small size of these counties, however, means that the high shares translate to a small number of workers. San Joaquin County has the largest population of supercommuters in the megaregion. In contrast, large urban counties with large working populations have small shares of supercommuters that translate to large numbers. Santa Clara, despite having among the lowest shares of supercommuters (6%), has more supercommuters than all but three counties.

Figure 5 provides a visualization of the share and number of supercommuters to avoid emphasizing places with high shares and low numbers and places with low shares but high numbers. The map shows the bivariate distribution of the share of supercommuters and the number of supercommuters based on tercile cutoffs (see Table 4). Supercommuting is concentrated along the boundary between the California Central Valley and the Bay Area. Most ZCTA in dark brown are immediately to the east of the Diablo Range and north of the inner bays in the counties of Solano, Stanislaus, San Joaquin, and Merced. The population centers closest to Bay Area counties are about 20 miles away from the first job center in the Bay Area (e.g., Tracy to Livermore).

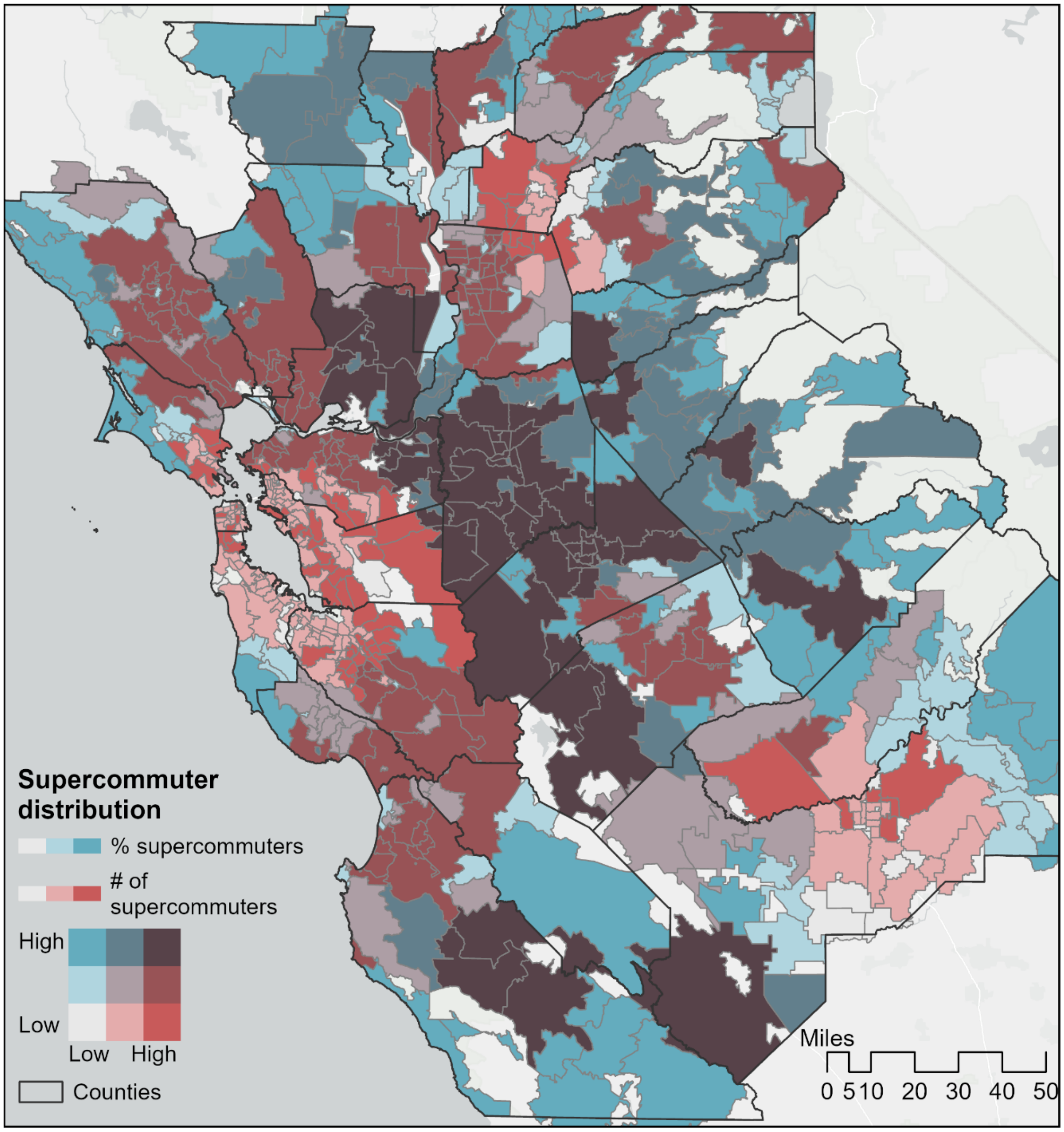
Beyond the areas of high concentration (high share and high volume) to the east of the Bay Area, additional clusters with high numbers of supercommuters that make up a middling share of all commuters are present to the south and north of the Bay Area and around Sacramento. Many of the counties are in what we call the Outer Bay Area. The lower rate of supercommuting in the Outer Bay Area reflects greater accessibility, which is internalized into higher home prices.

Table 3. Supercommuters by county

Megaregion sub-area	County name	Number of commutes > 40 miles	% commutes > 40 miles	Number of commutes > 50 miles	% commutes > 50 miles
BAY AREA	Alameda	58,156	8%	32,460	4%
	Contra Costa	102,714	21%	64,408	13%
	San Francisco	35,301	8%	13,946	3%
	San Mateo	22,759	6%	12,118	3%
	Santa Clara	96,262	11%	54,903	6%
	Solano	57,738	30%	37,704	20%
OUTER BAY AREA	Marin	13,816	14%	9,015	9%
	Monterey	24,264	17%	20,200	14%
	Napa	14,259	22%	9,565	15%
	San Benito	5,942	28%	3,851	18%
	Santa Cruz	20,094	19%	12,217	12%
	Sonoma	42,890	21%	32,512	16%
FRESNO AND FOOTHILLS	Amador	5,217	41%	3,590	28%
	Calaveras	6,140	45%	5,060	37%
	Fresno	26,598	8%	16,928	5%
	Madera	7,231	16%	4,486	10%
	Mariposa	2,091	43%	1,616	34%
	Tuolumne	5,078	31%	4,423	27%
SACRAMENTO	Colusa	2,213	33%	1,676	25%
	El Dorado	11,140	19%	7,223	12%
	Nevada	5,600	19%	3,897	14%
	Placer	14,882	11%	10,798	8%
	Sacramento	76,135	13%	62,900	11%
	Sutter	10,407	30%	4,880	14%
	Yolo	14,100	18%	11,038	14%
	Yuba	7,013	31%	3,328	15%
SAN JOAQUIN VALLEY	Merced	20,444	25%	15,401	19%
	San Joaquin	99,609	36%	79,169	29%
	Stanislaus	54,995	28%	48,376	24%

Housing cost and accessibility seem to shape the geographic pattern of supercommuting, but it is not the only factor. Many people who live in the most expensive areas supercommute out.

For example, as noted in Table 3, Santa Clara County has many supercommuters.[8] Many ZCTAs in the Bay Area core urbanized area have middle to high numbers of supercommuters. To shed light on these patterns, we use hotspots to group individual ZCTA.



Merced County Association of Gov, California State Parks, Esri, TomTom, Garmin, FAO, NOAA, USGS, Bureau of Land Management, EPA, NPS, USFWS

Figure 5. Number and share of supercommuters (as a percent of all commuters) at the ZCTA level in the Northern California Megaregion.

[8] This not due solely to the large size of the county. The distance from the southern edge of the county to central San Jose, is under 40 miles.

Table 4. Tercile cutoffs for Figure 5 bivariate legend.

