The Impact of Remote Working on Job and Housing Location in the Bay Area – Central Valley Region:

An Analysis of the Relationship Between Traffic, Telecommuting, and Migration During and After COVID-19

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A Research Report from the Pacific Southwest Region University Transportation Center

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16. Abstract

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We used four datasets: StreetLight for traffic data, LEHD LODES Workplace Area Characteristics (WAC) for job-related data, the American Community Survey (ACS) for demographic information, and USPS Change of Address (COA) for migration patterns. The study includes 487 zip code tabulation areas (ZCTAs) in the Bay Area and Central Valley region. Our methodology includes destination (workplace) analysis, origin (residential) analysis, origin-destination (O-D) flow analysis, and regression analysis.
Our findings indicated notable decreases in traffic volume across all regions, with the Bay Area experiencing the largest drop. We found that increased WFH rates are associated with decreased traffic recovery at job centers, while migration patterns suggest a shift to more remote living arrangements. However, workplace industry characteristics are more influential on traffic volumes than worker demographics and remote working status. These insights could provide implications for urban planning, housing policies, and transportation strategies in the post-pandemic era.

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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

Boarnet, Comandon, Rodnyansky, Randazzo, and Wang conducted this research titled, "The Impact of Remote working on Job and Housing Location in the Bay Area – Central Valley Region: An Analysis of the Relationship Between Traffic, Telecommuting, and Migration During and After COVID-19" at the Department of Urban Planning and Spatial Analysis, Sol Price School of Public Policy, University of Southern California. The research took place from August 1, 2023 to July 31, 2024 and was funded by a grant from the California Department of Transportation in the amount of $78,334 with additional funds in the amount of approximately $22,000 from the U.S. Department of Transportation. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

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We used five datasets: StreetLight for traffic data, LEHD LODES Workplace Area Characteristics (WAC) for job-related data, the American Community Survey (ACS) for demographic information, and USPS Change of Address (COA) and the US Census Current Population Survey (CPS) for migration patterns. The study includes 487 zip code tabulation areas (ZCTAs) in the Bay Area and Central Valley region. Our methodology includes destination (workplace) analysis, origin (residential) analysis, origin-destination (O-D) flow analysis, and regression analysis.

Our findings indicated notable decreases in traffic volume across all regions, with the Bay Area experiencing the largest drop. We found that increased WFH rates are associated with decreased traffic recovery at job centers, while migration patterns suggest a shift to more remote living arrangements. However, workplace industry characteristics are more influential on traffic volumes than worker demographics and remote working status. These insights could provide implications for urban planning, housing policies, and transportation strategies in the post-pandemic era.

Executive Summary

Work-from-home (also known as WFH, remote work, telework, and telecommute) has become much more prevalent since the COVID-19 pandemic in 2020, accelerating a trend that had been growing over the years. In 2019, only 6% of U.S. workers telecommuted. In 2022, 39% of U.S. adults reporting that they replaced some or all of their in-person work with telework. This change has had immediate economic impacts and may result in long-lasting shifts in work and residential patterns. By reducing the need for daily commutes, remote work has the potential to influence residential decisions, increasing housing demand in areas farther from traditional employment centers.

This study examines the early effects of WFH following the initial COVID-19 disruption, focusing on the changing relationship between work and residential locations in the Greater San Francisco Bay Area and Central Valley megaregion. The main goal is to look at changes in commute volumes at workplaces and how these relate to the rise in remote work at residential locations. It explores how increased WFH has impacted job and housing locations before and during the pandemic. Most studies on commute patterns during the pandemic have focused on trips from residential areas, without linking changes at work locations due to data limitations. This report aims to fill these gaps by understanding the spatial and economic impacts of remote work during and after the pandemic.

Traffic Reduction at Destination

Our analysis revealed a significant decrease in traffic volumes across the study regions from 2019 to 2021. The Bay Area experienced the largest drop at 20.5%, followed by the Central Valley at 16.4%, and Comparison counties at 17.6%. The industry composition of destination ZCTAs varied, with office jobs dominating in the Bay Area, while the trade and transport sector led in the Central Valley.

Industry composition highlights the critical role of economic dynamics in shaping traffic patterns. The distinct economic profiles of the Bay Area and Central Valley reflect varying degrees of impact on traffic reduction due to remote work. Office-centric regions like the Bay Area saw more significant decreases in traffic, while regions with higher shares of agriculture, manufacture, or trade and transport experienced smaller declines. In the Bay Area, office jobs had the highest share at 26.1%, while agriculture had the lowest at 0.3%. In the Central Valley, the trade and transport sector dominated with 18.2%, whereas agriculture accounted for 6.8%. In the Comparison counties, the highest share was in agriculture at 10.5%, and the lowest was in office jobs at 17.6%. This disparity underscores the need for tailored approaches to traffic management and urban planning in different economic contexts.

Work-from-Home Trend at Origin

The Bay Area saw the most significant increase in WFH rates, rising from 6.6% in 2019 to 16.6% in 2021. Central Valley (from 5.8% to 9.8%) and Comparison counties (from 7.2% to 12.3%) experienced smaller increases of 4 and 5 percentage points, respectively.

Compared to the pre-COVID period, areas with WFH growth exceeding 10 percentage points were mainly clustered in the South Bay Area, including cities like Mountain View, Santa Clara, Sunnyvale, and Fremont. There were also pockets of growth in the suburbs and exurbs of Sacramento. This shift underscores the tech industry's significant role in promoting remote work.

Migration Trends

Our analysis showed that regions with higher WFH rates tended to experience greater out-migration, driven by the opportunity to relocate without the constraint of daily commuting. The Bay Area saw a notable net cumulative migration loss, indicating a higher outflow of residents. During the pandemic (from March 2020 to October 2021), the Bay Area experienced a net cumulative migration loss of approximately 4 people per 100 residents. This migration pattern suggests that many workers took advantage of remote work flexibility to move away from high-cost urban centers to more affordable or desirable locations. The Central Valley and Comparison counties experienced smaller net losses, highlighting a more modest migration trend. Central Valley and Comparison counties had smaller net losses of around 1 person per 100 residents. The data from USPS Change of Address (COA) provided insights into these migration patterns, although limitations in the data prevented a comprehensive analysis of remote workers' specific migration destinations.

Impact of Work-from-Home Growth on Destination Traffic and Activities

The concept of "vanished trips" is used to estimate the reduction in trips due to increased remote working. The share of vanished trips to the overall traffic drop between 2019 and 2021 was 64.9% in the Bay Area, 39.4% in the Central Valley, and 31.5% in the Comparison counties. These patterns align with the observed increases in WFH rates and the decreases in destination traffic volumes.

Our analysis showed that higher WFH rates at the origin are associated with less traffic recovery at the destination. A 1 percentage point increase in WFH rate is linked to a 0.28 percentage point decrease in destination traffic volume. In addition, the net migration rate at the origin has a positive effect on traffic volume changes, with a 1 percentage point increase in net migration linked to a 2.76 percent increase in destination traffic volume.

However, industry composition at the destination is a more influential factor than origin characteristics. The analysis reveals that destinations with a higher share of office jobs experience the most significant declines in traffic volume. For example, office sectors show a significant negative impact, with a 1 percentage point increase in the share of office jobs associated with a 0.44 percent decrease in traffic volume. Other sectors, such as construction, manufacturing, education, and services, also negatively impact traffic recovery, though to a lesser extent. These findings highlight the critical role of workplace (destination) characteristics in shaping traffic patterns.

Chapter 1: Introduction

1.1 Background

The concept of work-from-home (WFH) has become more prevalent, especially due to the COVID-19 pandemic. About 4% of U.S. workers telecommuted in 2006, a share that increased to 6% by 2019 according to the U.S. Census American Community Survey. The spread of COVID-19 in early 2020 and the physical distancing mandates that followed caused a rapid and massive shift to remote working. Although many workers have returned to the office, 39% of U.S. adults still substitute some or all of their typical in-person work for telework (2022 U.S. Census Bureau Household Pulse Survey).

The changes in work and employment had an immediate impact on the economy and could lead to permanent shifts that last beyond the pandemic. Working from home, by eliminating or reducing the need to commute to an office, could affect workers' residential choices and increase housing demand in remote locations away from employment centers.

This study is one of the first to provide an early look at the impact of working from home after the initial COVID-19 shock, but when work and residential location relationships are still in flux and likely adjusting. The purpose of this research is to analyze the commute volume changes over time at workplaces (destinations) and to spatially connect these changes with the growing work-from-home phenomenon at residential locations. We evaluate the spatial configuration of work-from-home and jobs-housing reallocation during and after the pandemic, focusing on the combined Greater San Francisco Bay Area and Central Valley megaregion.

This research examines the growing phenomenon of work-from-home and its impact on job and housing locations before and during COVID-19. Due to data limitations, the causal effect between remote working and migration is still unclear. Current studies analyzing commute patterns during the pandemic are mostly based on trip productions, i.e., at the site of residential location. No studies have linked the changes at the work locations (i.e., trip attractions) with residential locations. In this research, we examine how traffic volumes at work locations (commute destinations) are linked to work-from-home rates at residential locations.

1.2 Research Purpose

This research addresses critical gaps in understanding the spatial and economic impacts of remote work during and after the COVID-19 pandemic. Specifically, we evaluate how the shift to remote work has reconfigured commuting patterns and residential choices within the Bay Area and Central Valley megaregion. We analyze changes in commute volumes over time at workplaces, connecting these changes to the rise of remote work at residential locations. In addition, we analyze the migration patterns at these residential locations. We use five datasets – StreetLight, American Community Survey (ACS), LEHD Origin Destination Employment Statistics (LODES), USPS Change of Address (COA), and US Census Bureau Current Population Survey (CPS) – at the zip code tabluatioon area (ZCTA) and county levels to analyze how remote work has reshaped the job-housing dynamics in California's Bay Area and Central Valley. The project aims to answer three questions:

1. Where and in which industries did traffic volume change the most during COVID-19?
2. Did work-from-home reduce traffic at job centers?
3. What is the migration pattern during COVID-19?

The rest of the report will provide a comprehensive understanding of the impact of remote work on workplace traffic patterns. Chapter 2 provides an overview of the existing state of knowledge on remote workers' attitudes and characteristics and the relationship between remote working, migration, and commuting. In Chapter 3, we discuss the data sources and methodologies used in the study. Chapter 4 presents a detailed analysis of destination (workplace) characteristics, origin (residential) characteristics, and an origin-destination analysis that weights destination traffic to residences to give insights into the relationship between work-from-home (origin) and workplace (destination) traffic flows. Chapter 4 also contains the main findings, including descriptive information on changes in traffic volumes, work-from-home growth, and migration patterns, and the results of our regression analysis. Finally, Chapter 5 concludes the report with a summary of findings, policy implications, data limitations, and suggestions for future research.

Chapter 2. Literature Review

The digital revolution of the 1970s and '80s quickly incited utopian visions of a commuter-less future, where individuals would forgo peak-period congestion and firms costly office space, and work tasks would take place in the comfort of one's home. Telecommuting, as this phenomenon was coined by Nilles in 1973, positioned communication as an alternative to transportation, with electronic channels replicating many of the productive functions of physical proximity. Additional terms subsequently emerged to describe telecommuting behavior: telework, remote work, e-work, work-from-home, WFH, flexplace, and even "electronic cottage" (1). Regardless of its name, the potential social benefits are profound: certain scholars argue that in aggregate, increased telecommuting can meaningfully reduce traffic congestion, fuel consumption, and GHG emissions (2–5). The scale of this transformation was expected to be large, as forecasts made in the 1980s estimated that by 2000 there would be 20 million telecommuters in the US (6), reflecting approximately 15% of the total labor force.

Despite such optimism, the first several decades of telecommuting were remarkably underwhelming. Contrary to projections, by 2000 just 9.3 million Americans worked from home at least one full day per week, and 4.2 million worked from home "usually"—representing just 7% and 3.3% of the total workforce (7). ACS data[1] tell a similar story, showing relatively stagnant telework rates, with once-weekly remote work growing by just 2.5 percentage points between 1997 and 2010, from 7% to 9.5%. In 2019, just before the onset of the pandemic, an estimated 13% of workers worked from home at least once every two weeks (8), while just 4.7% "usually" worked from home (9). Taken together, these figures reflect that despite remarkable improvements in computer processing power, smartphone capabilities, and internet connectivity, telework remained a fringe activity practiced by only a subset of the working population, a supplement to in-office work hardly sufficient to realize the social benefits espoused over the previous 40 years.

All this changed during the Covid-19 pandemic. Shelter-in-place orders and mandatory office closures forced business around the world to either embrace telework or halt operations. Estimates vary, but a Google Consumer Survey run by Brynjolfsson et al. (10) found that by May 2020, 35% of in-person workers were teleworking fulltime, which, along with pre-Covid teleworkers, boosted American WFH shares to above 50%. According to Barrero et al.'s (9) Survey of Working Arrangements and Attitudes (SWAA), 61.5% of full workdays were conducted remotely in May 2020, up from the roughly 5% prior to the pandemic.

As time has passed and Covid has waned as a public health threat, WFH shares declined from their early-pandemic peak but remain well above pre-pandemic levels: according to ongoing waves of Barrero et al.'s (9) SWAA, by May 2021, WFH days as a share of total workdays had dropped down to 33%; by May 2022, it accounted for 31.5%; by May 2023,

[1] No Commute? Americans Who Work at Home.

27.7%; and by April 2024 (the most recent available) 27.1%. The same survey shows that for all fulltime workers, in-person work remains the most common, accounting for 61.5% of workers; among workers *with the ability to telecommute*, however (thereby excluding certain service and blue-collar workers), hybrid arrangements are the most common, with 43.5% of these employees appearing in-person fewer than five times per week. On the labor demand side, Hansen et al., (11) find that in the U.S. the share of fully-remote or hybrid job postings was 3.7% in 2019, peaking at 11% in Fall 2022, and now hovers at around 9-10% in 2024. These trends simultaneously illustrate the long-term stability of remote work, the sustained prevalence of the traditional workplace within certain sectors, and the emergent flexibility in home-office arrangements.

As the United States navigates its post-pandemic recovery, urban planners and policymakers are questioning whether there will be a lasting transformation in commercial and residential spatial patterns and how urban centers will fare as a result, relative to pre-Covid conditions. What follows is a review of several sub-areas of remote work research that begin to flesh out remote work's ambiguous and multilayered future, with implications for the organization, operation, and development of our cities. We begin with attitudes towards WFH, followed by characteristics of teleworkers, impacts on location choice and real estate markets, and changing commuting behavior.

2.1 Attitude Towards Remote Working

How people feel about WFH is an essential consideration in the future sustainability and prevalence of remote work. Prior to Covid, telework offered little value for individual firms, reflecting additional geographical dispersal *within* individual workplaces in an already spatially dispersed economy. Indeed, managerial ambivalence towards telework was the predominate factor mitigating its widespread adoption (12–14). Managers were simply not comfortable giving up control over their working environment and had no clear motivation to replace face-to-face interaction with electronic communication. Corporate externalization and vertical disintegration were desirable under global knowledge economy conditions (15), but the loss of in-person oversight and interaction had little appeal for reasons both economic and cultural.

The pandemic upended this equilibrium, requiring businesses to adapt to an environment where in-person attendance was prohibited, with no clear notion if or when normalcy would return. Millions began teleworking for the first time, engaging in what was effectively a mass social experiment in remote productivity. Firms were forced to pay the fixed costs of learning how to make WFH functional and productive; in this view, Covid-19 provided an environment to force firms to solve a coordination issue that they used to ignore (16).

The results were surprisingly positive. Workers and managers quickly learned that remote work was not only commensurate with in-person productivity, but opened up new benefits that optimized corporate operations, improved the working experience, and enhanced individual wellbeing (9,17). Barrero et al. (9) report that 60% of SWAA respondents reported that WFH turned out better than expected, with both worker desire and employer plans for WFH increasing after the pandemic. Baert et al. (2020) relay similar findings, with 63% of respondents in a 14,000-worker survey hoping for more teleworking in the future.

