Post-pandemic travel patterns of remote tech workers

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Post-pandemic travel patterns of remote tech workers

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ABSTRACT

Almost half of all jobs in the San Francisco Bay Area are “remote-eligible” – more than any other metropolitan area in the United States, due to the high concentration of employees in the technology sector who were early to embrace teleworking at the start of the COVID-19 pandemic in early 2020. Any significant share of these tech workers staying remote may have profound long-term impacts on aggregate travel patterns in the region. This research seeks to predict the magnitude of these impacts and derive insights about the newly learned behaviors of tech workers, as indicative of remote-eligible workers in general.

A survey of over 660 tech workers ran from November 2021 to March 2022, asking about participants’ employers and remote work policies, commute details and mode preferences, non-work trips, and interest in relocation.

Respondents expected employer-driven hybrid arrangements of 2–3 days per week in the office after the pandemic, which in turn dictated the number of predicted future commuting trips and suppressed interest in relocation. Though almost half of respondents expressed interest in moving, they only planned to move a median of 20.93 miles – staying within the region but shifting away from their offices and towards less dense and more automobile-oriented suburban neighborhoods.

Additionally, those moving more than ten miles from their office are likely to switch to less sustainable travel modes. On the other hand, robust observed retention of online shopping habits for groceries and food delivery may mitigate the added vehicle trips caused by rebound effects.

1. Introduction

1.1. Context and objectives

The COVID-19 pandemic upended typical mobility patterns around the globe from 2020 through 2021, especially for people accustomed to commuting for work. Among so-called “knowledge workers” or the “creative class” (Florida, 2019), the combination of employer flexibility and asynchronous collaboration software (or ICT) enabled rapid acceleration of what was already a growing trend of remote work or telework (Molla, 2019). While past research has suggested about one-third of all jobs are “remote-eligible” (Dingel and Neiman, 2020) and less than half surveyed would want to stay remote on all weekdays (PwC, 2021), any amount of significant long-term teleworking would potentially have large repercussions on travel demand, traffic congestion, and public transit ridership.

More specifically, several transportation research questions have emerged as these remote-eligible workers transition into the post-pandemic era:

1. What is their future expected frequency of commuting trips, and how is this shaped by employers’ remote work policies?
2. What factors are influencing mode choices and future vehicle ownership?
3. How have non-work activities changed, and what are their impacts on total trips taken?
4. What are the implications of mode shift trends for public transit agencies?
5. How have remote work options affected interest in relocation, and what do migration patterns imply with regards to automobile dependency?

The San Francisco Bay Area is an outlier in that almost 50% of the 1.79 million jobs in the region are “remote-eligible” (Bay Area Council Economic Institute, 2020), more than any other metropolitan area in the United States. This is mostly due to the high concentration of employees...
in the technology sector, representing the fastest growing industry segment prior to 2020 (Metropolitan Transportation Commission, 2019) and one of the first groups to fully adopt remote work in the wake of the COVID-19 pandemic (Levy, 2020).

Hence, a survey of tech-sector employees from the Bay Area may reveal newly learned and forward-thinking behaviors that could serve as representative indicators for the ever-increasing numbers of remote-eligible workers across the country in general (Oldham, 2021). This research seeks to derive these behavioral insights as well as utilize stated preferences about the future to predict the magnitude of potential impacts on vehicle trips and transit ridership.

1.2. Prior work

Researchers have been debating the effects of teleworking on automobile usage in the academic literature for three decades, with findings varying by local context, personal preferences, and household characteristics. Prior work suggests that adoption of telework leads to net decreases in automobile usage only if it does not induce residential shifts away from the office (Lyons, 1998; de Abreu e Silva and Melo, 2018; Chakrabarti, 2018), other household members do not take advantage of freed-up vehicles (Kim et al., 2015), and any new or substituted trips for leisure (Hook et al., 2020) or a change in work environment (Lachapelle et al., 2018) are made using alternative modes of transportation in a smaller radius around the home (Chakrabarti, 2018). Otherwise, the reduction of automobile usage from telecommuting is negated by rebound effects (Lyons, 1998; Mohktarian, 1998), resulting in a counterintuitive net increase in vehicle miles traveled (VMT) that muddles policymaker expectations.