Share of supercommuters		Number of supercommuters	
Low	0-8.6%	Low	1 – 174
Medium	8.6 – 19.5%	Medium	175 – 808
High	19.5 – 100%	High	808 - 7199

Supercommuting hotspot overview

The hotspots serve to analyze areas of high supercommuting incidence using different data sources. Hotspots were constructed from PUMA based on two criteria. First, hotspots include PUMAs that intersect with ZCTAs that have large numbers of supercommuters. Second, The extent of each hotspot is meant to ensure geographic differentiation and a large enough sample size. Figure 6 shows the extent of each hotspot. Blue areas are large urban areas and include employment centers that exert a significant pull on surrounding counties. Green areas include smaller urban areas (e.g., Stockton) with smaller employment centers that attract workers primarily from within the county and with significant populations in exurban to rural areas.[9] We will delve into the demographics of hotspots in the next section, and we will focus here on establishing the extent to which supercommuters may sort into different locations based on where they need to go. That is, we examine whether people who commute from similar locations also drive to work in the same areas.

Table 5 shows the share of commuters who drove between 60 and 90 minutes and over 90 minutes in 2019 and 2023 for each of the hotspots. The pattern is consistent with previous results. Supercommuting rates went down from 2019 to 2023 in every location. Exurban counties have higher supercommuting rates, except for the Concord hotspot, which has the highest supercommuting rates of any location. The three San Joaquin Valley counties (Stanislaus, San Joaquin, and Merced) stand out for having higher rates of supercommuting over 90 minutes than at 60 to 90 minutes, reflecting the lack of jobs in locations between their population centers and the main job centers (in the Bay Area and Sacramento).

[9] San Joquin, Stanislaus, and Merced are all single county metropolitan areas.

Figure 6. Map of supercommuting hotspots showing 2020 PUMA boundaries.

The San Francisco Bay Area is the dominant job center in the megaregion. Figure 7 shows the location of job clusters in the megaregion. Each cluster is defined based on blocks where there are at least 1000 jobs, and the density of jobs is higher than 10,000 per acre (Blumenberg & King, 2021; Giuliano et al., 2007). The scale of the job clusters in the Bay Area compared to all others is immediately apparent and is reflected in how many supercommutes they attract. The job clusters in the megaregion attract about 29% of all supercommute trips based on LODES. Of those, 82% end in the Bay Area job clusters, and another 14% end in the Sacramento metropolitan area. This is in large part because many supercommuters live in the Bay Area and supercommute within it. The other areas where many supercommuters live, the three San Joaquin Valley counties, are feeders into the Bay Area as well. As such, supercommuting is not solely about people seeking cheaper housing on the outskirts of major job centers. There are many people who supercommute from within expensive areas. This may be to accommodate multi-worker households where working household members work in very different locations, amenities preferences, and the ability to work from home most of the time (see, e.g., Giuliano & Small, 1993).

Table 5. Supercommute shares by hotspots in 2019 and 2023, based on 1-year ACS PUMS data.

	Commute 60 – 90 minutes		**Commute over 90 minutes.**	
Hotspots	2019	2023	2019	2023
Bay Area	5.6	3.6	1.5	1
Concord	13.3	12.4	9	8.1
Fresno	2.1	1.8	1.8	1.5
Sacramento	3.8	3	2.7	2.3
Merced	6.6	6.4	9.3	10.4
San Joaquin	9.8	9.6	10.2	8.3
Stanislaus	4.4	5.4	9.3	8
Vallejo	10.6	6.9	4.7	3.8

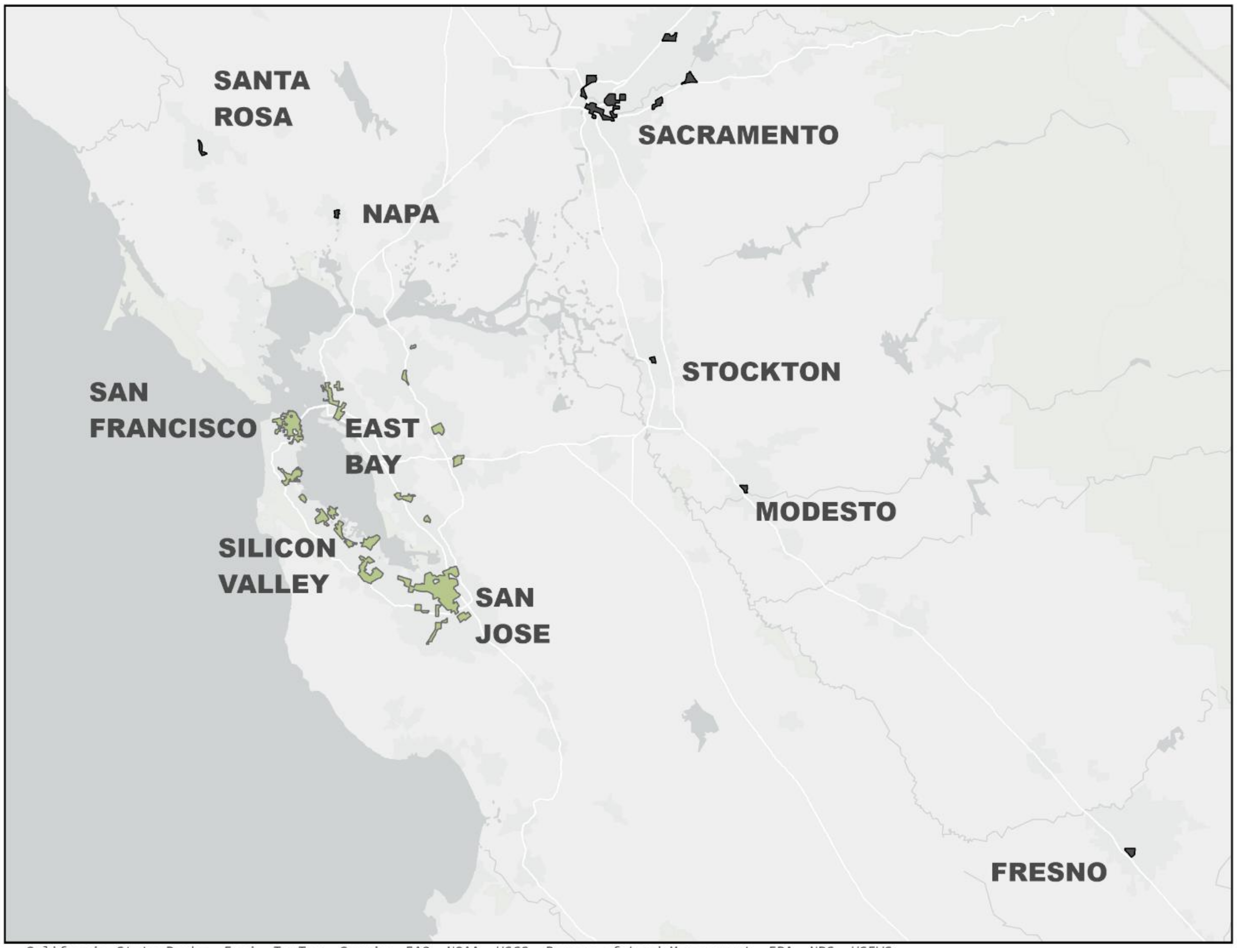


Figure 7. Map of major job clusters in the Northern California Megaregion. Job clusters in green are in the Bay Area and account for 82% of all supercommute trips that end in one of the job clusters.

We provide a broader view of supercommuting patterns by removing the restrictions that trips end in major job centers. Instead, we map the top 20 destinations ZCTA by the number of supercommute trips that end there from each of the eight hotspots. Some of the top destinations are the same across hotspots, resulting in 88 unique destinations, about 10% of all destinations for supercommute trips originating in the megaregion.

Figure 8 shows the geographical distribution of top destinations. In contrast to trips ending in job clusters, these maps highlight destinations that are outside main employment centers but still receive many supercommutes. The Vallejo and Tracy areas stand out as destinations for trips originating within the Bay Area and Sacramento metro areas. While these areas are not attracting as many trips as major job centers, the fact that people supercommute into areas that send many supercommuters reinforces the lack of correspondence between affordability and work destinations.