In a survey of workers in 27 countries, Aksoy et al. (17) found that workers primarily perceived daily commute time and money savings to be WFH’s principal benefit. Americans collectively saved roughly 61 million minutes per day during the pandemic, allocating one-third of this found time towards additional work and 60% towards household chores and responsibilities (18). The same survey revealed that workers also valued telecommuting for its increased workday flexibility, time saved on grooming and dressing, and fewer meetings. These changes were not unilaterally positive, as several key dimensions of work life suffered in the remote environment: namely, face-to-face collaboration, sociability, maintaining work-life boundaries, and work equipment quality.

Despite these drawbacks, telecommuting has emerged as an essential feature of one’s job: workers expressed willingness to take a 5% pay cut in exchange for WFH, and one-third of Americans stated that mandatory return-to-office policies (RTOs) would motivate them to seek employment elsewhere (9,17). Taken together, such research frames the experience of Covid as predominately *a shock to WFH preferences* that will influence long-term spatial equilibrium (19,20).

2.2 Remote Worker Characteristics

Although telework has proliferated throughout the global economy, it is not practiced universally nor unilaterally. WFH frequency varies greatly according to industry, occupation, gender, age, income, education, city, and nation, creating divergent conditions and outcomes in the post-Covid economy.

Beginning with economic variation, research shows that remote work is a practice concentrated in knowledge and advanced producer service sectors: namely, Information, Finance and Insurance, and Professional and Business Services. According to Barrero et al.’s (9) ongoing SWAA, in April 2024 just 32%, 36%, and 41% of workers in these three sectors were fully onsite, with the remaining majority split between remote and hybrid arrangements. Workers in the Arts and Entertainment and Real Estate sectors were also found to engage in high WFH, with 42% and 38% onsite shares. All other sectors, however, are majority in-person, led by Retail, Transportation and Warehousing, and Food and Hospitality, with 76%, 78%, and 83%, respectively.

Hansen et al.'s (11) job postings analysis shows similar patterns, with the highest share of remote or hybrid positions in the Finance and Insurance, Information, and Professional and Business Services sectors. The relative magnitude of remote work offerings is lower than worker reported WFH rates, however, reflecting a gap between employer expectations and worker preferences, as identified in the SWAA (9). Breaking out these data by occupation shows that high-skill knowledge work is more amenable to remote productivity. Certain occupations require similar skills and responsibilities across all industries: for example, sales and administrative jobs feature elevated remote work rates regardless of sector, with tasks executed predominately over email, spreadsheets, presentation decks, and the like (11,21).

With such close associations with knowledge-based productivity, work with higher telecommuting frequencies tends to be better paid and require higher education levels. Dingel and Nieman (21) find a positive correlation between the "remote workability" of a job and salary within the US and amongst higher income nations. The net social effect is that the welfare gains of remote work tend to be concentrated within the most advantaged class of employee. Additionally, remote workers tend to be younger, with no observable difference between genders (10). However, there is some evidence that women prefer WFH to men (17), and experience larger welfare gains, via pregnancy and parenting life stages (22).

Lastly, there exist sharp geographical differences in WFH frequency. Jobs in New York and San Francisco, which feature employment hubs for tech, media, and finance, are more than twice as likely to offer remote or hybrid work than jobs in Cleveland and Wichita (11). Similarly, national WFH levels differ according to industrial mix. As mentioned above, lower income nations with higher shares of manufacturing and farming employment exhibit little increase in telework, while highly developed nations with global financial and information centers have seen higher WFH rates (23).[2] In sum, planners and policymakers face a profound degree of local specificity in telecommuting trends in the post-pandemic landscape.

2.3 Impacts on Location Choice and Real Estate

Established by Alonso (24), Muth (25), and Mills (26) in the 1960s, the monocentric urban model holds that urban land markets are characterized by the tradeoff between land prices and travel costs to the city center. Kain (27) makes a similar claim, positing that households trade-off between commute and housing costs (as cited in 28). All else equal, an individual worker will be indifferent between housing in the urban core and the peripheral

[2] Interestingly, Adrjan et al.'s (2022) job posting dataset identifies Japan as a severe outlier, exhibiting exceptionally high-income levels but practically non-existent remote work, suggesting that national office culture has overpowered WFH's individual benefits.

suburbs. Despite its abstract nature and more recent turns towards polycentric metropolises, decades of urban economics research have verified these predicted patterns (see, i.e., 29,30), demonstrating the durable principle that as travel costs decrease, people are more willing to locate further from the city center (a comparative static result from the monocentric model).

With WFH a widespread practice in the post-Covid landscape, commuting costs have declined for millions of workers, particularly those living in the most expensive metros. The ability to commute only a few times per week or forgo the commute entirely gives city workers access to previously inaccessible land. Therefore, according to the monocentric city model, we should expect to see dense central neighborhoods become less desirable and individuals move further from the urban core. This tendency applies not just to workers but firms, especially those in knowledge industries where most productivity occurs on computers and digital networks. With the diminished intensity of in-person activity, firms should experience less of a need to occupy CBD real estate, able to either consume less office space or locate in more peripheral areas.

Ramani and Bloom (31) find evidence of such patterns, terming their findings the "donut effect," a metaphor for movement from the urban core to the fringe. The donut effect has gained traction in mainstream media, helping to set the terms of public debate on post-pandemic urbanism and the future viability of cities (see: 32–34). Incited by Covid and sustained by remote work, the observed "donut effect" has been experienced most acutely in large US cities, reflected by population and business outflows and diminishing rents and home values in dense, central city neighborhoods. Indeed, Liu and Su (35) report that decreased demand for proximity to highly telework-compatible jobs and visits to services and amenities during the pandemic both lowered the value of residential real estate in central cities and higher density neighborhoods. Whether declining amenity premia will persist in the long term is an open question, however; it is still too soon to tell to what degree agglomerations of consumption (i.e., in 36,37) will sufficiently drive urban land value. This last question is of utmost interest to real estate corporations that traditionally lease office space and to city governments that derive large portions of revenue from taxes on CBD real estate (38).

Remote work appears to be a strong motivator for residential mobility. Ozimek's (39) multi-wave survey finds that remote work capabilities are motivating people to move from the area where they currently live: between 6.9–11.5% reported a desire to move, corresponding to 14–23 million Americans—a plurality of which live in large cities (approx. 21%). For comparison, Census data from 2018–19 show that 3.6% of people had moved from the previous year, so remote work appears to spark a 2–3x increase in overall residential mobility. However, Ozimek's (40) follow-up survey reported that just 2.4% of Americans have moved "because of remote work, since 2020," suggesting that locational preferences for already-existing households may play out over the long term (if at all). Examining proprietary moving company data, Haslag and Weagley (41) identify growth in interstate migration amongst higher-income households into smaller metro areas. Following the pandemic, these movers increasingly cited lifestyle and financial reasons for their move as opposed to those related to work. Although Covid was the initial instigator, family (32%) outweighed work from home (17%) and job loss (14%) as the foremost motivator for long-distance relocation; therefore, remote work might be one of several considerations impacting residential mobility.

In the new telecommuting landscape, demand has increased for housing in general (19,42), both in locations beyond commuting distance and in smaller, more affordable metro areas. Ozimek (39,40) finds that 41% and 28% of likely movers report that they are looking to move at least four hours away, with an additional 13% (in both survey years) targeting between 2–4 hours away, presumably well beyond regular commuting distance. Of their "donut movers," Ramani and Bloom' (31) report that the majority (58%) are relocating in the same metropolitan region, scattered across lower density urban areas, inner-ring suburbs, and outer-ring exurbs. Another 29% of donut movers migrated to mid-sized metros outside the top twelve in terms of population, 9% chose other large cities, and 4% went to rural areas. New York and San Francisco appear to be the most impacted by the donut effect, experiencing the largest central migration outflows, significantly predicted by their high pre- and post-pandemic WFH shares. Cellphone data analysis from Chapple et al. (43) shows that as of Fall 2023, CBDs in smaller and medium-sized cities have more extensively recovered their pre-pandemic activity, while CBDs in larger, denser cities have lagged behind; NY and SF have each attained roughly two-thirds of their downtown activity.

Modeling spatial equilibrium, Delventhal and Parkhomenko (20) suggest that although elevated WFH levels have motivated remote workers to move further from density, this outmigration is backfilled somewhat by non-telecommutable workers, who are taking advantage of locations with shorter commutes and relatively lower demand. Interestingly, this model also finds that within the spatial jobs distribution, WFH produces an increase in jobs in below-median density locations, decrease in above-median density locations, and no change in the densest locations—i.e., Manhattan. As argued in Sassen's (44) seminal "global cities" theory. These high-density districts are among the most productive land in the world, shoring up their post-Covid competitiveness.

2.4 Changing Travel Behavior

As discussed above, when workers gain the ability to work remotely, the option to avoid commuting can affect workers' location choice. More directly however, all remote workers *regardless of residential mobility*, experience drastic changes in daily travel. Such transformations have profound implications for planners as city transportation systems must adjust to the new normal in real time.

Just prior to Covid, travel demand had already undergone profound changes with digitalization, as certain facets of daily life increasingly occurred online; e-commerce in particular has been the topic of considerable research, where firms like Amazon, Alibaba, and smaller direct-to-consumer companies (D2Cs) induced profound changes in personal and freight transportation (45–47). In this context, telecommuting represents just the latest phase in an ongoing digitalization process, where the work trip—which held fast as a point of daily orientation even in the digital age—has now been partially replaced, supplemented by a range of work–life configurations. The ultimate impacts on travel patterns remain to be seen.

In the past, researchers such as Janelle (48) and Graham and Marvin (49) believed (seemingly correctly) that telecommuting could prompt individuals to move farther away from their jobs to cheaper or higher quality residential locations. Such movement would generate longer commutes and lead to a net increase in individual vehicle miles traveled (VMT) on the days during which telecommuters would travel into the workplace. Other researchers disagreed, arguing that although telecommuting leads to longer one-way commutes, lower trip frequency meant shorter commute distances *on average* for teleworkers than non-teleworkers (50–52).

Today, with telework an indispensable part of economic life, the overall effect on VMT for households, cities, regions, and nations, is currently under review by scholars and planning professionals around the world. Early studies examining travel and post-pandemic telecommuting have already been published. Examining survey responses linked to mobile POI data from 2020–1, Obeid et al. (53) report a host of findings pertaining to post-Covid travel behavior. Firstly, they concur with Barrero et al.'s (9) findings that hybrid is largely more popular than full remote work arrangements. This means that while peak-period trips will be diminished, they will not decrease as dramatically as one might expect. They find that Wednesday is the most popular weekday for telecommuters, accounting for 18% of their commute days (Mondays and Fridays are the least popular, representing just 13% and 14.5%, respectively). Such weekday frequencies are important considerations, as low levels of in-person attendance can diminish the productivity of all in-person work (20,53): i.e., a worker who commutes into the office to hold meetings on Zoom and eat lunch alone experiences few of the benefits of co-location.

In terms of travel, Obeid et al. (53) find that for remote workers, travel distances are approximately 1% of those on commute days (0.12 km compared with 9.8 km). However, when working-from-home, workers tend to make one additional non-commute trip than days in-office. Although typically shorter than the commute, this extra travel nonetheless partially offsets the travel distance saved by telecommuting. It is likely that many of these additional telecommuter trips are for the purposes of non-office working. Citing Barrero et al. (9), Caros and Zhao (54) identify that although telework typically denotes working-from-home, about one-third of all remote work from November 2021–March 2022 occurred in a third place: whether a public space, friends' home, or a co-working space.

More recently, Zheng et al. (55) examine the relationship between workplace visitation and transit ridership and VMT data from April 2020 to October 2022. Using remote work suitability as an instrumental variable, they find a significant positive relationship between on-site workers and travel demand: a 1% decrease in in-person work attendance generates a 0.99% decrease in state-level VMT and a 2.26% decrease in MSA-level transit ridership, suggesting that public transit travel demand is more elastic with respect to telecommuting. Using these figures, the authors estimate that a 10% decrease in on-site workers corresponds with a 10% decrease in CO_2 emissions from the transport sector, and a 27% decrease in annual transit fare revenue.

Taken together, it's apparent that telecommuting represents transformative potential, introducing both highly sought after benefits and exacerbating existing costs. More research is certainly needed before forming definitive conclusions regarding WFH and transportation.

Chapter 3. Data and Methodology

In this chapter, we outline the data sources and methods used to analyze the impact of remote work on job and housing locations in the Bay Area and Central Valley megaregion. We describe the study area, the five primary datasets (StreetLight, ACS, LODES, USPS COA, and CPS), the observation period, and our methodology. The methodology includes destination and origin analyses, origin-destination (O-D) flow analysis, and regression analysis to understand the relationships between remote work, traffic volumes, migration, and workplace dynamics.

3.1 Study Area

This study focuses on the San Francisco Bay Area metropolitan area, the Central Valley region (which extends from the Sacramento metropolitan area south to the northern San Joaquin Valley metropolitan areas of Stockton, Modesto, and Merced), and the adjacent counties. The Bay Area is the home to some of the country's least affordable housing markets, highest incomes, and highest concentration of high-tech jobs. The Central Valley, separated from the Bay Area by a mountain range and river delta, faces higher unemployment and has a large agricultural and manufacturing base, with lower median incomes and housing costs. For this study, we analyze the telecommuting pattern before and after COVID-19 in the core Bay Area counties (Alameda, Contra Costa, San Francisco, San Mateo, and Santa Clara County) and nearby counties of the Central Valley (El Dorado, Merced, Placer, Sacramento, San Joaquin, Solano, Stanislaus, and Yolo County). We also included the populated area in the adjacent counties (Amador, Calaveras, Fresno, Madera, Marin, Monterey, Napa, Nevada, San Benito, Santa Cruz, Sonoma, Sutter, Tuolumne, and Yuba) as comparisons for the two contrasting regions. Figure 1 shows the study area counties and the ZCTA's within those counties which we use for much of our analysis.

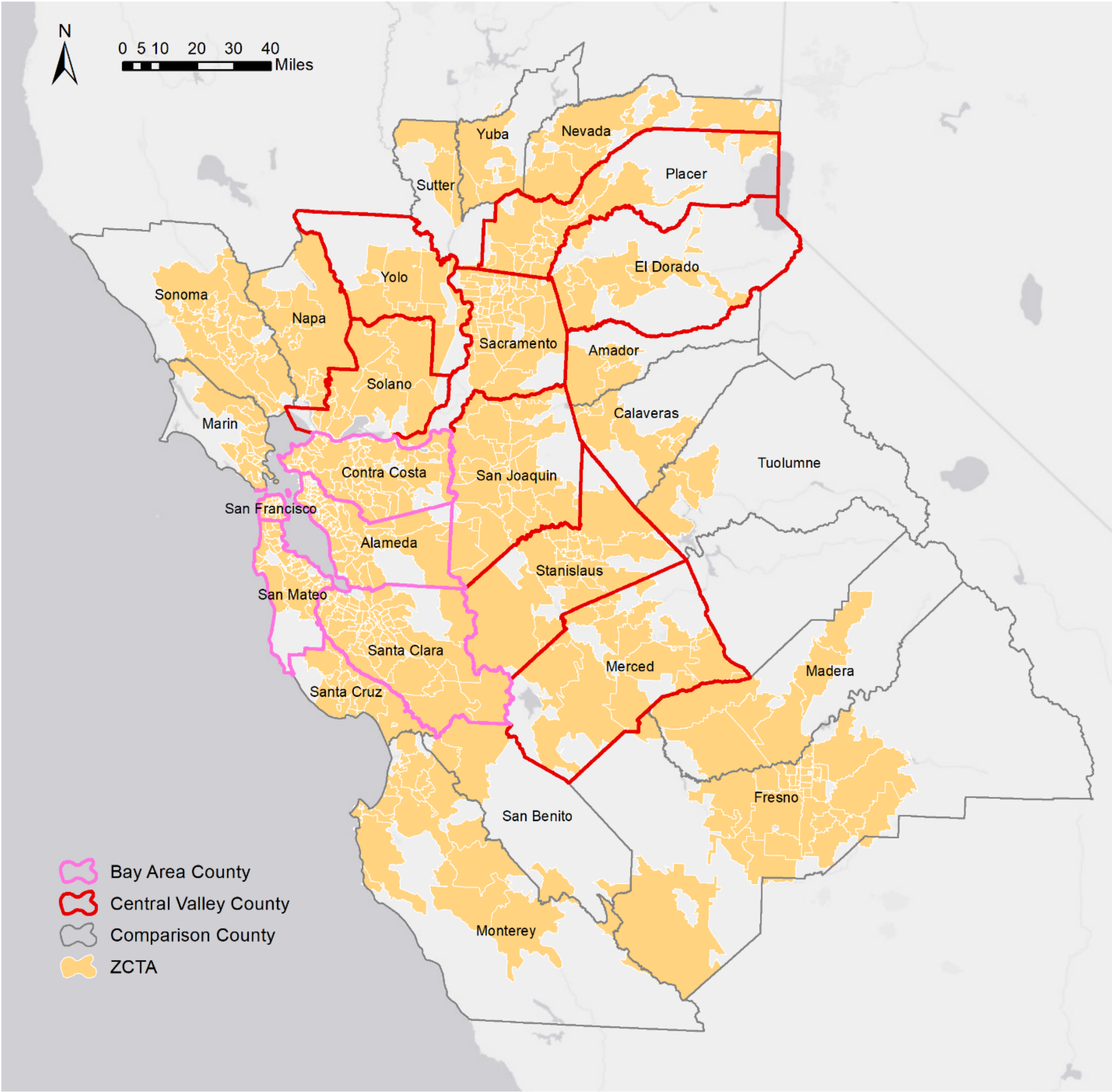

Figure 3.1.1. Study area counties

3.2 Data

1. StreetLight
   The traffic data we use for analyzing origin-destination flows before, during, and after COVID-19 is from StreetLight Data Inc. The platform provides information about travelers' origin and destination, travel distance, travel purpose, etc. StreetLight derives flow data from location-based services, apps that users enable and allow to share location data with vendors. The StreetLight database captures daily traffic at the ZCTA level on a daily basis and covers the general population based on a variable sampling rate that averages 8.5%.