Simultaneously, the COVID-19 pandemic has accelerated adoption and acceptance of telework. Employees have reportedly become so comfortable and productive (Shelburne and Coleman, 2022; Bay Area Council, 2021) with teleworking that they have started demanding it when seeking new job opportunities (Korolevich, 2021; Barrero et al., 2021). Many studies found strong positive preferences for a hybrid model that would allow teleworking at least 2–3 days per week (Bay Area Council, 2021; Drucker, 2021; Sea.citi, 2021; Korolevich, 2021). If these trends hold and employers are pushed to offer progressively flexible working arrangements (Rivera et al., 2021), an overall long-term increase in teleworking should be expected – at least among those granted the privilege to work from home.

Several more recent studies have suggested that the COVID-19 pandemic is leading to significant long-term population shifts from dense urban cores to suburban fringes, especially in the United States. Despite early research suggesting the introduction of telecommuting would not have a dispersal effect (Ory and Mohktarian, 2007), a 2020 model predicted a strong decentralization effect for employees who could work from home (Delventhal and Parkhomenko, 2020) which has played out in reduced housing demand in central city neighborhoods (Li and Su, 2021). Relocation data from the US Postal Service and Zillow illustrated a “donut effect” in which both households and businesses were relocating from central business districts to surrounding suburban rings, but mostly staying within the same metropolitan region (Ramani and Bloom, 2021). A study of primarily inter-state moves also found a strong trend of relocations towards less dense suburbs, as high-income households were mostly moving for “lifestyle” reasons (Haslag and Weegley, 2022). These trends seem durable as a study of mobility intentions through internet searches found a long-lasting increase in relocation interest through 2021 (Lei and Liu, 2022) and postings for high-income remote jobs have now exceeded those tied to any single U. S. city (Castaneda, 2021).

Similar trends exist outside of the United States as well. For example, white-collar remote workers were observed leaving Milan (Akan, 2022) and other large cities in Italy (Beria and Lunark, 2021). Young adults in Austria mostly returned to their families in rural hometowns (Kaufmann et al., 2020). In some cases, governmental programs even supported relocation of lower-income residents of cities to more rural areas (Farbotko and Kitara, 2021). However, some models found that extreme suburbanization was an unlikely outcome (Batty, 2021). Notably in Stockholm, remote-eligible workers were actually less likely to out-migrate than those with no remote eligibility – presumably due to the city’s relatively low existing density and high levels of desired amenities as compared to regional alternatives (Correa, 2022).

In San Francisco specifically, the lack of economic diversity and high percentage of jobs in information, professional, scientific and technical fields has meant that office occupancy remains anemic (Varghese, 2022) and downtown activity recovery lags all peer U.S. cities (Chapple, 2022). More than half of surveyed tech companies have downsized their office footprints (sf.citi, 2022), which has led to a projected 43% drop in commercial real estate valuations in the metro area (Troong, 2022). A sharp increase in outward migration from San Francisco during the pandemic followed, though surrounding counties seemed to be the primary destinations as opposed to other states (Neilson and Sumida, 2021).

While the existing literature has firmly established pandemic-driven dispersal patterns from major U.S. cities and San Francisco especially, no study has specifically targeted the employees of technology firms (representing the largest industry sector in the Bay Area region and arguably the most primed for telecommuting) to understand their unique motivations around potential relocation, desired destinations, and subsequent shifts in long-term travel behavior and mode choices.

2. Methods

2.1. Survey description

A digital survey ran from November 2021 to March 2022, targeted at employees working at Silicon Valley technology companies. Participants only needed to meet the criteria of having a full-time employer in the software/technology sector and an assigned office in the San Francisco Bay Area as of February 2020, thus allowing for employees who had relocated out of the region during the COVID-19 pandemic. Participant recruitment began with known contacts identified at the top 20 (in terms of employee count) technology firms headquartered in the San Francisco Bay Area, with subsequent waves reaching the target audience through social media, industry newsletters, internal employer mailing lists, and group chat forums. From there, the number of participants grew through snowball sampling.

The survey included questions about participants’ employers and their remote work policies, commute details and mode preferences, the nature of non-work trips, interest in relocation due to remote work, and basic demographic information. The questions used in the survey were crafted based on similar academic research regarding telework conducted on a national scale (Menon et al., 2020) and commissioned research on a similar audience but in a different region (Sea.citi, 2021).