Folsom and Roseville, to the northeast of Sacramento, are destinations for workers coming from the Concord, San Joaquin, and Vallejo hotspots, while central Sacramento is a destination only for trips from Concord. This may point to the importance of occupation in influencing the choice to supercommute. Sacramento's northern suburbs, for example, have higher concentrations of technology jobs.

Destinations for trips originating in Fresno are a mix of rural destinations and smaller job centers (Merced). The case of Fresno shows the limits of supercommuting. A commute from Fresno to San Jose would be considered extreme (over 100 miles), supercommuting rates in Fresno are generally low, and there are no other major employment centers within 100 miles. Merced, which is at the edge of the 100-mile catchment area for the Bay Area, shows a widespread set of destinations divided between Fresno, Stockton, and southern Santa Clara County. Merced County shows that areas that are outside the main urban area's catchment area and still have high shares of supercommuters do not necessarily send most commutes to large job centers. In this case, it is the county's lack of a job center combined with its position within a polycentric region that seems to be the main driver of supercommuting.

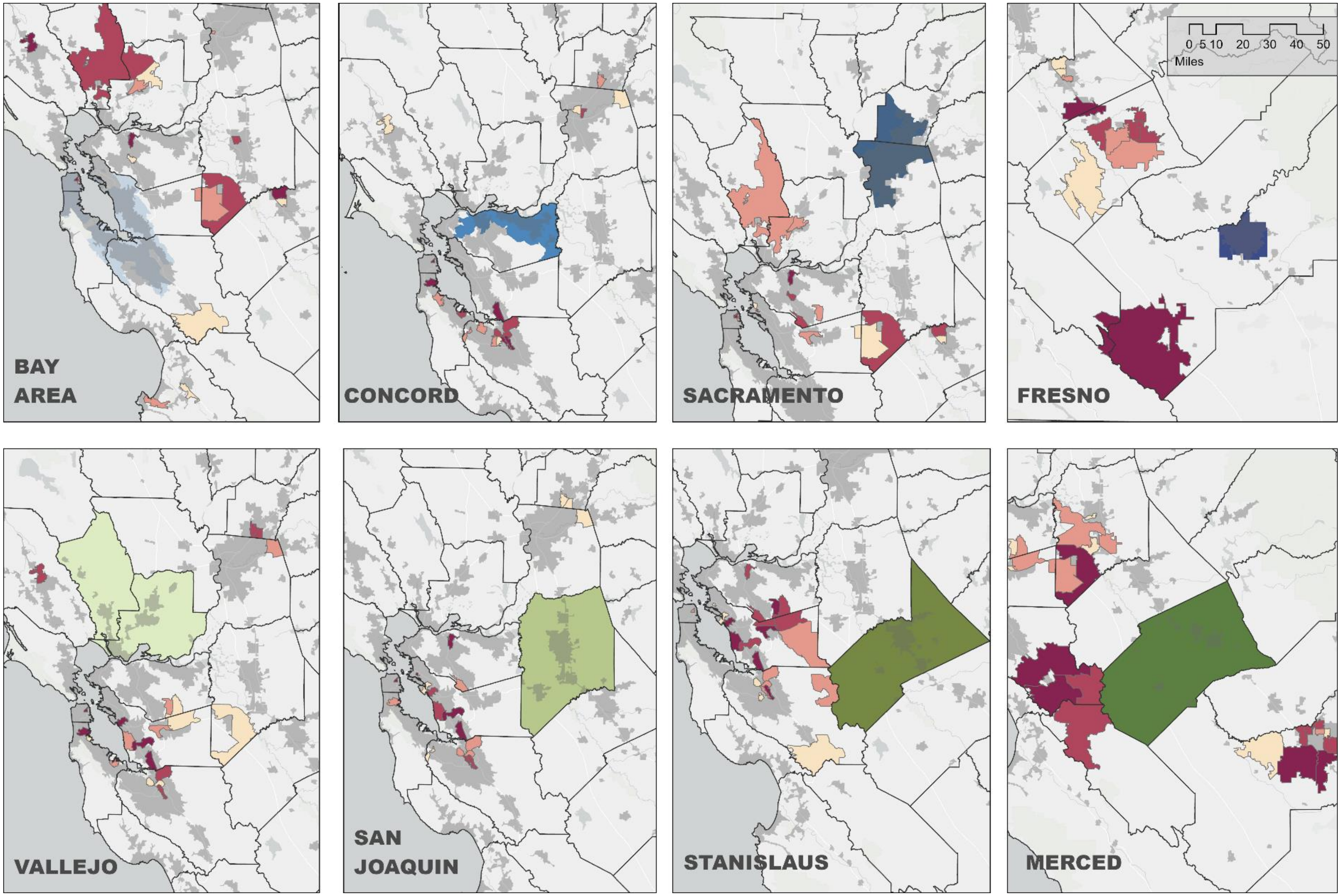


Figure 8. Top destinations from each hotspot. Dark red ZCTAs receive the largest number of supercommuters and light yellow the least.

Who supercommutes?

The previous section highlighted the scale of supercommuting, how many workers drive very long distances, where they tend to live, and where they work. This section delves into the demographic characteristics of supercommuters with an emphasis on socioeconomic standing (i.e., educational attainment, occupation, and income). The geographic patterns provide clues that many people who supercommute live in expensive areas rich in high-wage jobs, raising questions about why large numbers seem to commute outside such areas.

This section proceeds in two parts. The first part focuses on descriptive statistics for each of the eight hotspots using PUMS data from the 5-year 2019-2023 ACS data to show how the background of supercommuters varies with different contexts. The second part analyzes the determinants of supercommuting based on the same ACS data.

As a caveat, it is important to note the limitations of LODES data and the possibility that a share of those supercommutes is due to the data collection methodology and may not reflect people's daily habits. The same applies to PUMS data. The question on which the data are based specifies the usual length of commute in the previous week. The format of the question leaves open the possibility that someone's commute that week was not their typical travel.

Are supercommuters similar everywhere?

The Northern California Megaregion is economically diverse and divided. The region includes areas with a high concentration of technology industries and agriculture, which create wide disparities in income and socioeconomic standing. Table 6 provides an overview of the megaregion's socioeconomic composition, broken down by hotspot, and how supercommuters compare.

Supercommuters tend to have higher wages, although they do not necessarily belong to higher-income households at a higher rate. This is especially marked in the exurban counties where the share of supercommuters with wages above the regional median is up to 12 percentage points higher than for the population (in Merced).[10] The difference between wages and household income is relevant as it suggests that supercommuters may face increased pressure to live in lower-cost areas despite working in a higher-wage industry. Supercommuters who drive between 60 and 90 minutes own their home at a higher rate than all workers and supercommuters who drive over 90 minutes, but the differences are not consistent or as large as they are for wages. Similarly, educational attainment does not seem to differentiate supercommuters. Across all areas, workers with higher education are not overrepresented among supercommuters.

[10] The difference is significant at the 95% level.

Table 6. Demographic summary of all commuters and supercommuters in each hotspot based on 2019-2023 5-year ACS PUMS.

Hotspot	Homeowner	Low household income	High household income	Low wages	High wages	No high school diploma	High school diploma	Bachelor and above
Bay Area	54%	8%	74%	23%	57%	8%	18%	58%
Concord	71%	12%	65%	31%	45%	11%	31%	31%
Fresno	60%	23%	45%	38%	31%	13%	30%	30%
Merced	56%	24%	39%	40%	26%	22%	36%	18%
Sacramento	61%	16%	55%	32%	41%	7%	27%	39%
San Joaquin	65%	15%	56%	32%	38%	15%	37%	24%
Stanislaus	63%	19%	47%	36%	32%	15%	38%	21%
Vallejo	63%	13%	60%	32%	41%	10%	31%	32%
Supercommuters 60 – 90 minutes								
Bay Area	63%	6%	79%	17%	64%	8%	17%	59%
Concord	77%	9%	69%	25%	54%	11%	31%	30%
Fresno	53%	27%	46%	36%	36%	18%	30%	29%
Merced	71%	16%	44%	28%	38%	22%	41%	13%
Sacramento	63%	16%	55%	26%	48%	10%	30%	32%
San Joaquin	61%	11%	60%	30%	46%	21%	32%	21%
Stanislaus	65%	16%	50%	23%	41%	17%	38%	17%
Vallejo	69%	12%	65%	22%	50%	12%	33%	27%
Supercommuters over 90 minutes								
Bay Area	56%	9%	70%	19%	56%	10%	22%	50%
Concord	71%	6%	67%	17%	60%	14%	30%	35%
Fresno	62%	15%	56%	27%	48%	14%	29%	32%
Merced	56%	21%	38%	32%	33%	32%	37%	10%
Sacramento	68%	14%	57%	25%	48%	9%	31%	32%
San Joaquin	67%	12%	53%	22%	49%	22%	37%	20%
Stanislaus	64%	13%	51%	25%	45%	25%	39%	12%
Vallejo	66%	10%	61%	23%	48%	12%	31%	26%

Wages and educational requirements and levels can vary significantly by occupation. Table 7 focuses on supercommuters' occupations compared to the distribution for the megaregion. For this table, we do not report levels for each hotspot due to the large number of occupations and the lack of obvious regional patterns.