This data coverage begins before COVID-19, we use the data from June 11, 2019, to October 25, 2019, and extends past the period of most severe COVID-19 shelter-in-place and movement restrictions. The latest data we used in this study covers the time between June 15, 2021, to October 29, 2021 to match the reference period before the pandemic. StreetLight data does not differentiate between trip purposes beyond providing an estimated share of trips categorized as home-based work, home-based other, or non-home-based trips. We use all trips to calculate traffic flow because StreetLight uses its own algorithm to estimate trip purposes. This algorithm is a "black box," making it difficult to understand and reproduce the process. StreetLight also includes all modes in its estimate of traffic. Therefore, we are unable to differentiate between people who commute by car, public transit, or active transportation.

Our data access was limited to 500 geographic units. Given this limitation, we will analyze commute flows at the census zip code tabulation area (ZCTA) level to maximize geographic coverage. ZCTAs are the U.S. Census Bureau's approximation of US Postal Service (USPS) zip codes. We use ZCTAs rather than zip codes because ZCTAs more easily connect to census and American Community Survey (ACS) data. We reduced the number of ZCTAs within the study area counties (which exceeded the 500 limit) by only including ZCTAs that overlapped with an urbanized area or had a population greater than 3,000 based on the American Community Survey 5-year estimate from 2015-2019 (see Figure 3.1.1 for a map of included ZCTAs).

2. American Community Survey (ACS)
   Demographic characteristics data are drawn from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimates available at the Zip Code Tabulation Area (ZCTA) level from 2015-2019 and 2017-2021. Key demographic variables include age, sex, race, ethnicity, poverty status, and industry occupation. ZCTAs are the U.S. Census equivalent to the U.S. Postal Service's (USPS's) 5-digit zip codes (U.S. Census Bureau, 2018). In populated areas, ZCTAs have a high degree of overlap with zip codes (Hurvitz, n.d.; Langer, 2016) and have been used in geographic analyses (Grubesic and Matisziw, 2006). ZCTA to zip code crosswalks are available for public download (e.g., UDS Mapper, 2018). In addition to the limits on the number of geographic units for which we could pull data from StreetLight, ZCTA is the only unit for which we have small-scale migration data (see below).

3. LEHD Origin Destination Employment Statistics (LODES)
   We use the pre-COVID period, 2019 LODES WAC (Workplace Area Characteristic) data, to capture destination characteristics. The WAC data provides detailed job-related characteristics, including total jobs, worker age, earnings, job sector, ethnicity, and education level. All data is at the census block level, which we aggregate to the ZCTA level.

4. USPS Change of Address (USPS COA)
   USPS change of address data is used to serve as a proxy for migration patterns. The United States Postal Service has provided publicly accessible change-of-address (COA) data by

month for the last four years (2018-2022) at the zip code level. For privacy protection purposes, the data is only reported when the COA request volume is greater than 10. We calculate total net migration for each zip code by subtracting the number of COA requests originating from the specific zip code (outgoing) from the number of COA requests to that same zip code (incoming). The COA data includes three categories: family, individual, and business. For our analysis, we used only family and individual move types, excluding business requests. We converted family moves into individual counts by multiplying the number of family COA requests by 2.5, based on the average household size from the Census Bureau. We also convert zip code level COA data to ZCTA level using the zip code to ZCTA crosswalk (e.g., UDS Mapper, 2018) for consistency with data from other sources.

5. US Census Bureau Current Population Survey (CPS)
   The CPS provides comprehensive data on population change in US counties, with statistics reflecting yearly domestic and international migration. We utilize two CPS datasets, from 2010–2019 and 2020–2023, publicly available from the Census Bureau website. Counties are linked to Metropolitan Statistical Areas (MSAs) through the Office of Management and Budget's (OMB) core based statistical area delineation files, also available on the Census Bureau website.

3.3 Observation Period

For this study, we used StreetLight data from 2019 to 2021, collected at the ZCTA (Zip Code Tabulation Area) level on a daily basis. The data were analyzed for all-day periods (12 am to 12 am) to capture the full daily traffic volume. The observation period consists of 20 weeks each for the pre-COVID and post-COVID time frames (see Table 3.3.1 for details).

We measure the 20-week Post-Covid period from the week of June 14, 2021 up through the week of October 24, 2021. June 15, 2021, marks the date when California fully reopened its economy and moved beyond the Blueprint for a Safer Economy, making it an ideal starting point for the post-COVID era. On the end timing, we are limited by data: the furthest date available for download with our StreetLight license was October 29, 2021. Additionally, To ensure a consistent comparison between the pre-COVID and post-COVID periods, we selected observation periods from 2021 and then identified the corresponding weeks in 2019. Therefore, the post-COVID period extends from June 15, 2021, to October 29, 2021, while the pre-COVID period ranges from June 11, 2019, to October 25, 2019.

Table 3.3.1 shows the week pairs for the post-COVID and pre-COVID periods, with 20 weeks each. The weeks were paired based on the calendar week of the year. For example, the week of June 14-18, 2021 (Week 24 of 2021), corresponds to the week of June 10-14, 2019 (Week 24 of 2019). This pairing method aligns the same weeks across different years, facilitating a direct comparison of traffic patterns before and after the COVID-19 pandemic while minimizing seasonal fluctuations.

Table 3.3.1. Observation week pairs in 2019 and 2021

Week of the year	Post-COVID (2021)		Pre-COVID (2019)	
	Monday	Friday	Monday	Friday
Week 24	6/14	6/18	6/10	6/14
Week 25	6/21	6/25	6/17	6/21
Week 26	6/28	7/2	6/24	6/28
Week 27	7/5	7/9	7/1	7/5
Week 28	7/12	7/16	7/8	7/12
Week 29	7/19	7/23	7/15	7/19
Week 30	7/26	7/30	7/22	7/26
Week 31	8/2	8/6	7/29	8/2
Week 32	8/9	8/13	8/5	8/9
Week 33	8/16	8/20	8/12	8/16
Week 34	8/23	8/27	8/19	8/23
Week 35	8/30	9/3	8/26	8/30
Week 36	9/6	9/10	9/2	9/6
Week 37	9/13	9/17	9/9	9/13
Week 38	9/20	9/24	9/16	9/20
Week 39	9/27	10/1	9/23	9/27
Week 40	10/4	10/8	9/30	10/4
Week 41	10/11	10/15	10/7	10/11
Week 42	10/18	10/22	10/14	10/18
Week 43	10/25	10/29	10/21	10/25

3.4 Methodology

3.4.1 Analytical Framework

We use four datasets—StreetLight, the LEHD LODES Workplace Area Characteristics (WAC), the American Community Survey (ACS), and USPS Change of Address (COA) data—to analyze how the increased remote working phenomenon may impact traffic at workplaces for the 487 ZCTA in our study area.

Our study comprises four major steps:

1. **Destination (Workplace) Analysis:**
   We analyze the trip volume change at workplace destination ZCTAs from the pre-COVID period (2019) to the post-COVID period (2021). This highlights areas where trip volumes dropped the most during COVID and recovered the fastest in the post-COVID period. We

also examine the industry composition in these job destinations to understand the remote work potential for each area.

2. **Origin (Residential) Analysis:**
This analysis assesses work-from-home rate, demographic characteristics, and migration patterns at residential locations. This involves examining factors such as household income, ethnicity, vehicle ownership, housing value, and other variables that can influence remote work trends. Examining migration patterns helps us understand whether increased flexibility in remote working leads to people moving away from job locations to more distant areas.

3. **O-D (Origin-Destination) Analysis:**
We use StreetLight OD flow data (ZCTA to ZCTA) to link destination ZCTAs and origin ZCTAs together. Using OD flow allows us to determine the relative contribution of each origin ZCTA to the all-day traffic at destination ZCTAs. The more traffic sent by a specific origin ZCTA, the more important it is to the composition of workers at the destination ZCTA. Therefore, we use OD flow as weights to weigh work-from-home rates and other origin demographic characteristics (see section 3.4.2 below for more details).

4. **Regression Analysis:**
We conduct regression analysis to identify residential and workplace characteristics associated with higher or lower traffic recovery at destinations. This analysis examines the connection between origin and destination ZCTAs to understand how changes in one area could impact the other, particularly in terms of traffic volume. The regression analysis allows us to statistically test whether the increased work-from-home rate at residences is associated with the decrease in all-day traffic at work destinations.

3.4.2 O-D flow weights

In this section, we explain in detail the method used to apply origin-destination (O-D) flow weights in our analysis. The purpose of using O-D flow weights is to accurately attribute the characteristics of origin ZCTAs to their corresponding destination ZCTAs, based on the volume of traffic flowing between them. The basic principle is that the greater the share of people who commute from a residential location (origin) to a work location (destination), the more the workforce at the destination will resemble the population of the origin. Therefore, ZCTAs contributing greater shares of commuters have a higher weight in estimating the composition of the workforce at the destination. However, StreetLight data only capture vehicle trips and does not differentiate between trip purposes beyond providing an estimated share of trips categorized as home-based work, home-based other, or non-home-based trips. This approach allows us to better understand the impact of residential demographics and behavior on workplace destinations. The application of the O-D flow weights and analysis results can be found in Chapter 4.3 Vanished Trips. To calculate the O-D flow weights we follow these steps:

1. Define variables
   - D_j represents each destination ZCTA (where j ranges from 1 to 487, the total number of destination ZCTAs)
   - O_i represents each origin ZCTA (where i ranges from 1 to 487, the total number of origin ZCTAs).
   - t represents the time period in days (from March 2020 to October 2021).
   - $V_{D_{j,t}}$ represents the total volume of traffic received at destination D_j on day t.
   - $V_{O_i D_{j,t}}$ represents the volume of traffic from origin O_i to destination D_j (O-D flow) on day t..
   - $W_{O_i D_{j,t}}$ represents the weight of traffic from origin O_i to destination D_j on day t.
2. Calculate the total traffic volume at each destination ZCTA for each day t.
$$V_{D_{j,t}} = \sum_{i=1}^{487} V_{O_i D_{j,t}}$$
3. Calculate the O-D flow weight for each origin ZCTA to each destination ZCTA for each day t.
$$W_{O_i D_{j,t}} = \frac{V_{O_i D_{j,t}}}{V_{D_{j,t}}}$$
4. Applying O-D flow weights to characteristics at origin ZCTA for each day t.
   C_{O_i} represent a characteristic of the population at origin O_i (e.g., household income, work-from-home rates, etc.). The weighted characteristic C_{D_j}at each destination D_j for each day t is calculated by summing the weighted contributions from each origin:
$$C_{D_{j,t}} = \sum_{i=1}^{487} (W_{O_i D_{j,t}} \times C_{O_i})$$

We use O-D flows to determine the relative importance of each origin ZCTA to the destination ZCTA. To better explain our methodology, we provide an example of how we traced back from destination ZCTAs to origin ZCTAs using StreetLight daily OD flow data. The example below details the steps taken to calculate O-D flow weights and apply them to our analysis.

1. Data collection:
   - Example Destination ZCTA: 94043 (Mountain View)
   - All day traffic volume received: 151,190
     (Pre-COVID average daily traffic from 12 am to 12 am using StreetLight data)

2. Calculating O-D Weights:

- We collected data on the daily volume of traffic going to ZCTA 94043 from all 487 ZCTAs in our study area.
- The traffic volumes from different origin ZCTAs to the destination ZCTA were calculated to determine their respective shares of the total traffic received at destination ZCTA (Table 3.4.2.1).

Table 3.4.2.1 shows the traffic volumes and corresponding O-D shares for the top sending ZCTAs to destination ZCTA 94043. Figure 3.4.2.1 visualizes the OD flows between origins and the destination ZCTA. The destination ZCTA 94043 (colored yellow in Figure 3.4.2.1) itself is the largest sending origin, contributing 43,866 trips, which accounts for 29% of the total trips received. This indicates that 29% of trips in ZCTA 94043 originate in the same ZCTA 94043 -- a significant amount of local traffic. The second-largest contributor is ZCTA 94040, sending 11,394 trips to 94043, corresponding to 8% of the total daily trips at ZCTA 94043. ZCTAs 95129, 95110, and 94027 each contribute 1% or less of the trips to ZCTA 94043, making their impact on the activity at ZCTA 94043 relatively minor. The cumulative share shows that the top 10 sending ZCTAs account for a little more than half of the total traffic volume. While this shows that most of the traffic is generated locally, it also highlights that almost half of all traffic flow comes from other ZCTAa, contributing very small shares of the total.

This demonstrates the relative importance of high-contributing origin ZCTAs and their substantial influence on destination traffic patterns. For example, an increase in remote work in a highly influential origin ZCTA means fewer commuters commuting to the destination ZCTA, potentially leading to a significant decrease in traffic volume. In contrast, the same increase in remote work in a low-contributing origin ZCTA will have a much smaller impact on the traffic at the destination. By using O-D flows to weight demographics and other characteristics at the origin, we capture fluctuations in these ZCTAs and their impact on destination traffic.

In Chapter 4.3, "Vanished Trips," we will demonstrate how remote work at the origin can be measured at the destination. In Chapter 4.4, "Regression Analysis," we will examine the association between destination traffic recovery and origin characteristics, applying the O-D weights to ensure an accurate representation of the origin ZCTAs' impact.