Many questions asked about travel behaviors across three separate timeframes: before the COVID-19 pandemic (i.e., before February 2020), “currently” (at the time of survey participation), and a hypothetical future after the pandemic (defined as when respondents felt “COVID-19 was no longer a threat”) to capture stated preferences with regards to long-term remote work. If respondents felt they had already adapted to long-term remote work policies from their employers, the questions asking about their current practices would capture their revealed preferences. This is similar to the phasing structure used in a similar survey in Melbourne (Currie et al., 2021).

Participation in the study was completely anonymous; post-processing included coding and aggregating the results to protect privacy and encourage candor. The survey asked for names of participants’ employers though there was no grouping by these responses, nor were they reported to individual employers per IRB guidance.
2.2. Data verification and analysis

The demographic data was summarized and compared with publicly available statistics from the American Community Survey (Czepiel, 2016) and the U.S. EEOC (U.S. Equal Employment Opportunity Commission, 2014) to ensure survey respondents were relatively representative of the high-tech sector population as a whole as shown in (Table 1). The data verification process also included a review of the names of unique employers represented by the participants to ensure broad coverage and a diverse mix of both large and small technology companies.

2.3. Sample size

There were over 1100 survey participants in total, filtered down to 661 respondents who fit the screening criteria of working full-time in the software/technology industry and having an office in the San Francisco Bay Area as of February 2020. Sample sizes for each question varied between 300 and 500 due to item non-response (since all questions were optional).

There was representation from over 120 unique technology firms, from well-known Big Tech giants all the way down to small (sometimes unnamed) startups. Based on office zip codes reported by participants, these employers had offices throughout the San Francisco Bay Area with a slight concentration in downtown San Francisco (Fig. 1).

2.4. Analysis methods

Post-processing included converting survey responses into a set of categorical and continuous variables for analysis, with additional variables calculated based on conditions from multiple questions (e.g., a Boolean for whether grocery delivery was a new habit based on usage at the time of the survey versus prior to the pandemic). From there, it was possible to generate simple descriptive statistics for each of these variables as a precursor to further analysis, including:

- Paired sample t-tests to compare statistics before the pandemic, during the “current” timeframe, and the hypothetical post-pandemic future
- Chi-square tests to identify significant correlations between responses to pairs of survey questions
- Multivariate regressions for predictive modeling

A process to predict the impact of travel pattern changes on overall public transit usage involved combining respondents’ answers from multiple points in the survey to calculate an estimate of trips taken with this mode choice. For example, answers to a question about how often respondents engaged in certain non-work activities (i.e., shopping, social gatherings, entertainment, and medical appointments) were converted into a statistic of potential transit trips depending on whether “public transit” was selected as a mode choice plus a recoded frequency variable (e.g., “few times per week” was interpreted as 2-3 transit trips, assuming a roundtrip journey-three times during a week). This combined with estimates for work trips based on the same type of recoding on commute frequency allowed for an aggregate estimate of total trips

![Fig. 1. Geographical distribution of company offices based on reported zip codes (N = 424).](image)

3. Findings

3.1. Commute frequency

3.1.1. Employees expect hybrid schedules

At the time of the survey (November 2021 to March 2022), just 3% of respondents were commuting to an office every day, 66% were working fully remotely, and 31% were working in a hybrid fashion (Fig. 2). This is a near reversal of pre-pandemic behavior where 74% reported commuting every day and only 3% were fully remote.

Looking ahead to when respondents no longer perceived COVID-19 as a threat, most expected to shift back to their offices in some form but not at pre-pandemic levels. Only 8% of respondents said they expected to commute every day, 20% expected to stay fully remote (a sevenfold increase from before COVID-19), and 47% (the plurality) of respondents clustered on hybrid schedules of 2-3 days per week. These sentiments from tech workers mostly align with findings from similar studies of more general remote-eligible populations in the United States (Bick et al.), Australia (Beck et al., 2020), and other countries (Balbontin, et al., Impact of COVID-19 on the number of days working from home and commuting travel: A cross-cultural comparison between Australia, South America and South Africa, 2021).

Furthermore, a paired t-test of days in office in the future versus at the time of survey revealed a mean difference of +1.35 days (N = 408, Cohen’s d = 1.02, P < 0.01).