Construction and extraction are the occupational categories where a difference between supercommuters and the overall workforce is most obvious. The share of supercommuters at both the 60-90 minute (10% of supercommuters in this category) and over 90 minutes (18%) levels are significantly higher than the share in the workforce (5%). This is to be expected as construction often requires travel to different work sites.

Table 7. Share of commuters in each of the main occupational categories. Source: PUMS 2019-2023 ACS.

Occupation	Supercommuters 60 – 90 minutes	Supercommuters over 90 minutes	All commuters
Computer, Engineering, and Science	10%	6%	11%
Construction and Extraction	10%	18%	5%
Education, Legal, Community Service, Arts, and Media	8%	6%	10%
Farming, Fishing, and Forestry	2%	1%	1%
Healthcare Practitioners and Technical	12%	10%	12%
Installation, Maintenance, and Repair	4%	5%	3%
Management, Business, Science, and Arts	16%	16%	18%
Military	0%	0%	0%
Sales and Office	9%	8%	10%
Production	5%	5%	4%
Service	16%	15%	19%
Transportation and Material Moving	7%	9%	7%

Determinants of supercommuting

We complement the descriptive overview with an analysis of the ACS data. For this analysis, we combined all commuters who drive more than 60 minutes because separating out workers who drive more than 90 minutes did not produce markedly different results. The analysis is for the Northern California Megaregion and includes all employed persons with a reported wage. We use a Logit model with person weights and include year-fixed effects for each survey year (2019-2023).

The results show that carpooling is associated with greater odds of supercommuting. About 1% of supercommuters and 9% of commuters carpool. Carpooling, especially when measuring commute in terms of time, can substantially add to the total commute length by adding stops. This may not translate to longer commute distances, but the same logic applies if the driver must go out of their way to pick up or drop off passengers. Homeowners have greater odds of supercommuting. Results in Table 6 suggested that the relationship between greater rates of homeownership and supercommuting may not hold everywhere, and the analysis highlights the general nature of the relationship. Household size has a relatively small positive effect, while the number of workers in the household has a small negative effect. This may reflect a tendency for the larger households to struggle to find housing in core urban areas while multi-worker households benefit from locating in areas where all members' jobs are accessible.

Table 8. Results (converted to odds-ratio) from the Logit regression using 2019-2023 ACS PUMS data.

	Dependent variable:	
	Commute > 60 minutes = 1	
Carpool	1.067***	(0.003)
Own home	1.024***	(0.002)
Household size	1.004***	(0.001)
Employed household members	0.996***	(0.001)
Female worker	0.973***	(0.002)
Asian/Pacific Islander	0.999	(0.002)
Black	1.037***	(0.005)
Latino	1.013***	(0.002)
Other	1.005*	(0.003)
Log(wage)	1.012***	(0.001)
High school	0.999	(0.003)
Some college	1.002	(0.003)
Bachelor and above	0.984***	(0.003)
Construction	1.143***	(0.006)
Education	1.003	(0.003)
Farming	1.006	(0.006)
Healthcare	1.021***	(0.003)
Installation	1.053***	(0.007)
Management	1.012***	(0.003)
Military	0.985	(0.013)
Office	1.01***	(0.003)
Production	1.015***	(0.005)
Service	1.002	(0.003)
Transportation	1.011***	(0.004)
2020	0.97***	(0.003)
2021	0.964***	(0.003)
2022	0.971***	(0.003)
2023	0.979***	(0.003)
Constant	0.947***	(0.009)
Observations	211,486	
Log Likelihood	-37,470.85	
Akaike Inf. Crit.	74,999.71	
Note:	*p<0.1; **p<0.05; ***p<0.01	

The results point to some possible sources of inequality in terms of how much people must drive to work. Women have lower odds of supercommuting. The unequal gender distribution within occupations and by travel purposes likely contributes to this difference. Black and Latino workers have greater odds of supercommuting. In addition to occupational disparities, this may be related to the rapid growth of Black and Latino communities in the same counties outside the Bay Area where supercommuting is most common.

Education has little bearing on supercommuting except for people with a bachelor's or higher level of education who have lower odds of supercommuting. In contrast, higher wages are associated with higher odds of supercommuting. The size of the effect associated with wages suggests that as wages increase for people with a higher education, the odds that they supercommute increase. The relationship may also reflect the decision of new workers to live closer to work in the early stages of their career, moving farther away later in their life cycle.

The results for occupations parallel those in Table 7. All occupational categories are compared to workers in computer and engineering occupations. Workers in construction stand out as having the highest odds of supercommuting. Healthcare and installation occupations also stand out for their large effect. In contrast, education, farming, and service occupations have no significant relationship with supercommuting.

Emissions estimates

Even if the estimates that supercommuting accounts for close to a third of all commute VMT is an upper bond, the impact of supercommuting is sizeable. The evidence is consistent with thousands of people driving 80 miles or more every day. Given that transportation is the largest source of emissions in California, limiting emissions from supercommuting can significantly contribute to reaching state targets for greenhouse gas emissions (CARB, 2024). In this section, we build on the previous results to explore three mitigation strategies: remote work, electric vehicle adoption, and residential relocation.

As noted in the literature review, each of these strategies comes with limitations and challenges. The goal of this section is to provide plausible estimates for the reductions in emissions that could be achieved in the short term. The short term is defined here as changes that can happen without significant shifts in the population (e.g., the mix of occupations remains largely unchanged). This is important because local conditions impose constraints on how far a strategy might go. For example, remote work cannot be increased in a location where most people work in occupations that do not allow it, but there is the potential to increase it in locations where most people work in appropriate occupations but are not currently working remotely. In short, the implementation does not require complementary interventions (like training or additional subsidies for electric vehicles).

The goal of this exercise is to show what strategy would have the most impact given what is possible. In the next section, we will discuss the feasibility of the different strategies and what complementary action may enhance their impact. We focus on four exurban counties: Solano, San Joaquin, Stanislaus, and Merced. In addition to having high concentrations and large numbers of supercommuters, these counties illustrate different economic structures and levels of integration with the Bay Area. We are also limited to full counties because the EMFAC model used to estimate changes in emissions is designed to work for larger areas, and the county matches most closely with the previous analysis in this paper.

The output of the EMFAC scenario generator is highly comprehensive, including many types of emissions for different vehicle classes under all vehicle states (i.e., idle, running, etc.). To simplify the output in this illustrative exercise, we report total PM 2.5 emissions and CO_2 emissions. PM 2.5 is one of the main types of emissions that are typically reported and, therefore, more familiar. Unlike CO_2, another common type of emission, PM 2.5 is also produced by all vehicle types because it comes from various sources (tailpipe as well as brake and tire wear). As such, this type of emissions includes electric vehicles that would otherwise be excluded if focusing on CO_2 alone. We include only passenger vehicles and light-duty trucks, which represent the vast majority of non-commercial vehicles. Table 9 reports baseline PM 2.5 emissions for all passenger and light-duty trucks in 2023 for all four counties. All data are average daily levels and reported in tons per day (CARB, 2021).