Table 3.4.2.1. Example of OD weights between origin and destination ZCTAs

origin ZCTA	Trips to 94043	Share of trips received at 94043 (O-D weights)	Cumulative share
94043	43,866	29%	29%
94040	11,394	8%	37%
94041	6,401	4%	41%
94303	6,320	4%	45%
94089	4,834	3%	48%
94087	4,165	3%	51%
95129	1,319	1%	52%
95110	963	1%	53%
94027	258	0.01%	53.01%
...	...	...	...
Total trips received at 94043	151,190	100%	100%

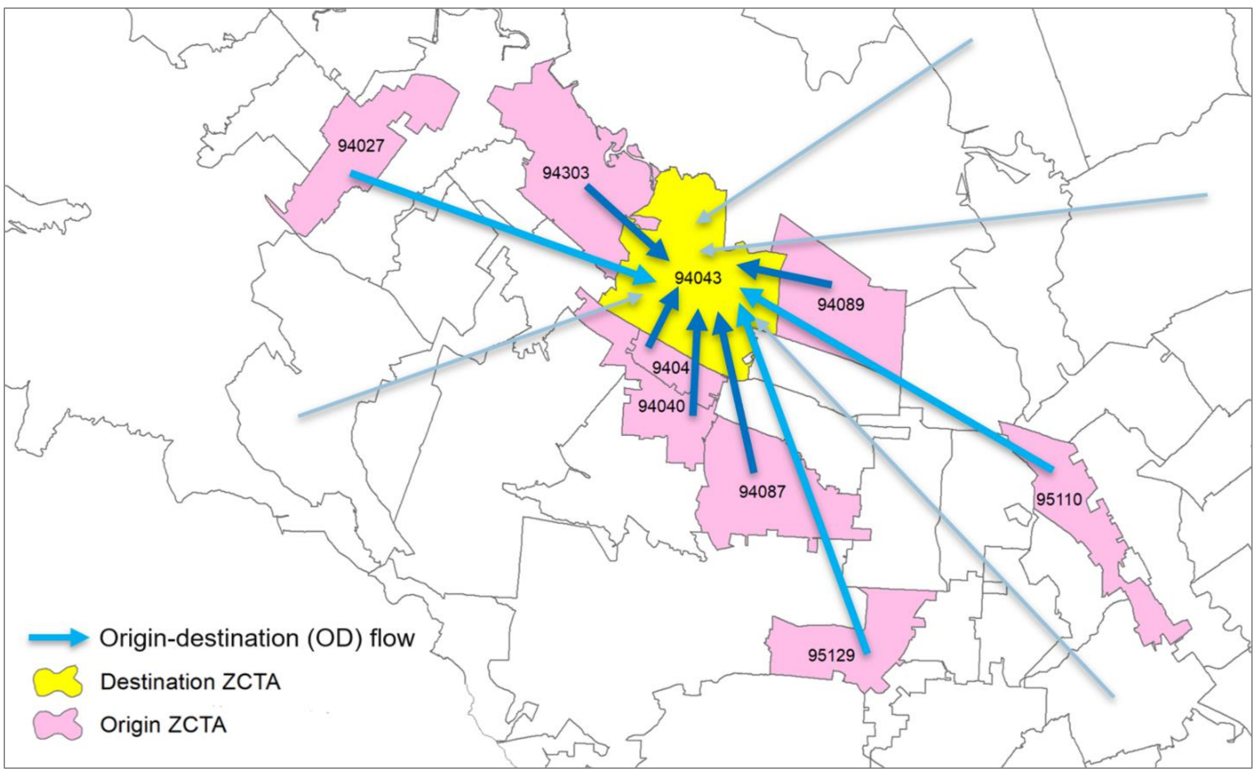

Figure 3.4.2.1. Example of daily OD flows to ZCTA 94043

Chapter 4. Results

This chapter presents the findings from our analysis, focusing on destination and origin characteristics, defining the concept of vanished trips (trip reductions at destinations which can be attributed, in a deterministic way, to work-from-home increases at origins), and a regression analysis to bring all the elements together. In our analysis, we separate between "destination" for workplaces and "origin" for residential locations. This distinction helps us study employment and living conditions separately, providing a better understanding of remote working dynamics. We then use Origin-Destination (O-D) flow weights to link destination and origin characteristics.

Table 4.1 provides a summary of descriptive statistics for key variables in the study, capturing traffic volumes, population changes, work-from-home rates, migration patterns, and job characteristics across different regions. Each variable is presented with the number of observations (Obs.), mean, standard deviation (Std. dev.), percentile values (25%, 50%, 75%), and data source. The unit of analysis for each variable is ZCTA. For numeric variables such as destination traffic volume and total population, the mean represents the average value across all ZCTAs. For percentage change variables, such as Δ Destination traffic volume and Δ % WFH, we calculate the percent change for each ZCTA individually and then report the average of these individual changes. We will discuss each variable in detail in the following subsections.

Table 4.1. Summary of Descriptive Statistics

Variable		Obs.	Mean	Std. dev.	25%	50%	75%	Data Source
Traffic	Destination traffic volume (2019)	487	81,293	61,518	28,953	72,095	119,972	StreetLight 2019, 2021
	Destination traffic volume (2021)	487	64,766	49,838	23,409	56,682	96,558	
	Δ Destination traffic volume	487	-18.3%	12.0%	-24.0%	-18.0%	-13.0%	
Origin	Total population (2019)	491	27,523	19,811	10,495	26,145	39,741	ACS 2015-2019, 2017-2021
	Total population (2021)	488	27,992	19,988	10,717	26,960	40,925	
	Δ Total population	487	2.4%	18.4%	-2.2%	0.9%	4.2%	
	% WFH (2019)	486	6.5%	4.1%	3.9%	5.6%	8.6%	
	% WFH (2021)	486	13.2%	8.3%	7.0%	12.1%	18.1%	
	Δ % WFH	486	6.6%	6.8%	2.3%	5.5%	9.8%	
	Cumulative Migration (2020 to 2021): Total from ZCTA	466	6,241	4,674	2,415	5,598	8,840	USPS COA 2020, 2021
	Cumulative Migration (2020 to 2021): Total to ZCTA	466	5,517	3,941	2,279	5,205	7,781	
	Net Cumulative migration (2020 to 2021)	466	-724	1,438	-1,286	-341	12	

* Numeric variables: the mean represents the average value across all ZCTAs.

* Δ variables: the mean represents the average of individual (ZCTA) percent changes.

Table 4.1. Summary of Descriptive Statistics (continued)

Variable		Obs.	Mean	Std. dev.	25%	50%	75%	Data Source
Destination	Total job (2019)	487	12,608	15,231	3,121	8,655	16,948	LODES WAC 2019
	% Agriculture	487	5.4%	13.5%	0.01%	0.2%	3.2%	
	% Construction	487	14.2%	12.6%	5.0%	10.7%	20.2%	
	% Trade and Transport	487	15.2%	9.4%	8.8%	13.5%	20.2%	
	% Office	487	21.2%	15.5%	10.7%	18.0%	27.2%	
	% Education and Services	487	43.7%	19.7%	29.9%	43.1%	56.1%	

* Numeric variables: the mean represents the average value across all ZCTAs.
* % variables: the mean represents the average of individual (ZCTA) percent.

4.1 Destination Characteristics

In our analysis, "destination" serves as a proxy for workplace areas. Therefore, when we mention “destination,” we are primarily referring to characteristics and trends associated with locations where people go to work, although of course not all trips in those locations are work trips. By analyzing destination characteristics such as traffic recovery and industry composition, we can gain insights into the trip dynamics at places that are job centers and hence (but not exclusively) work locations.

4.1.1 Traffic Recovery at Destination

Table 4.1.1.1 presents the average traffic volumes across different regions for 2019 and 2021, along with the percentage change between these two years, from pre-COVID to post-COVID. The results highlight a general decline in traffic volumes across all regions, with the Bay Area experiencing the largest drop of 20.5%, followed by the Central Valley at 16.4%, and the Comparison counties at 17.6%.

Table 4.1.1.1. Traffic volume by region – average per ZCTA

Variable	Bay Area Counties	Central Valley Counties	Comparison Counties
Destination traffic volume (2019)	97,446	81,519	59,962
Destination traffic volume (2021)	75,810	66,496	48,486
Δ Destination traffic volume (2019 to 2021)	-20.5%	-16.4%	-17.6%
Total ZCTAs	188	155	144

* Numeric variables: the mean represents the average value across all ZCTAs.
* Δ variables: the mean represents the average of individual (ZCTA) percent changes.

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Figure 4.1.1.1 shows the maps of traffic volume in 2019 (left) and traffic recovery in 2021 (right) at destination ZCTAs, based on Streetlight commute flow data for the 2019 and 2021 time periods. The traffic recovery rate is based on the ratio of commute trip flows into the ZCTA, 2021 time period, compared to the 2019 baseline. This data reveals significant regional differences in post-COVID traffic recovery.

In Figure 4.1.1.1, the left map shows higher baseline traffic volumes in the city centers of each county (darker area). The right map color codes indicate recovery levels: blue areas represent ZCTAs with less than 70% recovery, green areas show recovery between 71-80%, yellow areas show recovery between 81-90%, and orange areas show ZCTAs with recovery exceeding 90%. The results show that areas like South Bay, Oakland, and parts of San Francisco have seen a slower recovery, with 2021 traffic volumes remaining below 70% of the 2019 baseline. In contrast, more rural regions in the Central Valley (including San Joaquin, Sacramento, El Dorado, and others) have experienced a quicker recovery, with the 2021 traffic exceeding 90% of the 2019 levels.

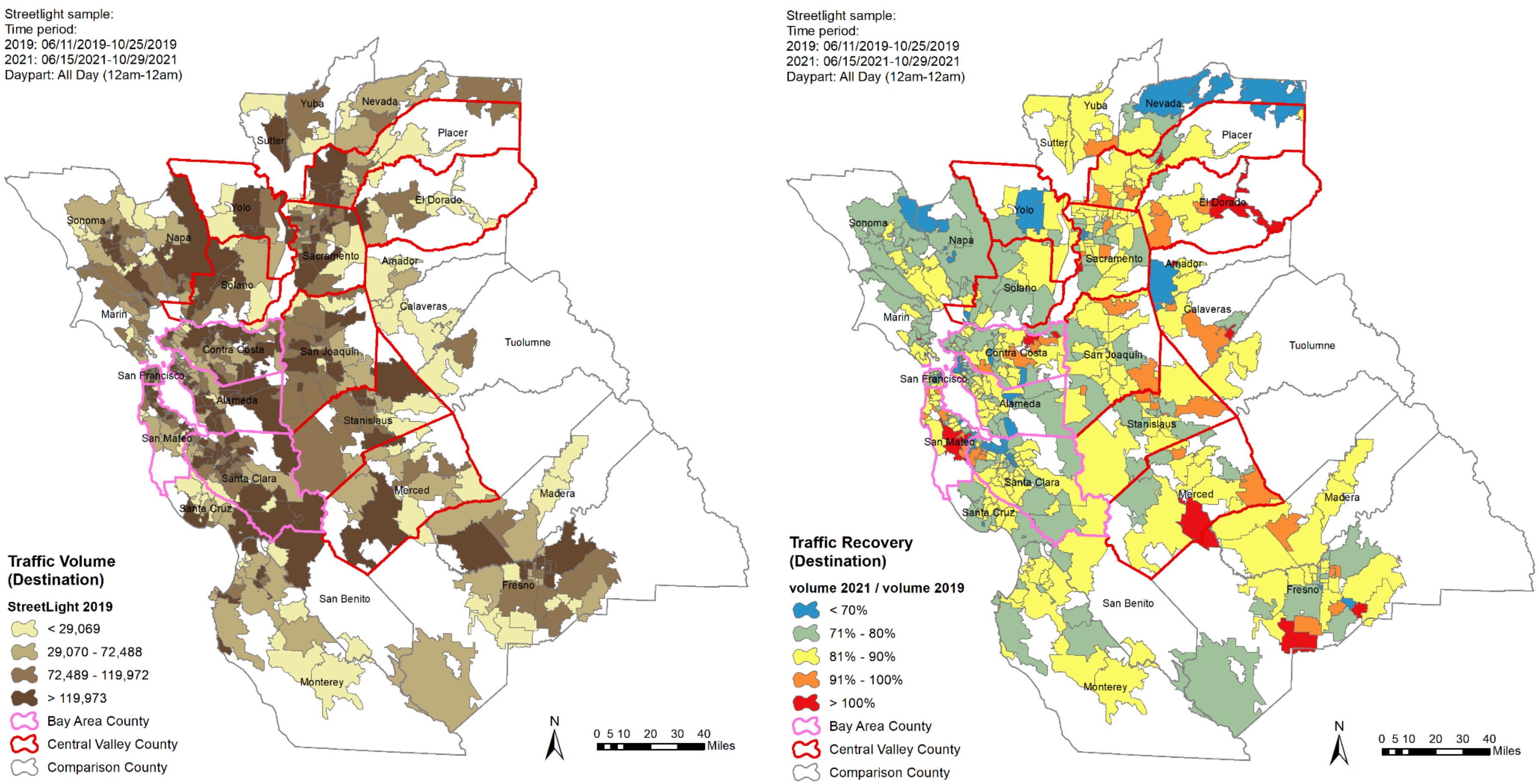


Figure 4.1.1.1. Left: 2019 Traffic volume at destination; Right: Traffic recovery at destination

4.1.2 Industry composition at Destination

The analysis of industry composition within destination ZCTAs is crucial for understanding the economic dynamics across Bay Area and Central Valley Counties. We use data from 2019 LODES WAC (Workplace Area Characteristic) to capture the employment pattern in the pre-COVID period. The results reveal distinct regional differences in employment sectors.

Table 4.1.2.1 shows the total number of jobs and the average share of employment across different industry sectors by region. In 2019, Bay Area Counties had the highest average number of jobs (17,827) per ZCTA. This is significantly more than the average 10,512 jobs per ZCTA reported in Central Valley Counties and the average 8,049 jobs per ZCTA in Comparison Counties, highlighting the Bay Area's larger economic activity compared to the other regions. We found that agriculture is a minor sector in the Bay Area, with only an average of 0.3% of jobs per ZCTA, but is much more significant in the Central Valley and the Comparison counties, where it accounts for an average of 6.8% and 10.5% of jobs per ZCTA respectively. Construction jobs are relatively more evenly distributed, with an average of 12.5% of jobs per ZCTA in Bay Area, 16.3% in the Central Valley, and 14.3% in other counties. Trade and Transport jobs are most prevalent in the Central Valley, accounting for an average of 18.2% jobs per ZCTA. In contrast, this sector only represents approximately an average of 14% of jobs per ZCTA in both the Bay Area and the Comparison counties. Office jobs are more common in the Bay Area, comprising an average of 26.1% of jobs per ZCTA there, compared to an average of 18.6% of jobs per ZCTA in the Central Valley and 17.6% in the Comparison counties. The Education and Services sector are most prevalent in the Bay Area, comprising 46.9% of jobs per ZCTA, compared to 39.9% in the Central Valley and 43.6% in other counties.

These statistics illustrate the different industrial characteristics of each region, revealing how economic activities are tailored to the urban or rural contexts of the respective areas.

Table 4.1.2.1. Industry composition by region – average per ZCTA

Variable	Bay Area Counties	Central Valley Counties	Comparison Counties
Total job (2019)	17,827	10,512	8,049
% Agriculture	0.3%	6.8%	10.5%
% Construction	12.5%	16.3%	14.3%
% Trade and Transport	13.9%	18.2%	13.8%
% Office	26.1%	18.6%	17.6%
% Education and Services	46.9%	39.9%	43.6%
Total ZCTAs	188	155	144

* Numeric variables: the mean represents the average value across all ZCTAs.

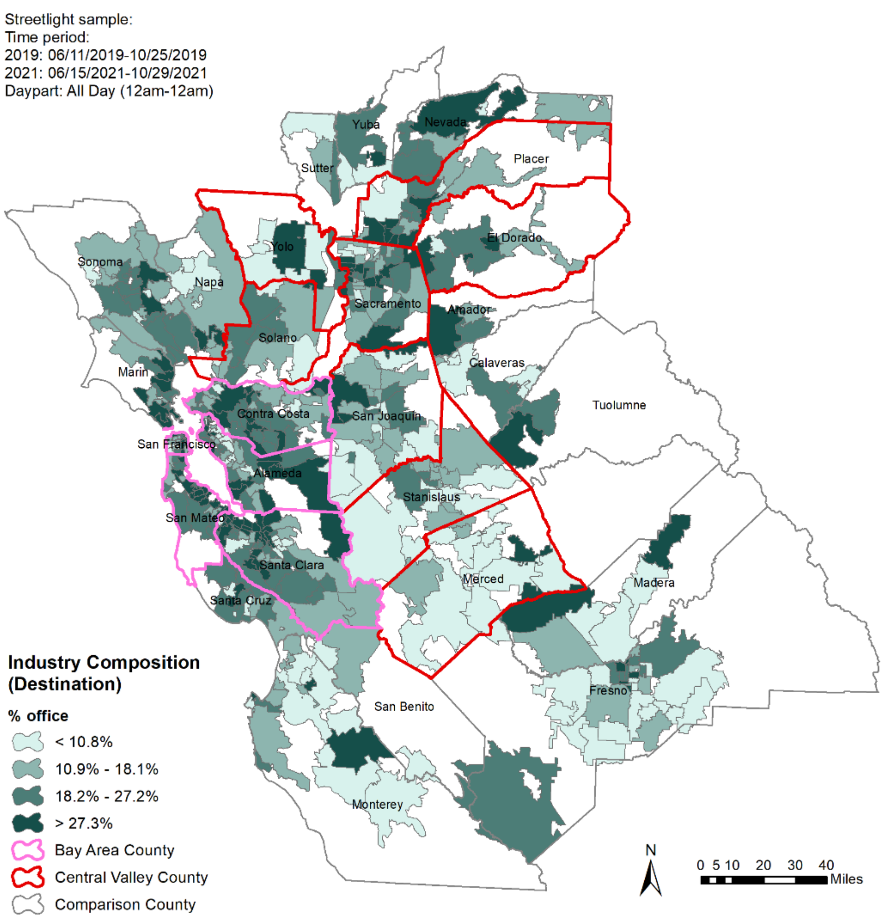
* % variables: the mean represents the average of individual (ZCTA) percent.