3.1.2. Employers will dictate future office trips

Given that the survey period began approximately-one and a half years into the pandemic but also amidst the emergence of the COVID-19 Omicron variant, not all employers had established post-pandemic policies for remote work. Some were even actively modifying their policies. Nevertheless, at the time of the survey, 10% of employers were
running a fully remote operation with another 46 % allowing individual employees or teams to decide policies on their own (Fig. 3). 29 % of employers were mandating at least some days in the office. Of the companies with an onsite work requirement, most (87 %) were requiring at least three days per week in the office.

Larger employers (those with 5,000 or more employees) were far more likely to have an onsite work requirement. Smaller companies, especially those with <100 employees, seemed to gravitate more towards being fully remote. A chi-squared test showed a correlation between employee count and remote work policy (N = 396, Cramér’s V = 0.22, P-Value < 0.01).

Employer remote work policies at the time of the survey were closely correlated with expected post-pandemic in-person versus remote work frequency. In fact, the number of employer-mandated days in the office accounted for 86 % of the estimated days in the office after COVID-19 in a linear regression model including employee count, age, and commute length as input variables (Table 2). An increase of 1 employer-mandated day was associated with an increase of 0.62 estimated days in the office after the pandemic. It is worth noting that other factors could be endogenous to employer mandates, such as the distribution of employee residences.

When comparing this model to previous studies that used binary random parameters logit models to determine workers’ likelihood of continuing to work-from-home after COVID-19 (Barbour et al., 2021), age was a common variable.

Overall, this analysis strongly suggests that employer policies will primarily drive future commuting patterns, which matches findings from other studies of factors influencing WFH choices (Balbontin, Hensher, and Beck, Advanced modelling of commuter choice model and work from home during COVID-19 restrictions in Australia, 2022; Jain et al., 2022). The more that employers enforce mandates to be in offices, the more employees see themselves as commuting regularly whether they want to or not. Politicians hoping to restore vibrancy back to central business districts seem to understand this, going as far as to work with business groups to encourage more such mandates (DiFeliciantonio, 2022; City and County of San Francisco, 2022).

3.2. Commute mode choice and vehicle ownership

3.2.1. Automobile use to remain elevated

Respondents as a group engaged in diverse and multi-modal commuting behavior prior to the pandemic, which is unsurprising given the mix of downtown and suburban locations of their offices. Before COVID-19, 36 % of respondents used some form of transit (i.e., public trains/buses or private company shuttles), 33 % used automobiles (i.e., drive alone, carpool, taxi or ridesourcing/TNCs), and 28 % walked, biked, or used a micromobility device (Fig. 4). Among the smaller number of respondents that were commuting during the survey period, commute modes also shifted. Notably, automobile use increased seven percentage points to 40 % while transit use...
declined eight percentage points to 28%.

In a hypothetical post-pandemic scenario, respondents expected their use of transit for commuting to return to the same pre-pandemic 36% level. However, respondents expected their automobile use to remain above pre-pandemic levels (35%), while expecting their share of walking/biking/micromobility use to be three percentage points lower (25%).

Participants also reported the number of vehicles they owned before February 2020 and at the time of survey. A slight upward trend was observed for most vehicle types including cars (from an average of 1.3 to 1.4), but the most notable changes were in personal mobility devices (i.e., bicycles, e-bikes, and scooters) which increased from an average of 1.3 to 1.5 (95% CI of mean difference of 0.11 to +0.23 additional vehicles per person, N = 434). These findings aligned with reported increases in demand for both cars and bicycles seen nationally throughout 2020 and 2021 (Furcher et al., 2021; CBS News - Moneywatch, 2021).

Respondents who stated they would drive alone to work in the future also tended to have more cars in the household (1.78 on average, N = 169) versus those who would not drive (1.10 on average, N = 265).

3.2.2. Commute length determines mode choices

Employees’ choice of travel mode for work trips (as well as their proclivity for using various vehicle types more generally) seemed highly dependent on their commute length, among other variables.

For example, there was a strong correlation between a respondent’s commute length and whether they drove a car alone to work before COVID-19. A chi-squared test of commute length (as a categorical variable) and whether respondents selected “drive alone” as a commute mode showed that 80.3% of those with a commute <5 miles did not drive, while 51.4% of those with a commute between 10 and 25 miles did drive (N = 427, Cramer’s V = 0.269, P < 0.00001).

These choices extended into the future as well, as shown with a binary logit model built for whether a survey respondent selected bicycle, bike share, scooter, or other micromobility as an expected commute mode after COVID-19 is no longer a threat (Table 3). Commute length accounted for 45% of the output variable, henceforth named Is Post-Pandemic Active Commuter. Controlling for other variables in the model, the odds of a survey respondent being an active commuter in the future was 8% lower with every 10-mile increase of commute length.