Table 9. Average daily VMT and emissions for the four focal counties.

County	Total VMT (in millions)	Total PM 2.5 emissions*	Total CO_2 emissions*
Solano	10.17	0.0610	3380
San Joaquin	15.43	0.1151	5204
Stanislaus	11.37	0.0852	3697
Merced	5.7	0.0389	1908

* PM 2.5 and CO_2 measured in tons per day

Clean Vehicle Adoption

The share of clean vehicles has increased rapidly in the 2020s. Based on the 2023 vehicle fleet data for California, 6% of light-duty models from the year 2019 or earlier were clean vehicles (i.e., hybrid, battery electric, and other partially zero-emission vehicles), and 1% were battery electric. Among models from the year 2020 or later, 25% were clean vehicles, and 13% were electric. This rapid increase, however, is not uniform, and clean vehicles are still more common among wealthier and more educated households.

The share of clean vehicles in a zip code (the level at which vehicle fleet composition is reported) is highly predictable. A simple regression analysis of the log of the percent of clean vehicles in a zip code can explain over 90% of the variation with five variables (Table 10, see Table A4 for summary statistics). The model includes the homeownership rate, the share of adults with a bachelor's degree or higher, the share of non-Hispanic white and Asian people, the average trip distance, and county-fixed effects. Educational attainment serves as a proxy for income and the share of people in professional occupations, two variables that are highly correlated in the aggregate within the megaregion. The average trip distance has a negative association with the share of clean vehicles, suggesting that zip codes where people drive more on average have lower rates of adoption. Rather than being associated with how much people drive, this variable likely reflects the higher average VMT in more rural locations where electric vehicles are not as common.

The results from this regression provide us with a way of estimating a plausible increase in clean vehicles. We use the residuals from the model (the difference between the predicted and the observed share of electric vehicles) to identify zip codes where clean vehicles are not as common as we would expect. In effect, we are assuming that places, where there are fewer clean vehicles than expected (given the socioeconomic context), could easily increase the adoption to match what is observed in similar locations. For each county, we add up the shortfall of clean vehicles to estimate the number of internal combustion engine vehicles that could be replaced. Figure 8 shows the share of clean vehicles in each zip code and the residuals.

Table 10. Results from regression analysis

				95% Conf. Int.	
Variable	**Coefficient**	**Std. Error**	**P Value**	**Min**	**Max**
Constant	1.6371	0.08	0	1.481	1.793
% Bachelor's Degree	0.016	0.001	0	0.014	0.018
% Homeowners	0.0011	0.001	0.083	0	0.002
% White Non-Hispanic	0.0034	0.001	0.001	0.001	0.005
% Asian Non-Hispanic	0.0085	0.001	0	0.006	0.011
Average Trip Length (Miles)	-0.0109	0.004	0.005	-0.018	-0.003

Dependent Variable: % EV/Hybrid (log)

Model R^2= 0.91 Adjusted R^2= 0.904 Observations = 470

The results from the regression are a first step in estimating the potential impact of increasing the use of clean vehicles among supercommuters. A relevant assumption in this assessment relates to whether supercommuters are more likely to drive clean vehicles than non-supercommuters. The regression in Table 10 suggested that places where people drive more tend to have fewer clean vehicles. This does not mean that people who commute longer are less likely to choose to drive clean vehicles. We test this assumption with NHTS data, the only data source that allows us to observe the kind of vehicle someone drives to commute and the distance of their commuter.[11]

The results in Table 10 rely on the share of clean vehicles in the entire fleet, which does not reflect the accelerating adoption since 2019. As an alternative approach we calculated the

[11] The 2017 NHTS predates the wider adoption of clean vehicles, but the 2022 sample is too small to adequately observe supercommuters and clean vehicle owners (two small populations to begin with).

number of additional clean vehicles in each county if the number of clean vehicles were to grow at the average county annual growth rate from 2019 to 2023. This rate could fluctuate but has been mostly stable (around 20%) for these years.

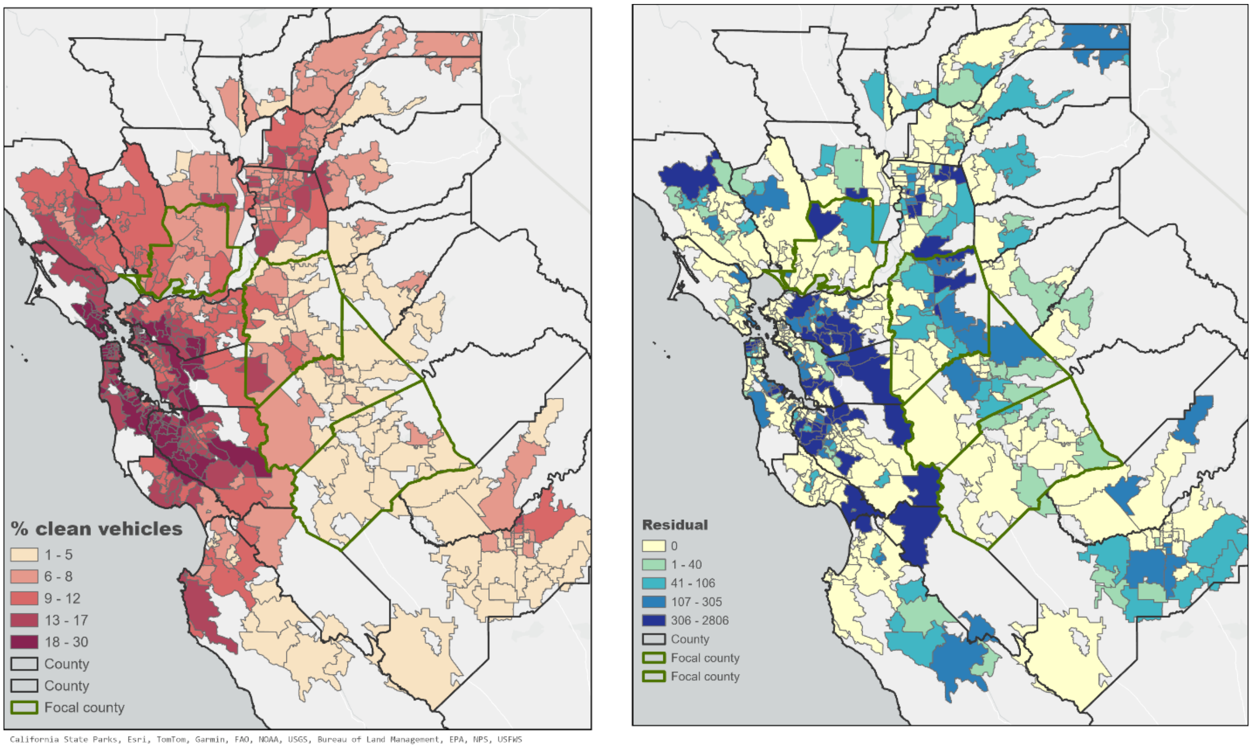


Figure 9. Map of ZCTA share of clean vehicles (left) and residual from regression model expressed in number of potential clean vehicles.

Table 11 shows that the share of households who own at least one clean vehicle is higher among households where at least one person supercommutes and is highest among households where one person commutes between 40 and 50 miles. We confirm this result with a regression analysis of supercommuters who drive a clean vehicle for their commute. The dependent variable is a binary that equals one if the commuter drives a clean vehicle and zero otherwise. Using a logit model, we show (see full results Table A3 in the Appendix) that the impact of supercommuting significantly increases the odds of driving a clean vehicle, though the magnitude is smaller than belonging a to a high income/high educational attainment household.

Table 11. Share of commuters who own clean vehicles by commute distance.

Max Commute Distance (miles)	Total households	Households with at least one clean vehicle	% with clean vehicles
NA, 0-29.9	10,154,357	888,533	8.7
30-39.9	511,960	66,552	13
40-49.9	249,206	33,979	13.6
50-99.9	301,657	33,663	11.2

The results from Table 11 and the regression analysis (Table A3) support assigning a higher share of clean vehicles to supercommuters in our scenario. We use 12% as a level within the range for people commuting longer than 30 miles and assign that share of additional clean vehicles (in Equation 1). That is, if there were the potential for replacing 100 ICE vehicles in a county where 20% of workers supercommute, we would assign two clean vehicles for our estimates (100*0.2*0.12 = 2.4). Switching to clean vehicles affects all driving. We, therefore, assume that a supercommuter who switches will use a clean vehicle for all their driving (see methods section).