The ability to work remotely depends largely on the type of work people do, which is, in turn, highly correlated with workplace characteristics. Understanding this association is crucial for addressing the intertwined relationship between remote working, migration, and commuting. The effect of occupation type on the potential to work remotely has been documented in prior literature (Dingel and Neiman, 2020). Previous research (e.g., Brynjolfsson et al., 2020; Wang et al., 2023) confirms that workers in office and desk-based roles are associated with a higher likelihood of being able to work remotely, while those in service-related jobs and manual labor are more likely to have a negative association with remote work.

Figure 4.1.1.1 illustrates the potential for remote working based on industry types. The left map shows the share of office jobs (high remote working potential) in each ZCTA, while the right map shows the share of agriculture, construction, trade, and transport jobs (low remote working potential).

In the left map, the dark blue areas indicate ZCTAs where office jobs constitute more than 27.3% of employment. These office jobs are concentrated in the city centers of each county and are more clustered in the Bay Area than in the Central Valley and the Comparison counties. The right map shows the share of agriculture, construction, trade, and transport jobs per ZCTA. The dark red areas represent ZCTAs where these jobs make up more than 47.2% of employment. Unlike office jobs, agriculture, construction, trade, and transport jobs are more concentrated in rural areas of the Central Valley and Comparison counties, with very few in the Bay Area.

The spatial distribution of jobs indicates that the Bay Area has a higher potential for remote working due to the concentration of office jobs, while the Central Valley and the Comparison counties have a higher proportion of jobs that requires manual labor and are harder to perform remotely, such as those in agriculture, construction, trade, and transport.



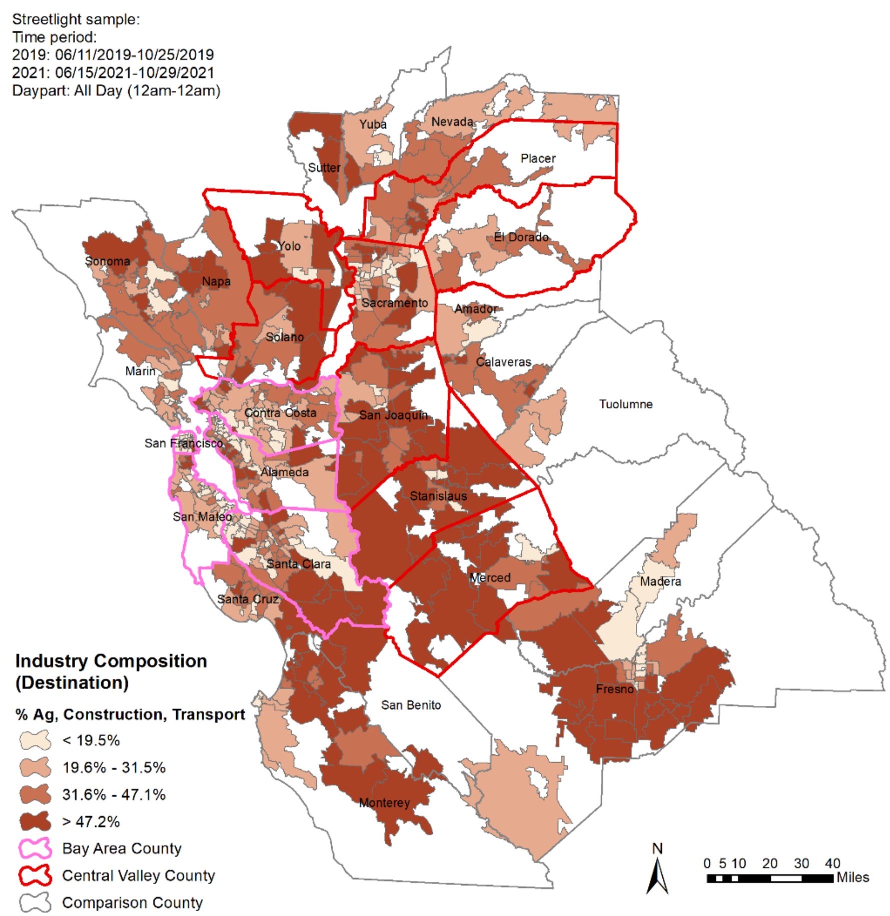


Figure 4.1.1.1. Left: Share of office jobs; Right: Share of agriculture, construction, and trade and transport jobs

4.2 Origin Characteristics

As mentioned in the previous section, the term "origin" is used to describe the residential locations from which individuals commute. By analyzing origin data, we can gain insights into the demographic characteristics of these residential areas. This information also helps us learn more about the socio-economic background of the residents. In this section, we will discuss trends in remote working (work-from-home), general demographics, and migration patterns.

4.2.1 Work-from-home Growth at Origin

We collect work-from-home data from ACS's survey on "Journey to Work", which asks respondents to select their usual mode of transportation to work from the previous week. Answer options include car, truck, van, bus, subway, commuter rail, light rail, ferryboat, taxi, motorcycle, bicycle, walking, and working from home.

Table 4.2.1.1 presents the results from ACS. The average share of workers working from home (WFH) in 2019 (pre-COVID) and 2021 (post-COVID) across our study regions shows a substantial increase in remote work. In the Bay Area, WFH rates increase the most, by 10 percentage points, from 6.6% in 2019 to 16.6% in 2021. In Central Valley Counties, the increase was from 5.8% to 9.8%. In Comparison Counties, rates went up from 7.2% to 12.3%. These changes show how the Bay Area's technological and professional service industries, which adapted quickly to remote work, are associated with the increase in WFH rates.

Table 4.2.1.1. Share of remote workers by region – average per ZCTA

Variable	Bay Area Counties	Central Valley Counties	Comparison Counties
% WFH (2019)	6.6%	5.8%	7.2%
% WFH (2021)	16.6%	9.8%	12.3%
Δ % WFH (2019 to 2021)	10.0%	4.0%	5.0%
Total ZCTAs	188	155	144

* % variables: the mean represents the average of individual (ZCTA) percent.

* Δ variables: the mean represents the average of individual (ZCTA) percent changes.

Figure 4.2.1.1 presents the share of work-from-home (WFH) rates at the ZCTA level for our study region, comparing pre-COVID in 2019 on the left with post-COVID in 2021 on the right. We grouped the 2019 WFH rates by quartile and applied the same categorization to 2021. The dark blue color indicates a WFH rate of more than 8.8%, which shows the most growth in the urban areas of each county.

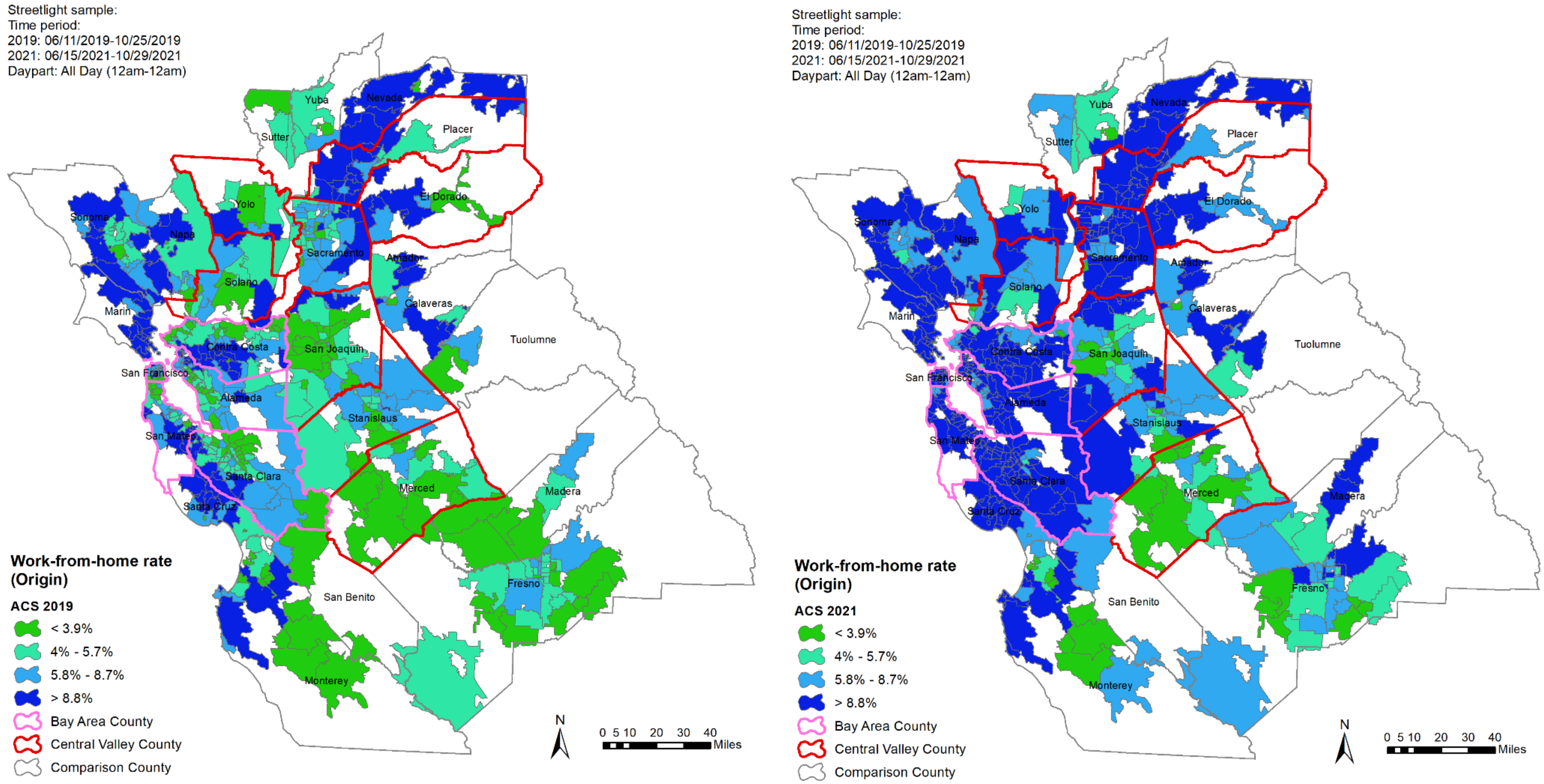
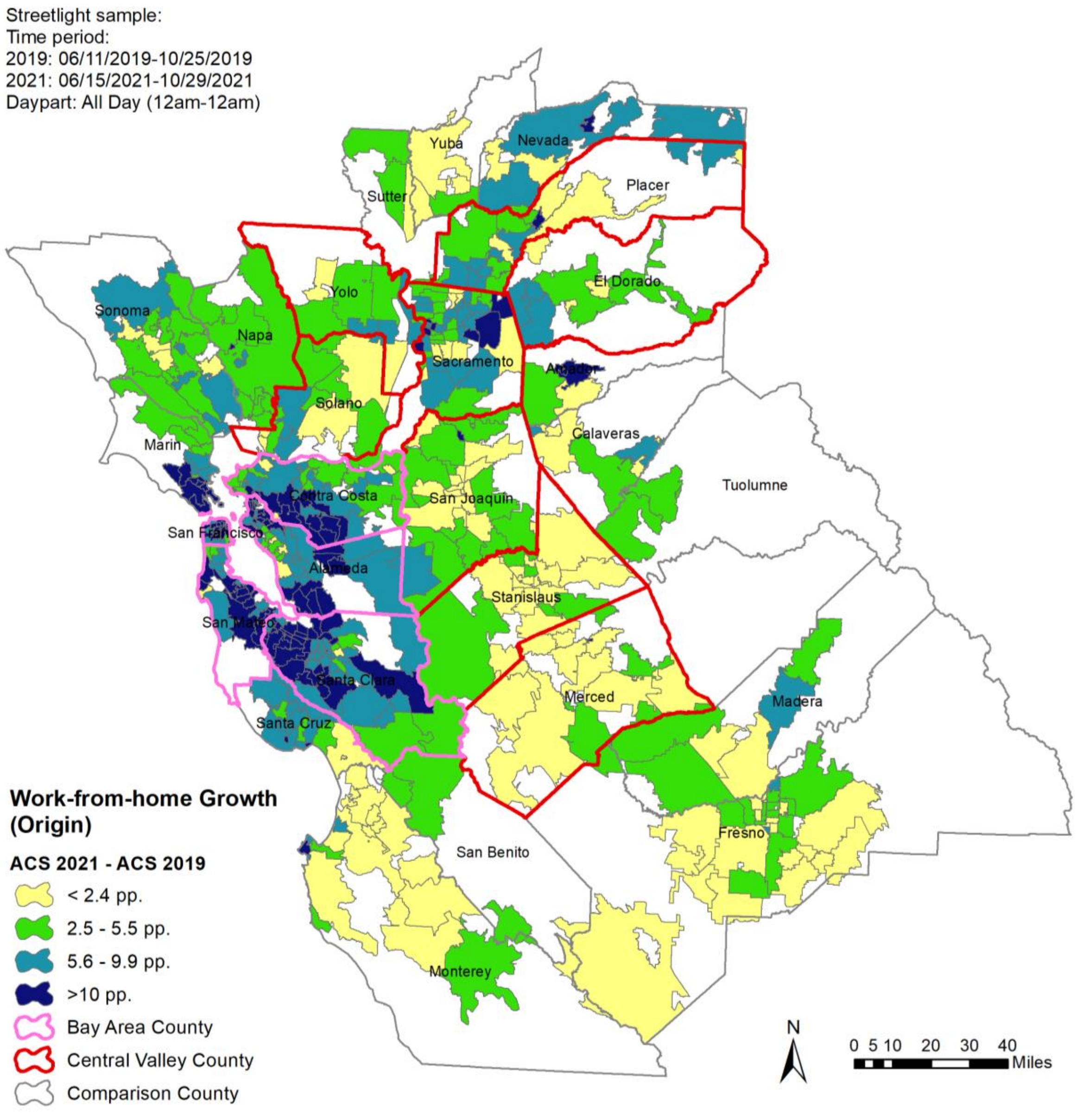


Figure 4.2.1.1. Share of workers working from home in 2019 (left) and 2021 (right)

Figure 4.2.1.2 shows the Work-from-home growth from 2019 to 2021. Compared to pre-COVID, the areas with WFH growth more than 10 percentage points clustered mostly in the South Bay Area, including the cities of Mountain View, Santa Clara, Sunnyvale, Fremont, etc., with pockets in relatively outlying locations that include suburbs/exurbs of Sacramento. This shift highlights the tech industry's role in advancing remote work.



* pp.=percentage points

Figure 4.2.1.2. Work-from-home growth at origin (ACS)

4.2.2 Demographic Characteristics at Origin

Table 4.2.2.1 presents the general demographic characteristics of our study regions. The average total population per ZCTA in 2019 was approximately 19,000 in each region. Median ages varied slightly, with Central Valley being the youngest (37.5 years), followed by Bay Area (39.7 years), and the Comparison counties being the oldest (41.1 years). Bay Area ZCTAs also had the highest average percentage of non-white residents at 58.4%, compared to 52.8% in Central Valley and 46.2% in the Comparison counties.

Bay Area ZCTAs reported the highest average of median income at $120,901, which is significantly more than Central Valley ($71,437) and the Comparison counties ($77,673). The poverty rates were lower in the Bay Area (an average of 9.0% per ZCTA) compared to 14.1% and 14.2% in Central Valley and Comparison counties. The average percentage of college graduates was also higher in the Bay Area at 53.5% per ZCTA, versus 26.2% in Central Valley and 31.6% in Comparison counties. This reflects the Bay Area's education and economic advantages, likely due to a concentration of high-paying jobs in tech and professional services. Housing costs also reflect this trend, with Bay Area's costs nearly double those of other regions: a median rent of $2,121 and median home value of $995,660, compared to $1,334 and $362,846 in Central Valley, and $1,465 and $543,242 in the Comparison counties. The median number of rooms per household remains consistent across all regions at about 5.5.