Furthermore, both commute length and the binary variable Is Post-

![Fig. 4. Distribution of commute modes before COVID-19 (N = 419), at the time of survey (N = 191) and estimated after COVID-19 (N = 358).](image-url)

### Table 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>Relative Importance</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commute Length</td>
<td>45 %</td>
<td>-0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Number of Cars</td>
<td>32 %</td>
<td>-0.11</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Is White</td>
<td>16 %</td>
<td>0.13</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Employer-Mandated Days in Office</td>
<td>7 %</td>
<td>0.05</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Pandemic Active Commuter accounted for a major portion of cars owned in a separate linear regression (Table 4). A 10-mile increase of commute length was associated with an increase of 0.10 cars owned, while an increase of 0.10 in Is Post-Pandemic Active Commuter was associated with a decrease of 0.033 cars owned.

However, it is notable that other factors such as age and number of children had higher relative importance in this model.

This makes intuitive sense, aligns with the existing academic understanding of the relationship between transportation and land use (sprawl), and suggests that mode shifts towards or away from driving individual automobiles are possible depending on relocation decisions discussed further below. If tech workers who had been living close to their offices decide to move more than 10 miles away but still need to commute occasionally, they would more likely complete that commute trip by driving and contribute to more unsustainable trips across the region.

### Table 4

<table>
<thead>
<tr>
<th>Variable</th>
<th>Relative Importance</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Children</td>
<td>29 %</td>
<td>0.99</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Age</td>
<td>27 %</td>
<td>0.02</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Commute Length</td>
<td>23 %</td>
<td>0.01</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Is Post-Pandemic Active Commuter</td>
<td>19 %</td>
<td>-0.33</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Income</td>
<td>2 %</td>
<td>2.99 × 10⁻⁷</td>
<td>0.65</td>
</tr>
</tbody>
</table>
3.3. Non-work activities

3.3.1. High retention of online grocery services

New pandemic-era habits of ordering food and groceries online seemed especially sticky. For example, online grocery delivery, a new service even for those in the tech industry, demonstrated high retention rates for those who tried it. Only 8% of survey respondents used it before the pandemic, but 17% were using it at the time of survey and 14% expected to continue using it even after COVID-19 is no longer a threat (Fig. 5).

A Fisher’s Exact Test comparing whether a respondent started grocery delivery during the pandemic (i.e., did not use it before but used it at the time of survey) with their stated preference of using it in the future showed a strong statistically significant relationship (N = 661, Cramér’s V = 0.528, P < 0.01). A similar phenomenon existed for food delivery, where 70.6% of those who started ordering food for delivery from a restaurant also planned to continue after the pandemic (N = 661).

3.3.2. Online shopping reduces trips, but mode shifts still apparent

This widespread adoption of online ordering may have mitigated some of the upsurge in trips historically predicted as rebound effects of remote work (Mokhtarian, 1998). Only 33% of respondents expected to shop for food/groceries at physical stores and restaurants in the future, down from 46% before the pandemic.

This suggests that as more people end up trying grocery and food delivery services, the convenience will be addicting and reduce the number of trips they take to grocery stores and restaurants themselves overall. However, it is notable that for those who would still make trips to physical locations (either to shop directly or just to pick up online orders, N = 381), their mode choices shifted towards driving (43%) and away from public transit (11%) and walking (28%) (Fig. 6).

The survey results also showed similar mode shift trends in trips for other types of shopping, social activities, entertainment, and medical appointments (see Table A.1, A.2, A.3, A.4 and A.5).

Another caveat is that the number of trips made by delivery drivers may increase while individuals reduce their own trips. A reduction in overall vehicle miles traveled may only be possible if drivers optimize the sequences of deliveries (i.e., a single driver can make multiple deliveries in one trip), which fortunately aligns with the long-term operational goals of online service providers.

3.4. Public transit trips

Public transit ridership declined throughout many regions during the COVID-19 pandemic, including within the San Francisco Bay Area. Unfortunately for transit agencies, declines in patronage from tech workers appear likely to persist into the future. Though respondents expected their transit commute mode share to return mostly to pre-pandemic levels, their significant reduction in commute frequency plus reductions in non-work trips due to e-commerce translates to a large decline in their expected overall number of public transit trips in the future.