Table 12. Results from the clean vehicle scenario

County	Residual clean vehicles	# of new clean vehicles	Reduction in PM 2.5	Reduction in CO_2
Solano	158	407	0.13%	0.35%
San Joaquin	606	1035	0.32%	0.58%
Stanislaus	248	310	0.14%	0.26%
Merced	19	90	0.07%	0.15%

Table 12 shows the outputs of the scenario analysis. The reductions in pollutants are based on the second column. The number of additional clean vehicles using the residuals is even smaller than under the linear growth assumption, which would result in still smaller reductions than the already small estimates. The small effect under this scenario reflects the size of the population involved and the still low penetration of clean vehicles in locations where supercommuting is most common. These estimates, however, represent change within one year and would be repeated every subsequent year, potentially with a higher magnitude as the number of clean vehicles increases faster.

Remote work

An increase in remote work should automatically result in a decrease in commute-related VMT. However, an area of concern has been that people who switched to remote work would replace work-based VMT with non-work VMT. There is little reliable data on this question, and we rely on the METRANS Remote Work and Migration Survey to establish some parameters for this scenario. The survey includes 505 respondents who did not work remotely before the pandemic and worked at least one day remotely in 2023. Of these respondents, about 85% reported driving as often or less often for non-work related activities after the pandemic, and only 10% reported driving farther for these activities.[12] Based on these results, we assume that non-work-related driving stays unchanged with a switch to remote work and that the main effect on driving is through the number of days people commute.

The other assumption we make here is that workers who supercommute do so five days a week. This may no longer hold true as a share of supercommuters are likely to work remotely some of the time. However, the phrasing of the question about commute time in the American Community Survey does not allow for this distinction. Because the question emphasizes what a typical commute is and includes a year before the COVID-19 pandemic, we assume that respondents supercommute more often than not.

Using equation 3, we estimate the reduction in the number of miles driven if people, on average, worked remotely one day a week. Table 13 shows the share of supercommuters who could work remotely based on the county's occupational distribution and the associated reduction in VMT and emissions. The results are for a single day of remote work and can be multiplied to obtain estimates for more days per week. Therefore, if most employers were to allow two days of remote work per week, VMT reduction would range from 6.8% in San Joaquin County to 2.8% in Merced County.

The reductions in PM2.5 and CO_2 emissions in Table 13 are mostly proportional to the reduction in VMT. In part, this reflects the close correlation between how much people drive and driving-related emissions. The small share of clean vehicles is another factor that affects the relationship. With increased shares of electric vehicles, reductions in VMT will have less of an effect on overall emissions.

Unlike the clean vehicle scenario, where emissions reductions could be expected to repeat and grow every year, remote work is a one-time reduction. Once a part of the workforce reduces the number of days they work remotely, there are no other opportunities for reduction. So, if the labor force composition and the number of days firms allow their workers to telecommute stays stable, the reduction will also stagnate. Under circumstances where firms reduce the possibility of working remotely, reductions may be reversed, and emissions worsened if people move to residential locations farther from their workplace (see Ma et al., 2024).

[12] These results stay the same if only including people who did not work remotely before the pandemic and worked remotely full time after (based on 202 respondents).

Table 13. Results from the remote work scenario

County	% of supercommuters who can work remotely	Reduction in daily VMT	Reduction in PM 2.5	Reduction in CO2
Solano	8.6%	2.8%	2.8%	2.8%
San Joaquin	7%	3.4%	3.4%	3.4%
Stanislaus	6%	2.7%	2.7%	2.7%
Merced	5.2%	1.4%	1.4%	1.4%

Residential location

Ideally, a jobs-housing balance enables people to work near where they live. As noted in the review, an important limitation to simple measures of work-housing balance is that they ignore the match between occupation and jobs available. In short, the balance is meaningless if the jobs are not in the right industry for residents or if the available housing is unaffordable. This can lead to distortions in metropolitan areas like the Bay Area, where high-wage industries, like technology, are highly concentrated and dominant.

The lack of fit between housing and employment opportunities is exacerbated when we take into account the myriad of other factors that influence where people choose to live. Evidence points to supercommuting being the product of occupation (notably in construction) and socioeconomic standing. Not all supercommuters live far from where they live by choice, but many do.

For this scenario, we first created catchment areas for all the destinations where supercommuters work. The catchment areas are based on the blocks that fall within the median distance of all commutes into that work location. For the average work location, the median commute distance in the megaregion is about 14 miles, meaning that half of all workers commute less than 14 miles to their workplace. The catchment area, then, includes all blocks within 14 miles of an average work location.

Figure 7 shows that many of the top destinations for supercommuters are themselves areas where many supercommuters live. This mismatch emphasizes the choices involved in where people live. Some people live in the most expensive parts of San Francisco and commute to relatively affordable Tracy. When mapping all catchment areas (see Figure A1 in the appendix), we see a similar pattern. Many of the locations where many supercommuters live are also areas where many supercommuters work.

The mismatch between work and home location complicates how we frame the effect of residential location on supercommuting. If evidence pointed to the lack of affordable housing as the main reason people supercommute, there would be a clear case for increasing the availability of affordable housing near common destinations. Still, there is a strong argument for enabling people to live closer to where they work, and if all supercommuters drove as much as the typical commuter who shares their work destination, VMT in exurban counties would drop dramatically (by over 50% in the case of San Joaquin where supercommuters are 28% of all commuters).

Unlike clean vehicle adoption and remote work, which provided some baseline for change, there is no clear guideline for how many people we could expect to move if more housing was affordable near their work location. We are basing the scenario on 5% of supercommuters electing to live within the catchment area of their work location to estimate impacts on VMT and emissions.

The estimates are based on the comparison of supercommuters' total VMT and the total VMT of workers living in the catchment area of their work location. Figure 10 shows the difference between supercommuters' VMT and their counterparts in the catchment areas. Lighter areas have the smallest excess VMT, meaning that supercommuters in those locations drive up to 62 miles more than the people working in the same location's catchment area. This could be because these locations have lower supercommuting VMT (i.e., they supercommute 50 miles and do not add much in non-work related commuting) or because most workers who share that work location also drive long distances (i.e., the catchment area is large). Areas in dark red are locations where the difference between supercommuters' VMT and that of the catchment areas is largest. Stanislaus generally has large differences.

We estimate the impact of changing location from the current location to within the catchment area (meaning at the outer boundary). Table 14 shows the average total VMT for supercommuters in the four focal counties and the resulting excess VMT per worker. The main determinant of excess VMT is the average supercommuting VMT, as the catchment area VMT is similar across counties (around 43 miles). The corresponding reduction in emissions if 5% of supercommuters were to move from their current location to within the catchment area of their work location falls between 1% for Merced and nearly 2% for San Joaquin and Stanislaus.