Commute mode also varied, with an average of 13.5% of workers in Bay Area ZCTAs using public transit, compared to only 1.7% and 2.3% in Central Valley and Comparison counties respectively. The share of households without a vehicle was highest in the Bay Area at an average of 9.7% per ZCTA, likely due to more accessible public transit options, compared to 5.8% in Central Valley and 5.3% in Comparison counties.

Table 4.2.2.1. 2019 Demographic characteristics by region – average per ZCTA

Variable	Bay Area Counties	Central Valley Counties	Comparison Counties
Total population	19,532	19,232	18,427
Median household income	120,901	71,437	77,673
Median age	39.7	37.5	41.1
Median rent	2,121	1,334	1,465
Median home value	995,660	362,846	543,242
Median number of rooms	5.2	5.5	5.2
% Non-white	58.4%	52.8%	46.2%
% Commute by public transit	13.5%	1.7%	2.3%
% Poverty	9.0%	14.1%	14.2%
% College graduated	53.5%	26.2%	31.6%
% No vehicle	9.7%	5.8%	5.3%
Total ZCTAs	188	155	144

* Numeric variables: the mean represents the average value across all ZCTAs.

* % variables: the mean represents the average of individual (ZCTA) percent.

4.2.3 Migration at Origin

Cumulative migration refers to the total number of individuals moving into and out of specific geographic areas over a set period. In our study, we examine cumulative migration at the ZCTA level to understand how residential patterns have shifted during the COVID-19 pandemic, from March 2020 to October 2021.

We use USPS change of address (COA) data to track migration patterns at the ZCTA level. The COA data only records moves within the US and does not include people relocating from abroad. This dataset records the total number of COA requests submitted for each 5-digit ZIP Code monthly. To ensure consistency with our other data, we convert these ZIP codes into ZCTAs. The COA data have three categories on change of address requests: family, individual, and business. For our analysis, we only used Family and Individual move types, excluding Business COA requests as they do not represent residential moves. We converted family moves into individual counts by multiplying the number of Family COA requests by 2.5, using the average household size from the Census Bureau. This factor provides a more accurate representation of the total number of individuals moving. Individual COA requests were counted as one individual each. By summing thse adjusted family requests and the individual requests, we obtained the total number of individuals who submitted COA requests each month over the past four years. The net migration rate during COVID-19 (from March 2020 to October 2021) is then calculated using the following equation:

$$Cumulative\ net\ migration\ rate = \frac{total\ moves\ to\ ZCTA - total\ moves\ from\ ZCTA}{total\ population\ at\ ZCTA\ in\ 2020}$$

Calculating net migration helps us compare the inflow of new residents to the outflow of existing residents relative to the total population within each ZCTA. A positive net migration rate indicates more people moving into the area than leaving, while a negative rate suggests a higher number of leaving than entering.

Table 4.2.3.1 provides an overview of the cumulative migration patterns across different regions from March 2020 to October 2021. It includes both the total net migration (total persons) and the net migration rate (standardized by ZCTA population). This standardization allows comparisons across ZCTAs with varying population sizes.

The total ZCTA population for the three regions is quite similar, with each having around 19,000 persons. The Bay Area Counties had the highest number of both move-outs (8,248) and move-ins (6,774), resulting in the largest net cumulative migration loss of 1,473 people. The Central Valley and Comparison counties experienced smaller inflows and outflows, resulting in a net loss of around 200 people each.

In the Bay Area Counties, the standardized cumulative migration rate from 2020 to 2021 shows a net loss of 4 people per 100 residents. The result indicates a higher outflow from the Bay Area, potentially driven by factors such as high living costs and the more remote work, which allow residents to relocate to more affordable regions. In contrast, the Central Valley and Comparison counties experienced smaller net losses, with a net loss of 1 person per 100 residents.

Table 4.2.3.1. Cumulative migration by region – average per ZCTA

Variable		Bay Area Counties	Central Valley Counties	Comparison counties
Number of Persons	Cumulative outflow (2020 to 2021): Total from ZCTA	8,248	5,660	4,075
	Cumulative inflow (2020 to 2021): Total to ZCTA	6,774	5,414	3,861
	Cumulative Net migration (2020 to 2021)	-1,473	-246	-214
Standardized by ZCTA population	Cumulative outflow rate (2020 to 2021): Total from ZCTA	0.25	0.20	0.19
	Cumulative inflow rate (2020 to 2021): Total to ZCTA	0.21	0.19	0.18
	Cumulative Net migration rate (2020 to 2021)	-0.04	-0.01	-0.01
Total ZCTAs		185	150	131

Figure 4.2.3.1 shows a map of the cumulative net migration rate at origin ZCTAs. The yellow color indicates a net migration loss of more than 4 people per 100. The orange color indicates a net migration rate between -3.9 and -1.7 people per 100. The brown color represents a net migration gain between -1.6 and 0.1 people per 100. The dark brown color indicates a net migration gain of more than 0.2 people per 100.

We found that downtown areas and city centers in San Francisco, the South Bay area, and Sacramento experienced negative cumulative net migration, indicating more people moving out than moving in. This trend suggests that urban cores, which are traditionally high-density and often more expensive, are losing residents. Contributing factors could be the high cost of living, the shift to remote work, and the desire for more space and affordability.

In contrast, the suburbs and exurbs of these counties saw a positive net migration, with more people moving in than exiting. These areas are likely attracting residents due to their relatively lower housing costs, larger living space, and better living environments. This shift reflects a trend of people prioritizing quality of life, especially with the increased flexibility of remote work arrangements in the post-pandemic era.

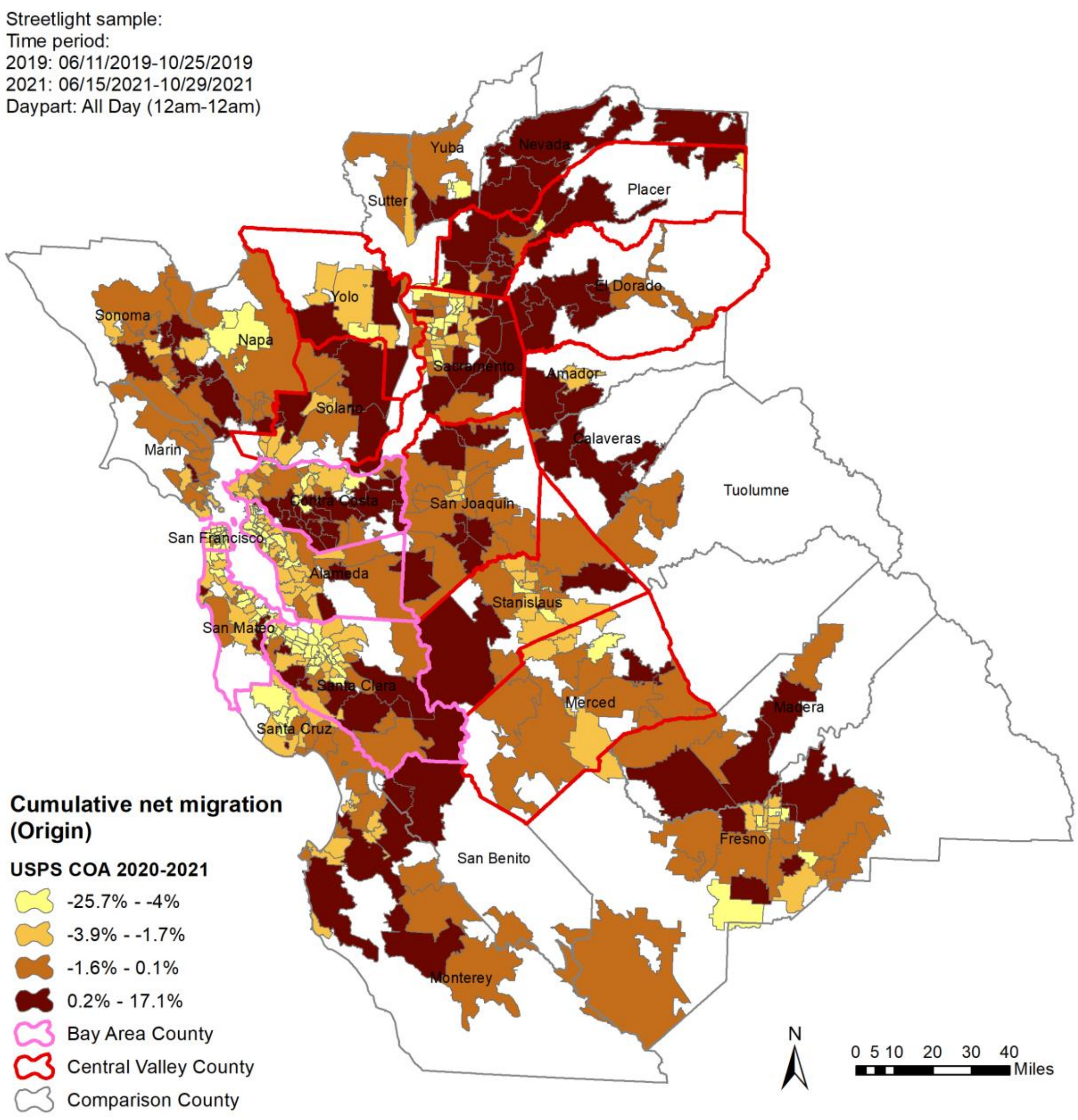


Figure 4.2.3.1. Cumulative net migration rate at origin

4.2.4 A National View of Migration

The trends described above can be placed in context with data on national migration trends. The US Census Bureau's Current Population Survey (CPS) allows an analysis of migration trends, for counties, at a national level.

Descriptive analysis of CPS data from 2010–2023 reveals the following MSA-level migration trends. We find evidence of large metropolitan county out-migration, and in-migration to medium, small, and very small MSAs, supporting existing research (i.e., Ramani and Bloom, 2021; Liu and Su, 2021). Additionally, rural counties have seen increasing population inflows and lead all MSAs in domestic migration rate, relative to population size. Using Census population counts and OMB metropolitan delineation files, we organize counties into five groups based on 2023 population: the top-15 most populous MSAs, MSAs ranked 16–30, MSAs ranked 31–50, MSAs ranked 51–100, and completely rural counties or counties with a population of less than 2,500. For reference, we add one additional group comprised of counties in the San Francisco and New York metropolitan areas, as the literature identifies those two cities as the most affected by WFH due to their extensive knowledge agglomerations, density, and housing costs.

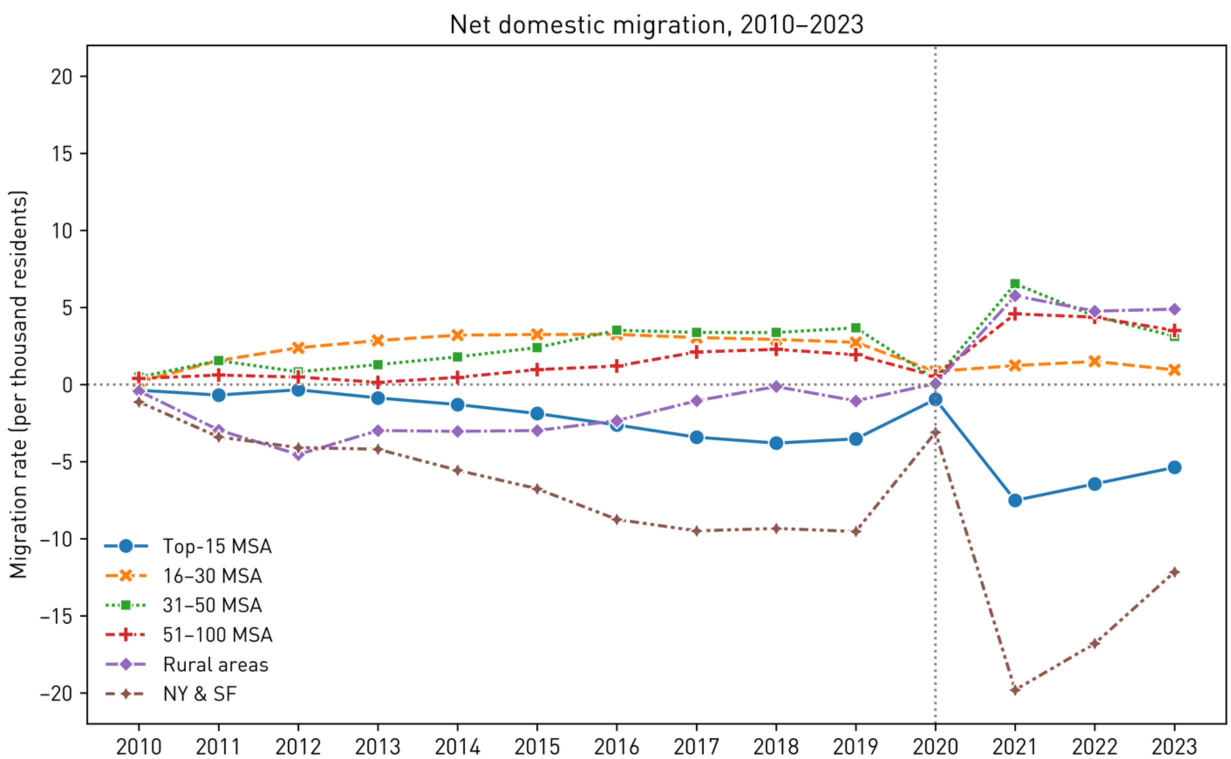


Figure 4.2.4.1. Net domestic migration rate

Examining domestic migration flows reveals a sharp divergence in migration rate following COVID. Figure 4.2.4.1 shows the domestic migration rates in the largest cities drop sharply between 2020 and 2021, reaching approximately -7 outmigrants per thousand residents. San Francisco and New York counties experienced the largest domestic outmigration, reaching nearly -20 in 2021 before rebounding to a still substantial –11. However, these large cities were experiencing increasing domestic outmigration rates prior to Covid, suggesting that the pandemic and WFH might have exacerbated already-existing patterns, or led to pent up demand for locational change that exploded in 2021 and 2022. In this latter scenario. The 2023 data reflect a return to pre-Covid trends.

By contrast, most other groups experienced increases in domestic migration rate and remained above 0, indicating growth following the pandemic. The MSAs 16–30 saw little change in domestic migration through 2020, while MSAs 31–50 and 51–100 experienced increased inflows above pre-pandemic levels. Within rural areas, 2020 marks the end of at least a decade of domestic outmigration; in 2021 rural areas began to gain domestic migrants at a rate that has remained relatively stable through 2023. Taken together, the relatively parallel trends pre-pandemic and symmetrical divergence afterwards suggests that Americans are flowing out of large cities, mainly into smaller metros and rural counties.