Multiplying survey results on trip frequency and mode choice shares led to rough estimates of how many trips respondents made and will make on public transit (Table 5). Respondents took an estimated average of 14.2 trips on transit per week before the pandemic, which dropped to 1.9 trips per week at the time of the survey. This is understandable as transit commuters who went from fully in-person to fully remote shed at least 10 trips per week. In the future when COVID-19 is no longer a threat, respondents will take merely an estimated 3.4 transit trips per week, representing barely 24% of pre-pandemic levels. This suggests transit agencies cannot depend on these remote-eligible workers to support their ridership metrics in the future.

3.5. Relocation interest and destinations

20% of respondents stated they already made a move by the time of the survey, with an additional 33% considering a move (N = 382). These two groups were classified together as having interest in relocation, and 64% of them cited remote work options as a primary factor in their consideration while the remaining respondents were planning moves not specifically due to having remote work options.

Several data points suggest that these moves are a dispersal towards more suburban and automobile-oriented areas. First, 43% of respondents explicitly stated in the survey that they would potentially live away from Silicon Valley (at least among tech workers). In fact, the median relocation distance was only 20.93 miles (N = 168), suggesting that most potential moves were

![Fig. 5. Distribution of methods for obtaining food before COVID-19 (N = 397), at the time of survey (N = 396), and after COVID-19 (N = 389).](image-url)
within the San Francisco Bay Area region as opposed to between states. When mapped, it becomes clear that most participants with relocation interest were planning to stay within California (Fig. 8).

However, these moves also appear to further distance these workers from their offices. The median distance between respondents’ stated office zip code and their origin zip code was 5.01 miles, while the median distance between their office zip code and their destination zip code was 21.45 miles. A paired sample t-test also showed a mean difference of +205.86 miles (N = 155, P < 0.01).

These findings match the longer-term trend of growth in suburban rings as opposed to inner cities. (Muller, 2017) The COVID-19 pandemic seems to have accelerated the timeline for these tech workers who now have fewer reasons to live close to their offices.

---

Table A.1

<table>
<thead>
<tr>
<th>Method</th>
<th>Before COVID-19</th>
<th>Currently</th>
<th>After COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Go to physical store</td>
<td>47.7 %</td>
<td>37.29 %</td>
<td>41.31 %</td>
</tr>
<tr>
<td>Order online (delivery)</td>
<td>41.87 %</td>
<td>45.11 %</td>
<td>41.9 %</td>
</tr>
<tr>
<td>Order online (pickup)</td>
<td>10.12 %</td>
<td>17.29 %</td>
<td>16.5 %</td>
</tr>
<tr>
<td>Other</td>
<td>0.31 %</td>
<td>0.3 %</td>
<td>0.29 %</td>
</tr>
</tbody>
</table>

Table A.2

<table>
<thead>
<tr>
<th>Method</th>
<th>Before COVID-19</th>
<th>Currently</th>
<th>After COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive my own car</td>
<td>35.94 %</td>
<td>42.63 %</td>
<td>39.02 %</td>
</tr>
<tr>
<td>Carshare / Zipcar</td>
<td>2.34 %</td>
<td>0.87 %</td>
<td>1.26 %</td>
</tr>
<tr>
<td>Taxi / Cab / TNCs</td>
<td>7.19 %</td>
<td>4.68 %</td>
<td>4.9 %</td>
</tr>
<tr>
<td>Public transit</td>
<td>19.06 %</td>
<td>12.82 %</td>
<td>16.75 %</td>
</tr>
<tr>
<td>Bicycle / bikeshare</td>
<td>8.75 %</td>
<td>10.75 %</td>
<td>10.9 %</td>
</tr>
<tr>
<td>Motorcycle / moped</td>
<td>1.09 %</td>
<td>0.87 %</td>
<td>1.11 %</td>
</tr>
<tr>
<td>Scooter / micromobility</td>
<td>1.09 %</td>
<td>1.21 %</td>
<td>1.58 %</td>
</tr>
<tr>
<td>Walk</td>
<td>24.53 %</td>
<td>26.17 %</td>
<td>24.49 %</td>
</tr>
</tbody>
</table>