Table 14. Results from the residential location scenario

County	Average VMT for supercommuters	Average excess commuting VMT	Reduction in PM 2.5	Reduction in CO_2
Solano	106	63	1.2	1.1
San Joaquin	112	69	1.8	1.9
Stanislaus	124	81	1.8	1.8
Merced	128	83	1	1

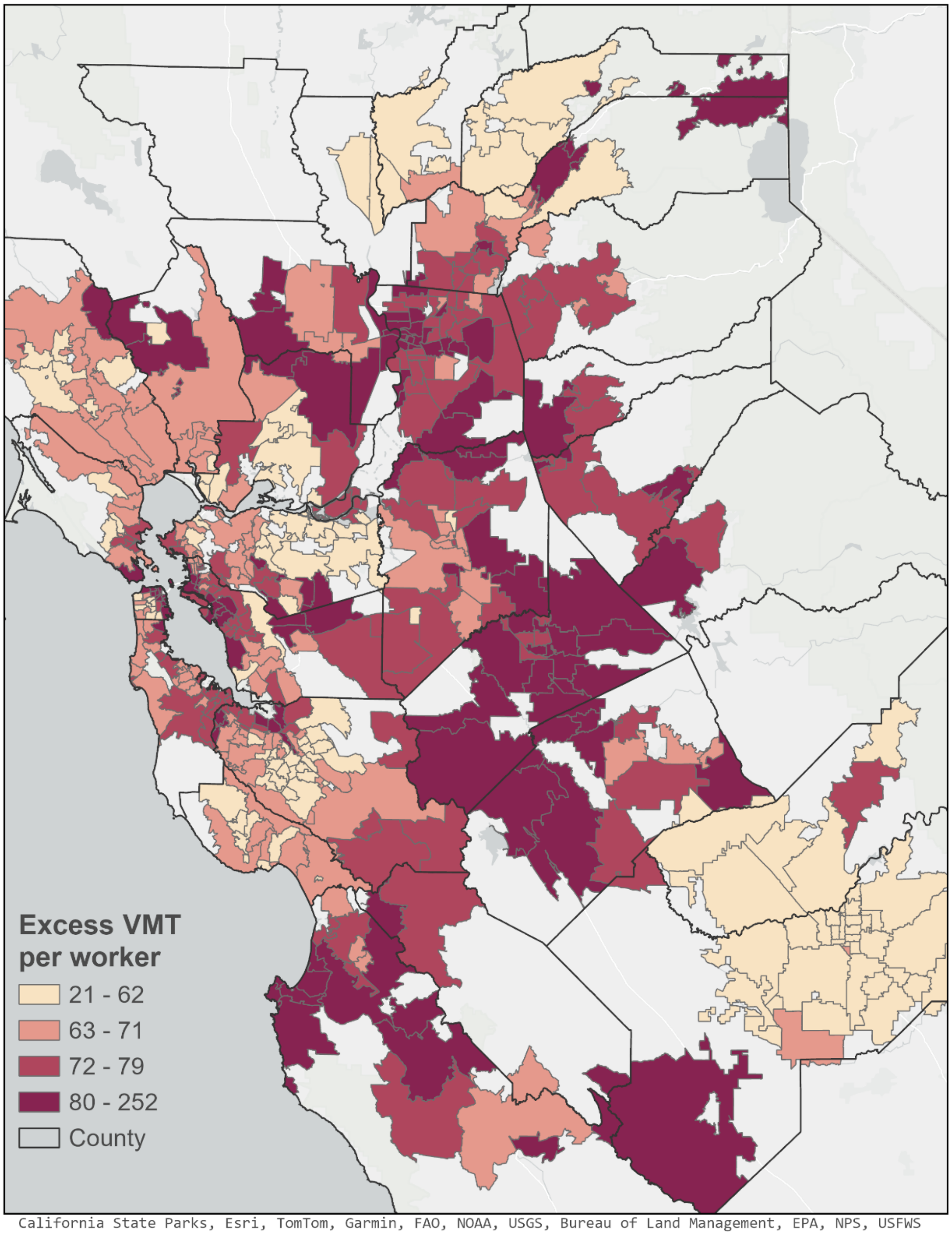


Figure 10. Excess VMT at the ZCTA level.

Policy discussion

The scenarios above explored three possible ways of mitigating supercomputing's environmental impact. In each case, the reduction was modest, ranging from less than 0.5% to a 3.5% decrease in two primary sources of pollution. The scenario focused on exurban counties as the locations where supercommuting is both a higher share of all commutes and represents a larger number of commuters. In discussing potential policy interventions, we focus on these counties but point to differences with more urban or rural counties where circumstances will differ markedly, and which would require different approaches.

Based on the results, remote working stands out as the most impactful area for mitigation in the short term. It is the only policy strategy that requires no direct investments (in infrastructure or housing), and unlike the other scenarios, remote work takes vehicles off the road entirely, thus reducing congestion. It is also a solution that can be applied regardless of the location. There are possible benefits in urban and rural areas, though the benefits would likely be larger in counties where people drive more and are more car reliant.

There is too little evidence to establish how non-work-related driving interacts with remote working. The METRANS Remote Work and Migration Survey suggests that there is no marked increase in driving for people switching from in-person work to remote work. Yet, despite a persistently higher rate of remote work in the workforce, national VMT per capita has increased from 2019 to 2024, though not in California, where remote work is common (Milam et al., 2024).

Remote working had the largest impact on emissions, but that is, in part, due to the scenario assuming that all workers who could work remotely did. In other words, there is a rigid limit on how much emissions can be reduced. The occupational composition of counties like San Joaquin and Stanislaus is unlikely to change rapidly. In addition, remote work is not an area highly responsive to policy interventions (outside government employees). The number of employees allowed to work remotely is in flux, and employers may face different incentives to have more or less of their workforce remote. This is an area of labor policy states have not engaged in, leaving the decision to allow remote work to firms.

In contrast to remote working, clean vehicle adoption has benefited from various policy interventions, including tax rebates for buying electric vehicles and investments in charging infrastructure. Clean vehicle subsidies are expensive in the short term (less so over the longer term in relation to environmental benefits) but essential for lower-income buyers (Sheldon & Dua, 2024; Sheldon et al., 2023). Supercommuters are an opportune target population for incentives that bring the cost of ownership closer to the cost of gas vehicles. Many of the zip codes with the highest shares of clean vehicles are in areas where people do not drive the most. Offering additional incentives for supercommuters, a group already more likely to drive a clean vehicle, has the potential to multiply the impact of the switch.

Areas that underperform in terms of clean vehicle adoptions are at the eastern edge of the Bay Area (i.e., from Livermore to Concord, see Figure 9). These areas include high-income enclaves and large middle-income communities, populations that generally do not need subsidies and for whom subsidies represent an inequitable expenditure of resources (Sheldon, 2022; Fischer et al., 2019). Areas where supercommuting is most frequent tend not to underperform because incomes are lower, and (possibly) people who commute long distances have higher odds of driving clean vehicles. Yet, the share of clean vehicles in these areas is generally lower than in the Bay Area. This suggests a policy approach that targets these communities more specifically (in the form of county-specific incentives, perhaps).

In addition to the cost of vehicles, charging infrastructure is particularly relevant for people living in the areas where supercommuting is frequent. The most common supercommuting routes traverse large areas that are sparsely populated and may heighten range anxiety. Developing and advertising charging infrastructure along key supercommuting corridors would be an important step in supporting electrification.

Carpooling, while not addressed in the scenarios, is an important complementary strategy. Switching vehicles to clean fuels does not decrease the number of vehicles on the road, and as long as a majority of vehicles burn fuel (which is likely to be the case for decades to come), congestion exacerbates emissions (Xu et al., 2024). Carpooling and other forms of shared mobility are important facets for mitigating the impact of supercommuting. Figures 6 and 7 show that a small number of zip code pairings account for large numbers of supercommuting trips. According to the 2023 ACS, about 9% of supercommuters carpool. Increasing that share, through incentives such as high-occupancy lanes, can multiply the benefits of clean vehicle adoption by decreasing the total number of vehicles on the road. Despite having the smallest impact, vehicle electrification has no limits (until 100% of the fleet is clean), has a robust policy framework already in place, and benefits from the continuing decline in the cost of electric vehicles, which makes the scenario estimates a floor rather than a ceiling.

Incentivizing living in locations that enable low-VMT routines is difficult. Existing programs like the Affordable Housing and Sustainable Community program provide funding to build affordable housing in locations that are transit-rich and have high accessibility, but there is currently no provision to target people who would move from a high-VMT area to a lower-VMT area so that the impact on VMT is unclear.[13]

Alternatively, policies may encourage greater polycentricity. The Northern California Megaregion is already polycentric but lacks a policy framework to encourage balanced and connected development (Boarnet et al., 2023). Research shows that people change jobs more

[13] The best examples of program that assist people in living close to where they work are employer specific. See, e.g., Regent Policy 5309: Policy on the University of California Employee Housing Assistance Program: https://regents.universityofcalifornia.edu/governance/policies/5309.html#:%7E:text=A.%20University%20of%20California%20Housing%20Assistance%20Program%20Program,employees%20with%20the%20purchase%20of%20a%20primary%20residence.

readily than they change home, and influencing where employers go may prove easier than investing in housing, where employment is most concentrated already. The California Bay Area has committed to expanding it commuter rail system, which may provide a leverage point for encouraging a more evenly distributed employment landscape as well as providing alternatives to driving for people living in areas where many people currently supercommute.