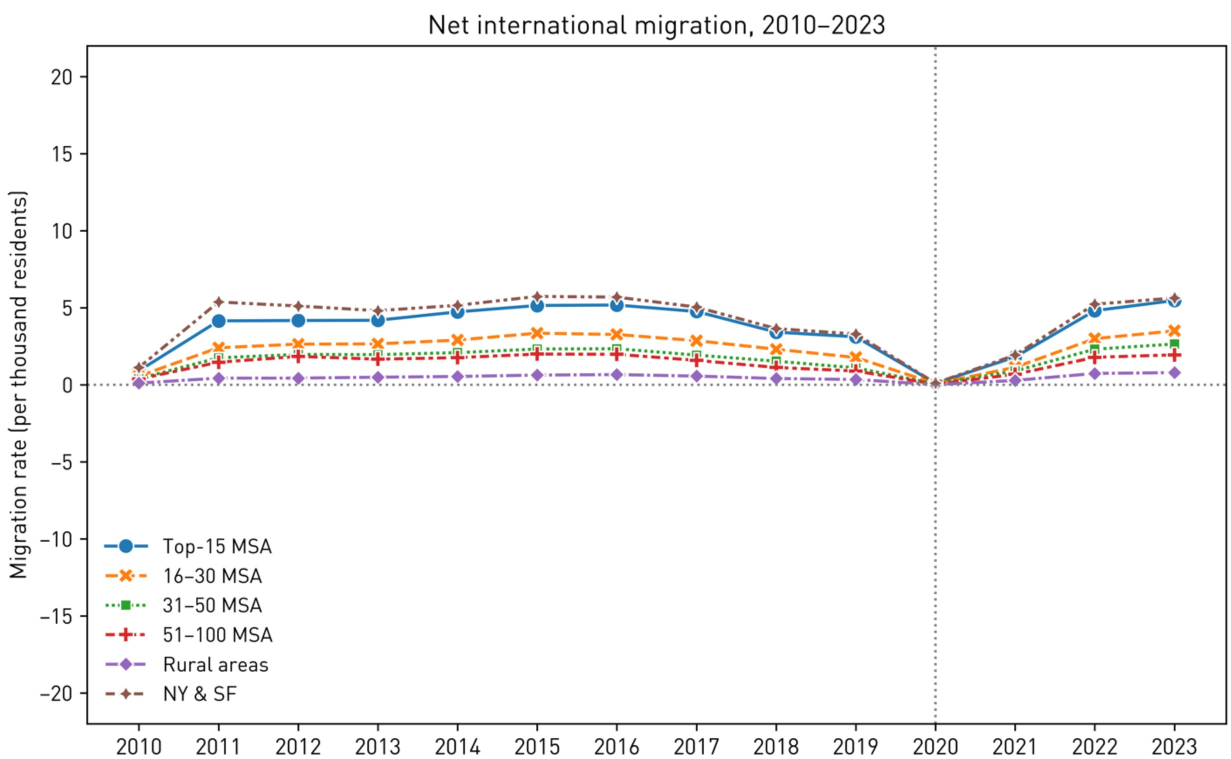


Figure 4.2.4.2. Net international migration rate

International migration rates show less variation through the pandemic. International migration clearly favors large metropolitan counties, which, despite a dip towards zero in 2020 due to pandemic restrictions, consistently outpaces other county groups. This trend is expected, as international immigrants typically locate in urban areas for increased work opportunities and a greater likelihood of familial connections. With rates of nearly 5 for the largest MSAs, international migration helps to fill-in the gap left by domestic outmigration, keeping overall population more stable for these counties than would otherwise be the case. The overall change in migration patterns is depicted in Figure 4.2.4.3 below, which demonstrates the larger magnitude of domestic population movement relative to international.

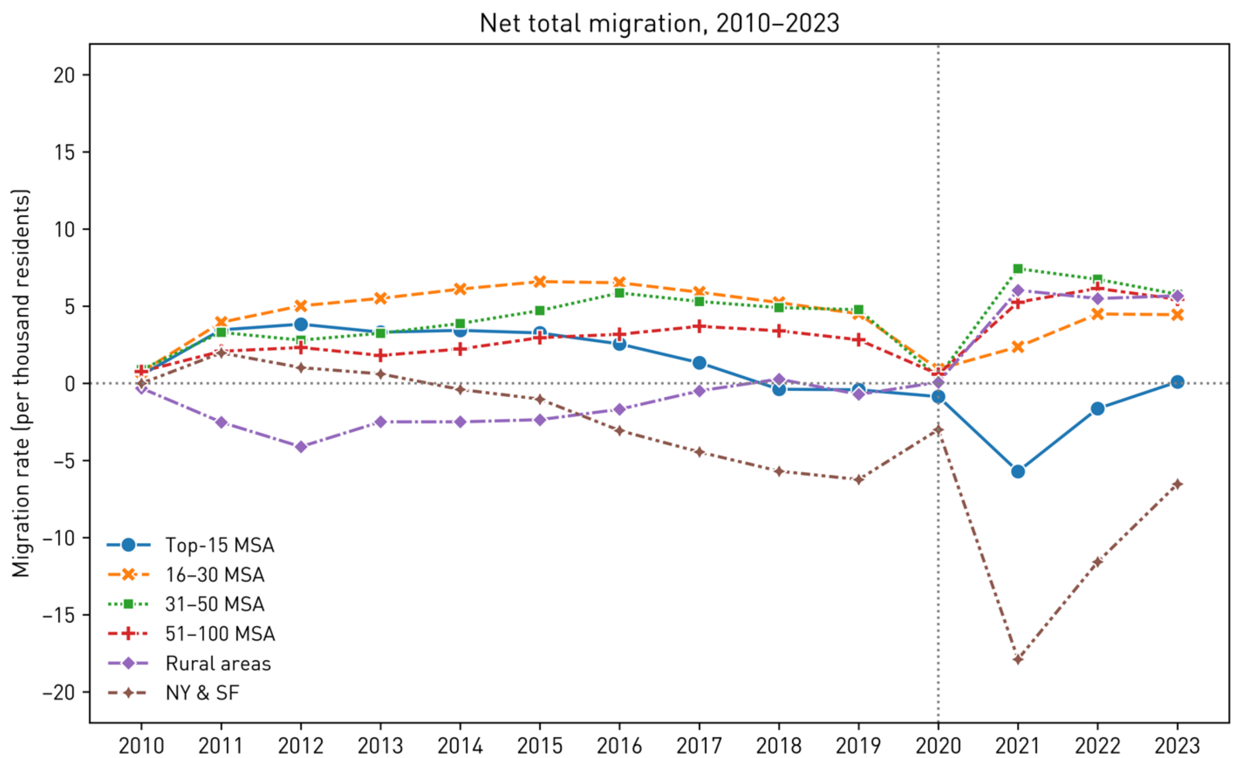


Figure 4.2.4.3. Net total migration rate

Turning next to California, we map net migration rates on the county--level, comparing 2019 and 2023 to provide a snapshot of pre-pandemic flows relative to the least Covid-impacted data in the post-pandemic era. Figure 4.2.4.4. depicts that California counties are not just losing population, but that many of the counties that were growing pre-pandemic (primarily concentrated in the North and Sierra Nevada foothills) are now shrinking. Figure 4.2.4.5 shows the same data restricted to Bay Area,Central Valley, and adjacent counties in the study area. In this smaller sample, we see the same trends in miniature, with most counties continuing to experience net migration outflows and slowing or ceasing their inflows. Notably, only two counties moved from net population outflows to inflows: San Francisco County, which grew from -1.8 to 0.34 total migrants per thousand residents thanks to positive international migration, and Fresno County, which jumped from a -3.8 to 11.4 migration rate, due to increasing domestic inflows. Along with the MSA-level migration data presented above, it is apparent that the outmigration from the San Francisco-Oakland-Fremont MSA is driven primarily by outflows from San Mateo, Alameda, and Contra Costa counties, not necessarily the metropolitan core itself. Meanwhile, in the Sacramento-Roseville-Folsom MSA, only Placer County continued to gain residents while Sacramento and El Dorado counties went from positive to negative net migration rates.

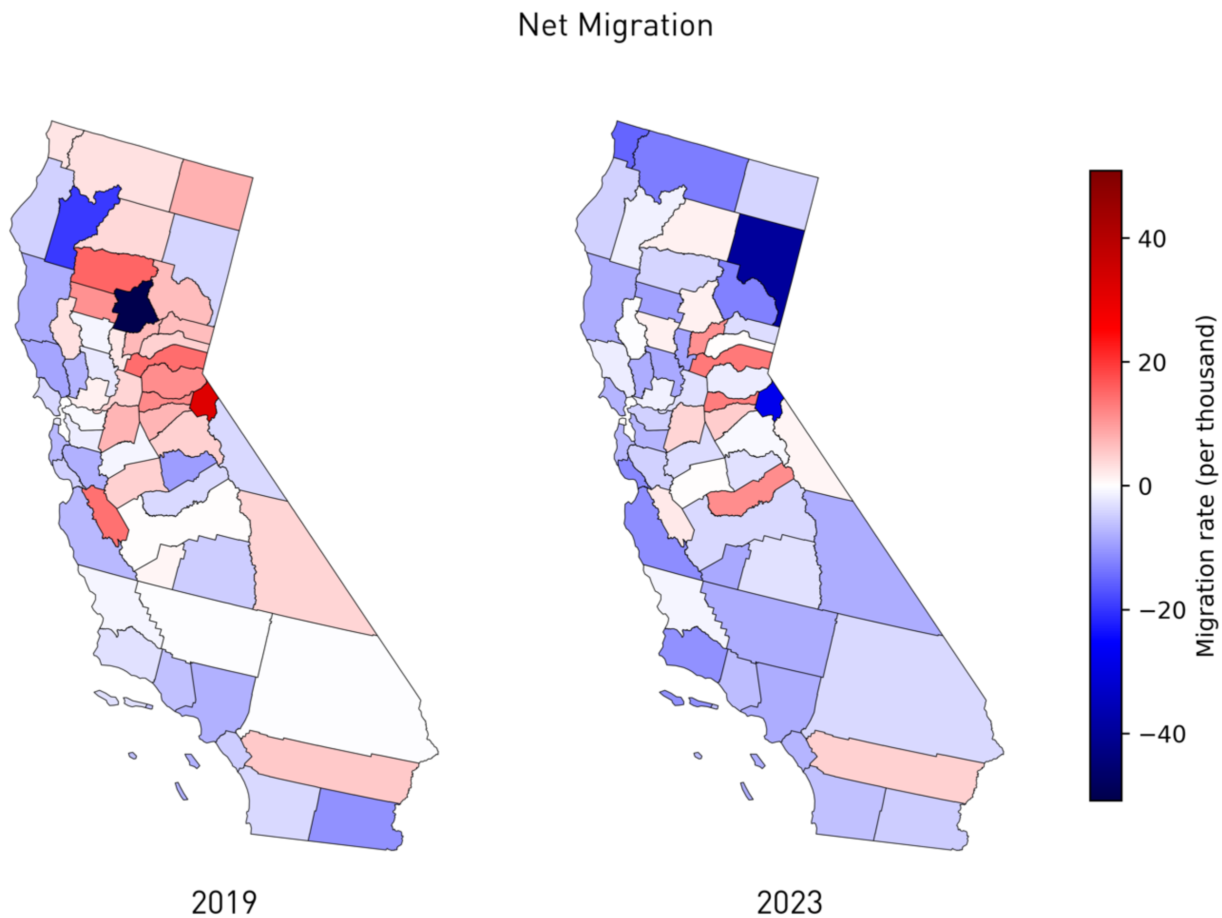


Figure 4.2.4.4. California county net migration rate

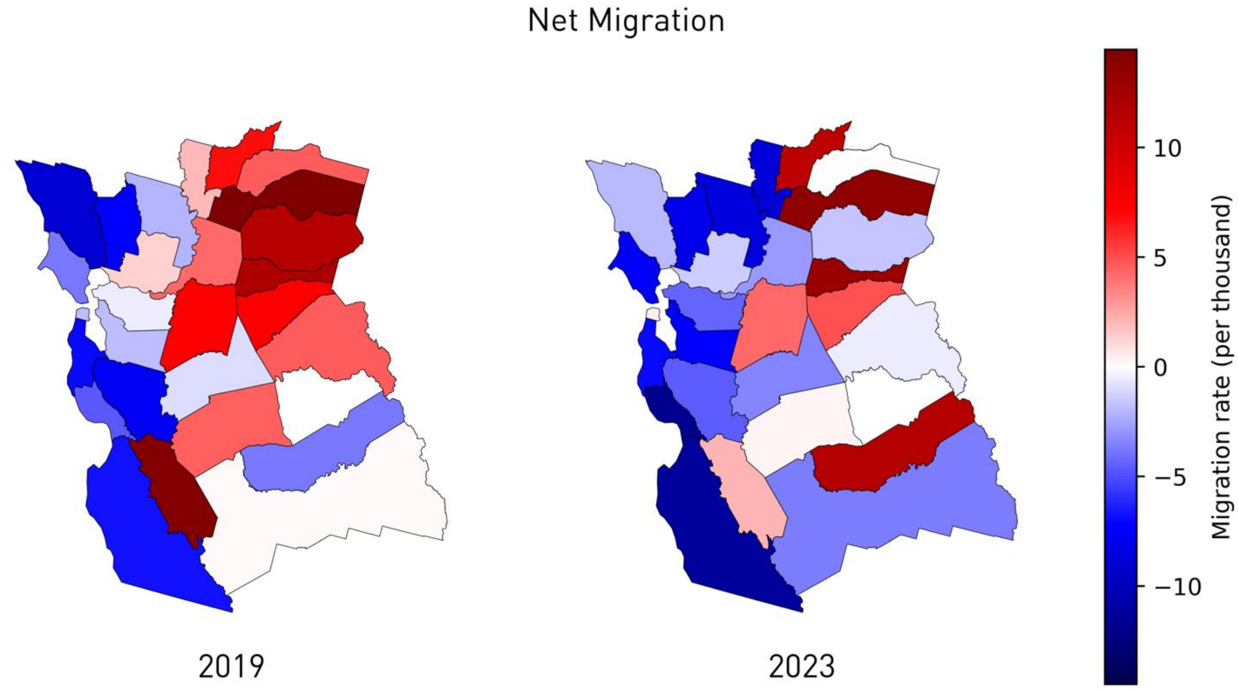


Figure 4.2.4.5. Study area county net migration rate

4.3 Vanished Trips at Destination

To establish a connection between the observed traffic recovery at destination ZCTAs (workplaces) and the increasing trend of remote work at trip origins (residences), we use Origin-Destination (O-D) flows to weight the work-from-home characteristics back to origin ZCTAs. This methodology is detailed in Chapter 3.4.2 "O-D Flow Weights." Our underlying assumption is that, in the absence of COVID-19, the O-D pattern in 2021 would mirror that of 2019. Thus, any reduction in trips (vanished trips) to the destination can be attributed to the increase in remote work at the origin. In order words, “vanished trips” measures the share of the decrease in trips that is attributed to an increase in remote work. We use the following equation to estimate this phenomenon:

$$2021\ vanished\ trips_{jt} = W_{jt} = \sum_{i=1}^{n} \{ (\ 2021\ \%\ wfh_i - 2019\ \%\ wfh_i) \ *\ 2019\ OD_{ijt} \}$$

i = origin ZCTA
j = destination ZCTA
t = day
W= vanished trips
wfh= share of workers working-from-home
OD= origin-destination flow

Vanished trips are a construct—the estimated number of trips to the destination that would vanish if changes in work-from-home rates directly result in changes in traffic flows. We use O-D flows to weight the change of workers working-from-home at origin ZCTAs. However, StreetLight data only capture vehicle trips and does not differentiate between trip purposes beyond providing an estimated share of trips categorized as home-based work, home-based other, or non-home-based trips. O-D flow weights provide the relative importance of each origin ZCTA to the destination ZCTA. By applying the O-D weights, we can accurately attribute changes in traffic volumes at destination ZCTAs to the increase in remote work at origin ZCTAs. For example, if origin ZCTA A contributes 30% of the total trips received at destination ZCTA C, and origin ZCTA B contributes only 1%, then an increase in remote workers would have a significantly different impact on the traffic volume at destination ZCTA C from these two origins. Specifically, under the assumption outlined above, a rise in remote workers in ZCTA A could reduce up to 30% of the traffic volume at destination ZCTA C, while a similar increase in remote workers in ZCTA B would only reduce up to 1% of the traffic.

Table 4.3.1 presents the descriptive statistics for vanished trips along with related information on destination traffic and work-from-home (WFH) rates from analyses in previous sections. Although destination traffic and origin WFH rates cannot be directly linked, we use vanished trips (O-D weighted WFH growth) to establish this connection.

The volume of vanished trips, which represents the estimated number of trips that no longer occur due to increased remote working, was highest in the Bay Area at 10,183 per ZCTA, followed by 4,324 in the Central Valley Counties, and 2,873 in the Comparison Counties. When examining the share of vanished trips as a percentage of the 2019 baseline destination traffic volume, the Bay Area Counties experienced the most significant impact with 13.6% of trips vanishing (which is the average for the Bay Area ZCTAs). This is in contrast to the Central Valley and Comparison counties, which saw ZCTA averages of 6.7% and 9.7% of their 2019 traffic volume vanish, respectively. These vanished trip volumes align with the observed increases in the work-from-home (WFH) rates and the decreases in destination traffic volumes.

The variable, "Share of Vanish Trips to Traffic Drop," represents the proportion of vanished trips relative to the overall reduction in traffic volume. It indicates how much of the traffic decline can be attributed to the increase in remote work, with Bay Area Counties showing the highest share (64.9% average for the Bay Area ZCTAs), suggesting that a significant portion of their traffic drop is due to increased work-from-home phenomenon. Central Valley Counties and Comparison Counties show lower shares, at 39.4% and 31.5% respectively, indicating a less impact of remote work on their traffic volumes.