Table A.3

<table>
<thead>
<tr>
<th>Method</th>
<th>Before COVID-19</th>
<th>Currently</th>
<th>After COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive my own car</td>
<td>26.35 %</td>
<td>33.94 %</td>
<td>29.85 %</td>
</tr>
<tr>
<td>Carshare / Zipcar</td>
<td>2.71 %</td>
<td>1.54 %</td>
<td>1.46 %</td>
</tr>
<tr>
<td>Taxi / Cab / TNCs</td>
<td>20.35 %</td>
<td>15.36 %</td>
<td>17.72 %</td>
</tr>
<tr>
<td>Public transit</td>
<td>20.24 %</td>
<td>15.78 %</td>
<td>19.05 %</td>
</tr>
<tr>
<td>Bicycle / bikeshare</td>
<td>8.82 %</td>
<td>10.34 %</td>
<td>9.95 %</td>
</tr>
<tr>
<td>Motorcycle / moped</td>
<td>1.53 %</td>
<td>1.12 %</td>
<td>1.33 %</td>
</tr>
<tr>
<td>Scooter / micromobility</td>
<td>18.71 %</td>
<td>1.68 %</td>
<td>1.58 %</td>
</tr>
<tr>
<td>Walk</td>
<td>0.24 %</td>
<td>20.25 %</td>
<td>18.81 %</td>
</tr>
</tbody>
</table>

Table A.4

<table>
<thead>
<tr>
<th>Method</th>
<th>Before COVID-19</th>
<th>Currently</th>
<th>After COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive my own car</td>
<td>21.01 %</td>
<td>27.03 %</td>
<td>24.7 %</td>
</tr>
<tr>
<td>Carshare / Zipcar</td>
<td>2.37 %</td>
<td>1.35 %</td>
<td>1.52 %</td>
</tr>
<tr>
<td>Taxi / Cab / TNCs</td>
<td>23.08 %</td>
<td>18.58 %</td>
<td>20.43 %</td>
</tr>
<tr>
<td>Public transit</td>
<td>22.49 %</td>
<td>18.92 %</td>
<td>21.65 %</td>
</tr>
<tr>
<td>Bicycle / bikeshare</td>
<td>8.88 %</td>
<td>10.47 %</td>
<td>10.37 %</td>
</tr>
<tr>
<td>Motorcycle / moped</td>
<td>2.37 %</td>
<td>2.36 %</td>
<td>2.13 %</td>
</tr>
<tr>
<td>Scooter / micromobility</td>
<td>1.78 %</td>
<td>2.03 %</td>
<td>1.83 %</td>
</tr>
<tr>
<td>Walk</td>
<td>18.05 %</td>
<td>19.26 %</td>
<td>17.38 %</td>
</tr>
</tbody>
</table>

Table A.5

<table>
<thead>
<tr>
<th>Method</th>
<th>Before COVID-19</th>
<th>Currently</th>
<th>After COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive my own car</td>
<td>28.41 %</td>
<td>37.18 %</td>
<td>33.33 %</td>
</tr>
<tr>
<td>Carshare / Zipcar</td>
<td>0 %</td>
<td>3.85 %</td>
<td>0 %</td>
</tr>
<tr>
<td>Taxi / Cab / TNCs</td>
<td>19.32 %</td>
<td>12.82 %</td>
<td>14.29 %</td>
</tr>
<tr>
<td>Public transit</td>
<td>19.32 %</td>
<td>7.69 %</td>
<td>15.48 %</td>
</tr>
<tr>
<td>Bicycle / bikeshare</td>
<td>12.5 %</td>
<td>11.54 %</td>
<td>11.9 %</td>
</tr>
<tr>
<td>Motorcycle / moped</td>
<td>2.27 %</td>
<td>2.56 %</td>
<td>2.38 %</td>
</tr>
<tr>
<td>Scooter / micromobility</td>
<td>1.14 %</td>
<td>3.85 %</td>
<td>2.38 %</td>
</tr>
<tr>
<td>Walk</td>
<td>17.05 %</td>
<td>19.23 %</td>
<td>20.24 %</td>
</tr>
</tbody>
</table>

Table 5

<table>
<thead>
<tr>
<th>Timeframe</th>
<th>Sample Size</th>
<th>Average</th>
<th>CI of Avg.</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before COVID-19</td>
<td>216</td>
<td>14.2</td>
<td>13.28 to 15.05</td>
<td>6.6</td>
</tr>
<tr>
<td>Currently</td>
<td>639</td>
<td>1.9</td>
<td>1.57 to 2.29</td>
<td>4.6</td>
</tr>
<tr>
<td>After COVID-19</td>
<td>639</td>
<td>3.4</td>
<td>2.91 to 3.83</td>
<td>5.9</td>
</tr>
</tbody>
</table>

was 21.45 miles. A paired sample t-test also showed a mean difference of +205.86 miles (N = 155, P < 0.01).