An important aspect of residential location the scenario did not discuss is that housing policy can prevent people from becoming supercommuters. Geographic and demographic data show that a share of supercommuters would be unlikely to shift behavior because of housing costs; there is undoubtedly a share of supercommuters that are price sensitive and choose to live farther from work, trading off a lower housing cost for a higher commuting cost. We do not have good estimates on what share of the population makes that choice, but we know that areas where many people migrate from the Bay Area into the Northern San Joaquin Valley correlate with high rates of supercommuting (Boarnet et al., 2023). Increasing the supply of housing at all levels of affordability is a priority for the state and many cities, and while the impact on emissions may not be substantial, the scenario provides a conservative estimate.

Conclusion

Supercommuting is a large source of excess emissions. A rough estimate based on the comparison of the average supercommuter's VMT to the average of people who live near their work destinations suggests that the elimination of supercommuting could cut supercommuters' VMT in half. Considering supercommuting's disproportionate contribution to total VMT, this could represent a decrease equal to 2-3% of total VMT, close to the equivalent target for yearly GHG reduction in California for one year (Lazo, 2024).

Eliminating supercommuting altogether, however, is unlikely to be achievable. The results in this report show that a substantial share of supercommuters travels long distances by choice and that there may be little to undo these patterns. Mitra and Saphores (2019) emphasize that socioeconomic factors work indirectly on long-distance commutes through residential location selection. People appear more likely to change jobs than to move when dissatisfied with their commute, but this decision does not seem to affect commute distance (Ma et al., 2024). In short, commute burden, for some, is not a dominant determinant in their residential location choice, and housing is sticky. People may be reluctant to move even if their commute increases markedly due to a change in jobs.

Changing residential location is not a sufficient solution, however. The analysis shows that trading a supercommute for a median commute significantly decreases how much people drive, but overall driving would decrease only marginally. Vehicle electrification is a strategy that can improve transportation-related emissions for all commute types, but given the high cost of subsidies and other incentives, the benefits are greater if the switch to clean fuels is among the people who drive the most. The maps of supercommuting incidence show clear geographic clustering, and city or county-level programs may provide an effective way to incentivize clean vehicle adoption among a group that is already more likely to likely to switch. Geographic clustering also points to shared mobility solutions as a possible approach, especially when origins and destinations are the same for many supercommuters.

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Data Management Plan

Products of Research

We used data from six sources, four of which can be released to the public and 2 of which, due to data confidentiality, cannot be released.

<u>Public data sources:</u>

1. American Community Survey (ACS)
   Demographic characteristics data are drawn from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimates is available at the Zip Code Tabulation Area (ZCTA) level from 2015-2019 and 2019-2023.
2. LEHD Origin Destination Employment Statistics (LODES)
   We use the pre-COVID period, 2019 LODES Origin-Destination data, to estimate commute distance.
3. California 2023 Vehicle fleet
   We use the vehicle fleet data to determine the share of clean vehicles in every zip code.
4. National Household Travel Study (NHTS) 2017 California add-on
   The public version of the NHTS provides information about commute distance, vehicle ownership, and demographic characteristics.

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

1. StreetLight
   The traffic data we use for analyzing average VMT at the ZCTA level. The platform provides valuable up-to-date information about travelers' origin and destination, travel distance, travel purpose, etc.
2. METRANS Remote Work and Migration Survey. The survey provides information about residential locations, workplace, and remote work arrangements before and after the pandemic.

Data Format and Content

We will deposit the ACS, LODES, vehicle fleet, and scenario data used in this study in the Dataverse data repository. The files will contain information about the data and variables.

Data Access and Sharing

The public can access the data via Dataverse.

Reuse and Redistribution

Traffic data from StreetLight and the METRANS Remote Work and Migration survey were made available to the research team through agreements that require that those data not be released publicly.

Appendix

Megaregion sub-area	County Name	% commutes 50-100 miles (LODES)	% out of county (LODES)	% out of county (PUMS)
BAY AREA	Alameda	4.3	51%	38%
	Contra Costa	13.3	60%	42%
	San Francisco	3.1	34%	23%
	San Mateo	3.3	58%	43%
	Santa Clara	6.1	25%	14%
	Solano	19.8	63%	45%
OUTER BAY AREA	Marin	8.9	58%	33%
	Napa	14.7	45%	26%
	Santa Cruz	11.6	40%	20%
	Sonoma	16.2	31%	14%
FRESNO	Fresno	5.3	14%	8%
	Madera	10.2	46%	40%
SACRAMENTO	El Dorado	12.1	52%	41%
	Placer	8	53%	34%
	Sacramento	10.6	29%	19%
	Yolo	13.9	59%	39%
SAN JOAQUIN VALLEY	Merced	19.1	42%	31%
	San Joaquin	28.8	49%	28%
	Stanislaus	24.4	41%	26%

Table A1. Share of commuters who travel outside their county of residence in 2019.

County	30-40 miles	40-50 miles	50-100 miles	All trips
Alameda	14	1	1	209
Amador	2	2	2	24
Calaveras	4	5	3	35
Colusa	1	No Obs.	1	21
Contra Costa	16	7	11	219
El Dorado	11	1	4	100
Fresno	6	3	8	267
Madera	No Obs.	No Obs.	No Obs.	21
Marin	5	1	No Obs.	49
Mariposa	1	1	1	15
Merced	4	1	5	61
Monterey	10	2	12	280
Napa	No Obs.	2	No Obs.	29
Nevada	5	5	6	135
Placer	12	No Obs.	3	274
Sacramento	28	9	13	979
San Benito	4	4	2	40
San Francisco	9	3	3	71
San Joaquin	6	11	9	157
San Mateo	5	2	1	143
Santa Clara	10	4	4	380
Santa Cruz	28	16	8	244
Solano	7	2	5	69
Sonoma	2	2	2	93
Stanislaus	8	2	8	149
Sutter	8	1	1	39
Tuolumne	1	1	2	70
Yolo	8	4	1	137
Yuba	3	1	2	21

Table A2. Sample size from the 2017 NHTS California add-on for work trips originating in each county of the Northern California Megaregion

Variable	Coefficient	Std. Error	P Value	95% Conf. Int. Min	Max
Constant	-2.2906	0.023	0	-2.336	-2.245
Supercommuter in Household (50-100 miles)	0.2887	0.143	0.043	0.008	0.569
Dependent Variable: EV/Hybrid in Household (dummy)					
Pseudo R^2= 0.0003 Observations = 22,938					

Table A3. Results from Logit regression for ownership of clean vehicles.

Note: this regression represents all households for which data in the persons table was not reported and that owned any vehicle. (If they did not own a vehicle, they would not have a value for the dependent variable). Univariate regressions with distance bands of 40-100 and 30-100 miles for supercommuting have slightly larger coefficients for supercommuter in household (.48 and .45). We tried these with a large set of covariates and found a larger pseudo R squared, but supercommuting became insignificant.

Variable	% EV/Hybrid (log)	% Bachelor's Degree	% Homeowners	% White Non-Hispanic	% Asian Non-Hispanic	Average Trip Length (Miles)
Count	470	470	470	470	470	470
Mean	2.2	40.6	59.5	44.4	16.2	10.1
Std. Deviation	0.7	22.2	18.6	23.5	16.3	2.8
Min	0.03	0	0	0	0	6.3
Median	2.3	38.1	61.5	43.4	9.9	9.4
Max	3.4	91.9	100	98.3	77.3	32.8

Table A4. Summary statistics for variables used in analysis in Table 10.

Figure A1. Map showing all destinations of supercommuters used to calculate catchment areas.