Table 4.3.1. Descriptive statistics for vanished trips – average per ZCTA

Category	Variable	Bay Area Counties	Central Valley Counties	Comparison Counties
Destination Traffic	Destination traffic volume (2019)	97,446	81,519	59,962
	Destination traffic volume (2021)	75,810	66,496	48,486
	Δ Destination traffic volume (2019 to 2021)	-20.5%	-16.4%	-17.6%
Origin WFH Rate	% WFH (2019)	6.6%	5.8%	7.2%
	% WFH (2021)	16.6%	9.8%	12.3%
	Δ % WFH (2019 to 2021)	10.0%	4.0%	5.0%
Vanish Trips	Vanish trips volume	10,183	4,324	2,873
	Share of Vanish trips: Vanish trips / 2019 destination traffic volume	13.6%	6.7%	9.7%
	Share of vanish trips to traffic drop: Vanish trips / (2021 traffic volume – 2019 traffic volume	64.9%	39.4%	31.5%
Total ZCTAs		188	155	144

4.5 Regression Analysis

After weighting all trip origin demographic characteristics to the destination using Origin-Destination (OD) flows (per the method in Chapter 3.4.2 “O-D Flow Weights”), we estimate the correlation between changes in traffic volume at the destination and the characteristics at their respective origin ZCTAs. The hypotheses we are testing in our regression analysis are:

1. Higher WFH rate at origin is associated with less traffic recovery (i.e., lower inbound traffic flows) at destination.
2. Higher in-migration at origin is associated with higher traffic recovery at the destination.
3. Traffic recovery at destination is associated with industry composition (e.g. tech vs. service). Traffic recovery is spatially uneven, related in part to the industry types at destinations.

To test these hypotheses, we run an Ordinary Least Squares (OLS) regression using the equation:

$$\Delta\,\%\,Vol_{jt} = \beta_0 + \beta_1 W_{jt} + \beta_2 C_{ijt} + \beta_3 O_{jt} + \beta_4 M_{ijt} + \varepsilon_{jt}$$

(Week-fixed effects and robust standard errors are applied)

$\%\,Vol_{jt}$ = % change in destination volume (Dependent variable)
Observation: ZCTA, days (indexed by "t")

i = origin ZCTA
j = destination ZCTA
Pre-COVID sample period: 06/11/2019 – 10/25/2019
Post-COVID sample period: 06/15/2021 – 10/29/2021

W = vanished trips at destination j (OD weighted wfh change)
C = demographic characteristics weighted by origin-destination flow i to j
O = share of industry composition at destination j
M = change in cumulative net migration (from USPS change of address data) = (total moves into ZCTA minus total moves out of ZCTA) / total population

Table 4.5.1 shows the descriptive statistics for all variables. The dependent variable, percentage change in destination volume, shows an average decrease of 18.4% indicating a decreasing trend in traffic flow changes across destination ZCTAs.

For origin characteristics, the weighted change in work-from-home (WFH) rates from 2019 to 2021 averages 12.8%, with a substantial range from 4.3% to 20.9% at the 25th and 75th percentiles, primarily due to the diverse range of industries across the Bay Area and Central Valle. The cumulative net migration rate, weighted by 2021 OD volumes, averages -2.3%, reflecting a net outflow in many areas. We weight the cumulative net migration (from March 2020 to October 2021) with 2021 OD flow rather than 2019 OD flow to more accurately capture the impact of recent migration patterns on current traffic volumes. By using 2021 OD flow, we ensure that the weighting accounts for any changes in origin-destination relationships that may have occurred due to the pandemic. In contrast, other demographic variables are weighted using 2019 OD flow to establish a baseline comparison to pre-COVID conditions. Per capita income and total population, both weighted by 2019 OD volumes, have means of 44,064 and 35,015, respectively. The share of non-white population, commute by public transit, households with no vehicles available and median numbers of rooms serve as control variables to provide additional demographic context.

The destination industry composition variables at the destination level show that service and education sectors dominate, with an average of 43.8%, followed by office sectors at 21.3%, trade and transport at 15.3%, and construction and manufacturing at 14.3%. Medians are similar to means in every case except for construction and manufacturing. This suggests that outside this latter employment category, occupation shares are distributed somewhat evenly about the mean.

Table 4.5.1. Descriptive statistics for all variables used in the regression

Variable		Obs.	Mean	Std. dev.	25%	50%	75%
Dependent Variable	% change in destination volume	48,095	-18.4%	22.5%	-26.7%	-19.0%	-11.9%
Origin	Δ % wfh * 2019 od vol	48,095	12.8%	9.8%	4.3%	12.3%	20.9%
	Δ % Net migration rate * 2021 od vol	48,095	-2.3%	2.6%	-3.6%	-1.9%	-0.7%
	per capita income * 2019 od vol	48,095	44,064	16,729	31,775	39,913	53,940
	Total population * 2019 od vol	48,095	35,015	10,881	27,850	35,729	41,498
	% non-white * 2019 od vol	48,095	54.3%	17.6%	41.6%	56.3%	68.3%
	commute by public transit * 2019 od vol	48,095	6.6%	8.0%	1.3%	3.0%	9.0%
	median # room * 2019 od vol	48,095	5.23	0.52	4.92	5.26	5.54
	no vehicles available * 2019 od vol	48,095	7.6%	5.6%	4.8%	5.9%	7.7%
Destination	% construction and manufacturing	487	14.3%	12.0%	5.0%	5.1%	20.3%
	% trade and transport	487	15.3%	9.5%	8.9%	13.6%	20.3%
	% office	487	21.3%	15.6%	10.7%	18.0%	27.2%
	% service and education	487	43.8%	19.7%	29.9%	43.1%	56.2%

Note: The total number of observations (Obs.) is calculated by multiplying the number of days in our observation period by the total number of ZCTAs. However, it's important to note that not all destination ZCTAs received trips every day. Furthermore, due to privacy protection, StreetLight does not report trip counts for specific ZCTAs if the number of trips is identifiable.

Table 4.5.2 presents the regression results, where the dependent variable is the percentage change in all-day traffic volume in destination ZCTAs from 2019 to 2021. The results from the regression analysis indicates that lower traffic recovery at the destination is associated with increasing remote workers at the origin and a higher share of office jobs at the destination. The findings from Model 1 indicate that a 1 percentage point increase in the work-from-home (WFH) rate is linked to a 0.28 percent decrease in destination traffic volume[3]. Multiplying this coefficient by the mean share of vanished trips derived from our descriptive analysis reveals that a 13-percentage point increase in WFH corresponds to a 3.64 percentage point decrease in destination commute trip volume. This relationship remains significant in Model 2, though slightly reduced to -0.247, even when accounting for net migration rate changes. Model 2 also shows a significant positive effect of net migration rate on traffic recovery, with 1 percentage point change in the net migration rate is associated with a 2.756 percentage point change in traffic volume.

Model 3 introduces industry composition variables, showing significant negative impacts of construction and manufacturing (-0.188), office (-0.513), and education and service (-0.156) sectors on traffic recovery. Although almost all job sectors see a decrease in volume, office jobs decrease the most traffic volume (-0.513) in terms of the magnitude of the coefficient. Model 4 includes the full set of controlling demographic variables. The results indicate that a higher share of non-white population and households with no vehicles available are associated with decreased traffic recovery. The coefficient for vanished trips decreases to -0.102, although it remains significant. This suggests that, in terms of the magnitude of the coefficients, workplace industry characteristics are more influential on traffic volumes than worker demographics and remote working status. However, industry composition and residence demographics may be slower to change.

To test the robustness of these findings, we conducted a robustness check in Table 4.5.3, using yearly average data instead of daily data. By averaging OD weights data over the entire period, results in Table 4.5.3 aimed to provide a more stable estimate of the relationships, minimizing potential noise from daily fluctuations in traffic volume.

Upon comparison, the results from Table 4.5.3 largely corroborated those from Table 4.5.2. Despite the change in data frequency, the observed associations between the independent variables and the dependent variable remained consistent. Specifically, the negative relationship between vanished trips and traffic volume, as well as the significant impact of the share of office jobs at the destination, persisted in Table 4.5.3. This consistency suggests that the identified relationships are robust to variations in the frequency of data aggregation. Overall, the results presented in Table 4.5.3 supports and strengthens the conclusions drawn from Table 4.5.2, providing confidence in the observed relationships between remote work, industry composition, and destination traffic volume changes.

[3] This is an elasticity that, if it holds in later analyses, is at the high end of elasticities of vehicle miles traveled with respect to land use variables. (See the summaries of VMT-land use elasticities available at https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/research-effects-transportation-and-land-use.)

Despite the similarity in results between Table 4.5.2 and Table 4.5.3, the choice to use daily data in Table 4.5.2 offers advantages in terms of capturing the dynamic nature of traffic patterns, which may be masked when averaging data over longer time periods.

Table 4.5.2. Regression results, dependent variable = percentage change in all-day traffic volume in destination ZCTAs, daily, 2019 to 2021

OD	Variables	1	2	3	4
Origin	Vanish Trips: W = Δ % wfh * 2019 od vol	-0.279***	-0.247***	-0.023	-0.102***
	Δ % Net migration rate * 2021 od vol		2.756***		0.341
	per capita income * 2019 od vol				0.00001***
	Total population * 2019 od vol				0.00001***
	% non-white * 2019 od vol				-0.096***
	commute by public transit * 2019 od vol				0.019
	median # rooms * 2019 od vol				0.031***
	no vehicles available * 2019 od vol				-0.287***
Destination (omitted: % agriculture)	% construction and manufacturing			-0.093***	-0.188***
	% trade and transport			0.032	0.03
	% office			-0.444***	-0.513***
	% education and service			-0.088***	-0.156***
Constant		-0.185***	-0.181***	-0.077***	-0.024
Observations		48095	48095	48095	48095
R-squared		0.036	0.039	0.11	0.144
Adjusted R-squared		0.036	0.039	0.11	0.143

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

Table 4.5.3. Regression results, dependent variable = percentage change in all-day traffic volume in destination ZCTAs, yearly average, 2019 to 2021

OD	Variables	1	2	3	4
Origin	Vanish Trips: W = Δ % wfh * 2019 od vol	-0.230***	-0.083	-0.075	-0.032
	Δ % Net migration rate * 2021 od vol		1.131***		-0.476
	per capita income * 2019 od vol				-0.000
	Total population * 2019 od vol				-0.082
	% non-white * 2019 od vol				-0.306
	commute by public transit * 2019 od vol				0.102
	median # rooms * 2019 od vol				0.054*
	no vehicles available * 2019 od vol				-0.000
Destination (omitted: % agriculture)	% construction and manufacturing			0.066	-0.008
	% trade and transport			0.103	0.087
	% office			-0.264***	-0.286***
	% education and service			0.014	-0.027
Constant		-0.154***	-0.147***	-0.149***	-0.346*
Observations		487	487	487	487
R-squared		0.035	0.078	0.172	0.247
Adjusted R-squared		0.033	0.074	0.163	0.229

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

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Chapter 5. Conclusion

The COVID-19 pandemic has significantly reshaped commuting patterns and residential choices, with remote working becoming a new norm for many workers. This study analyzes the impact of remote work on job and housing locations in the Bay Area and Central Valley region. Our research aims to understand how the rise in work-from-home (WFH), also known as remote working, or telecommuting, influences traffic volumes, residential migration, and workplace dynamics.

We focused on three primary research questions: 1) Where and in which industries did traffic volume change the most during COVID-19? 2) Did work-from-home reduce traffic at job centers, and has this been a more permanent shift? 3) Have telecommuters been more likely to move further away from job centers, and if so, have they been more likely to supercommute?

To address these questions, we used four datasets: StreetLight for traffic data, LEHD LODES Workplace Area Characteristics (WAC) for job-related characteristics, the American Community Survey (ACS) for demographic data, and USPS Change of Address (COA) for migration patterns. The study area consisted of 487 ZCTAs in the Bay Area and Central Valley. Our methodology included destination (workplace) analysis, origin (residential) analysis, origin-destination (O-D) flow analysis, and a regression analysis to bring everything together.

For destination characteristics, we found a notable decrease in traffic volumes across all regions from 2019 to 2021. The Bay Area experienced the largest drop at 20.5%, followed by the Central Valley at 16.4%, and Comparison counties at 17.6%. The industry composition of destination ZCTAs reveals distinct economic dynamics across the Bay Area and Central Valley. In the Bay Area, office jobs had the highest share at 26.1%, while agriculture had the lowest at 0.3%. In the Central Valley, the trade and transport sector dominated with 18.2%, whereas agriculture accounted for 6.8%. In the Comparison counties, the highest share was in agriculture at 10.5%, and the lowest was in office jobs at 17.6%. The education and service sectors were significant across all regions but had the highest share in the Bay Area at 46.9%.

For origin characteristics, the Bay Area saw the most significant increase in WFH rates, rising by 10 percentage points from 6.6% in 2019 to 16.6% in 2021. Central Valley and Comparison counties saw increases of 4 and 5 percentage points, respectively. The Bay Area experienced a net cumulative migration loss of 1,473 people (approximately 4 people per 100 residents), indicating a higher outflow, potentially driven by high living costs and remote work flexibility. Central Valley and Comparison counties had smaller net losses of about 200 people each, representing a net loss of around 1 person per 100 residents.

We used Origin-Destination (O-D) flow weights to connect the characteristics of destination and origin ZCTAs. This method helps us understand how residential demographics impact workplace locations by weighting the contribution of each origin ZCTA to destination

ZCTAs based on traffic volume. This approach allows us to accurately link origin characteristics to their destinations, providing a clearer picture of how factors like work-from-home growth at origin affect traffic patterns at destination.

The concept of "vanished trips" is used to estimate the reduction in trips due to increased remote working. The Bay Area experienced the highest volume of vanished trips at 10,183, accounting for 13.6% of its 2019 traffic volume. The Central Valley and Comparison counties saw 4,324 (6.7%) and 2,873 (9.7%) vanished trips, respectively. These vanished trips align with the observed increases in WFH rates and the decreases in destination traffic volumes.

Our regression analysis showed that higher WFH rates at the origin are associated with less traffic recovery at the destination. A 1 percentage point increase in WFH rate is linked to a 0.28 percentage point decrease in destination traffic volume. In addition, the net migration rate at the origin has a positive effect on traffic volume changes, with a 1 percentage point increase in net migration linked to a 2.76 percent increase in destination traffic volume.

However, industry composition at the destination is a more influential factor than origin characteristics. The analysis reveals that destinations with a higher share of office jobs experience the most significant declines in traffic volume. For example, office sectors show a significant negative impact, with a 1 percentage point increase in the share of office jobs associated with a 0.44 percent decrease in traffic volume. Other sectors, such as construction, manufacturing, education, and services, also negatively impact traffic recovery, though to a lesser extent. These findings highlight the critical role of workplace (destination) characteristics in shaping traffic patterns.

Our study period covers only up to October 2021, so ongoing changes might not be fully captured. In addition, the COA data does not allow us to fully analyze the migration patterns of remote workers. Future research could focus on where these remote workers have moved, where they came from, and how that affects urban structure.

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Data Management Plan

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

<u>Public data sources:</u>

1. 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 2017-2021.
2. LEHD Origin Destination Employment Statistics (LODES)
   We use the pre-COVID period, 2019 LODES WAC (Workplace Area Characteristic) data, to capture destination characteristics.
3. USPS Change of Address (USPS COA)
   USPS change of address data is used to serve as a proxy for migration patterns. The United States Postal Service has provided publicly accessible change-of-address (COA) data by month for the last four years (2018-2022) at the zip code level.
4. US Census Bureau Current Population Survey (CPS)
   CPS data provides yearly statistics reflecting population change and migration patterns on the county-level.

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

1. StreetLight
   The traffic data we use for analyzing origin-destination flows before, during, and after COVID-19 is from StreetLight. The platform provides valuable up-to-date information about travelers' origin and destination, travel distance, travel purpose, etc.

Data Format and Content
We will deposit the ACS, LODES, COA, and CPS data used in this study in the Dataverse data repository. The files will contain information about the data and variables.

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

Reuse and Redistribution
Traffic data from StreetLight was made available to the research team through agreements that require that those data not be released publicly, to protect subject confidentiality.