These findings match the longer-term trend of growth in suburban rings as opposed to inner cities. (Muller, 2017) The COVID-19 pandemic seems to have accelerated the timeline for these tech workers who now have fewer reasons to live close to their offices.

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Fig. 6. Distribution of travel modes taken for food-related trips before COVID-19 (N = 386), at the time of survey (N = 377), and after COVID-19 (N = 381).
Prior research suggested that the COVID-19 pandemic will lead to sustained teleworking and that these newly remote employees will be unlikely to reduce their overall vehicle miles traveled due to “rebound” effects. However, the findings from this study paint a more nuanced picture, in some ways confirming and other times countering patterns described by the literature.

On one hand, there is a precedence for automobile-centric design in transportation networks throughout San Francisco Bay Area suburbs, which suggests major future increases in vehicle miles traveled (VMT) unless planners and political leaders in these communities can pivot their development patterns to be less automobile centric. Such changes will take decades to implement, however, so the result will be years of paralyzing traffic congestion in the meantime.

This does not bode well for the region’s VMT-reduction goals, especially if reluctance to use public transit where available is ongoing. This reluctance has persisted throughout the pandemic for mostly contagion-related reasons but might continue for other reasons such as concern for personal safety or system reliability, perennial problems in the San Francisco Bay Area. On the other hand, factors such as increased automobile traffic on roadways and higher gas prices may eventually tip the scales back towards public transit in the future (Chitnis, 2022). Until then, transit agencies can expect depressed ridership for a prolonged period, especially if employees stick to a schedule of no more than 3 commuting days per week.

However, the surprisingly rapid adoption of online shopping, particularly for food and groceries, does offer a counterbalance to potential rebound effects from teleworking. Instead of making spontaneous trips to stores and restaurants with the time saved from commuting, some tech employees seem likely to continue their habit of ordering deliveries while extending their working hours. While this may help reduce overall VMT (with optimization of delivery trips), planners should consider that the potential negative side-effects (such as muted street-level activity in commercial centers and less societal interaction) may be worse overall.

Local policymakers could also attempt to counteract the potential increases in vehicle usage by investing in amenities to keep residents in walkable neighborhoods (discouraging relocation) or by encouraging more full-time teleworking to cut commuting entirely. However, attempts at remote work mandates by the local Metropolitan Planning Organization (MTC) have faced fierce opposition in the past due to their potentially devastating impact on the financial stability of public transit agencies (Long, 2020). Regardless, planners can assist in crafting policies that encourage usage of alternative modes (e.g., investments in public transit expansion for additional coverage of sprawling suburbs or incentives to try micromobility solutions for last-mile travel).
4.3. On relocation trends

The findings mostly reflect the “donut effect” found by (Ramani and Bloom, 2021), as most relocation interest remained within the immediate suburbs of the San Francisco Bay Area. This paints a narrative of tech workers, flush with cash & stock equity during the COVID-19 pandemic, deciding to finally leave their expensive apartments in San Francisco and purchase larger homes in the surrounding suburbs. Notably, the lower cost of living in other states did not sway them and they did not migrate in significant numbers to places like Texas or Florida. While there may have been some fleeting interest in more far-flung relocation, employers’ pressure to come back into the office at least some days of the week tempered that interest significantly.

Unfortunately, the implications of this high-income worker dispersion from urban centers are severe. By default, this encourages negative forms of suburban sprawl, with all its infrastructure inefficiencies and environmental impacts (Denham, 2021). In the long-term, the fundamental geography of economic activity will shift as polycentrism becomes more established. This would lead to a sizable number of non-tech workers to also disperse from the urban core, as the need for in-person services and the commercial opportunities for small businesses increase in the suburbs.

CRediT authorship contribution statement

Simon Tan: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Visualization. Kevin Fang: Validation, Writing – review & editing, Conceptualization, Supervision. T. William Lester: .

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Data availability

Data will be made available on request.

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