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Employment concentration, dispersion, and the changing commute in the San Francisco Bay Area

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Abstract: In the first decade and a half of the twenty-first century, the San Francisco Bay Area experienced rapid job growth (17% from 2002 to 2015). Employment growth greatly exceeded housing production, resulting in rising housing prices. The mismatch between jobs and housing potentially contributed to an increase in commute distance, as workers relocated to outlying neighborhoods in search of affordable housing. In this paper, the authors analyze changes in commute distance over time, with a focus on the spatial location of employment and, in particular, downtown job growth. They find that commute distance increased slightly between 2002 and 2015 throughout the Bay Area (from 17.2 to 17.8 mi.), with the greatest increase among workers in job centers located in outlying parts of the region (from 19.1 to 20.8 mi.). Increases in census tract jobs was by far the strongest predictor of commute distance increase, though this overall relationship in the region was likely moderated by the increase in employment in downtown San Francisco (44%) where, all else being equal, workers travel shorter distances (14.4 mi. in 2002 and 15.4 mi. in 2015) relative to other workers. This relationship may be due to the demographic composition of San Francisco residents: high-wage, young, single workers who are able to afford high-priced housing close to downtown. A better balance between jobs and housing would allow workers the option of self-selecting into neighborhoods closer to their jobs, underscoring the importance of policies to spur housing production in high-cost metropolitan areas.

Keywords: Commute distance, employment clusters, housing, regional planning, San Francisco Bay Area

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1 Introduction

Long distance commutes—particularly those in private vehicles—can be detrimental to the environment and contribute to congestion (Deakin et al., 1996). They also are negatively associated with work outcomes (van Ommeren & Gutiérrez-i-Puigarnau, 2011), have significant emotional costs (Stone & Schneider, 2016), and are linked to reductions in time spent doing nearly all other activities except for work (Morris et al., 2020). Concern about increasing commute distances has grown with the San Francisco Bay Area often serving as the poster child for this problem (Barrera, 2016; Britschgi,

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2021; Dougherty & Burton, 2017; Lufkin, 2022; Wong, 2023). For example, in 2017 the *New York Times* published a story profiling Sheila James who relocated to California's Central Valley swapping more affordable housing for a lengthy commute to her job in San Francisco (Dougherty & Burton, 2017).

Previously, scholars have examined commutes in the San Francisco Bay Area, with much of this research centered on the impact of job decentralization in the 1990s (Cervero, 1989, 1996). However, since the 1990s, the San Francisco Bay Area has experienced both rapid job growth and industrial change. From 2009 to 2019, the years following the Great Recession, employment increased by more than 22 percent across the nine-county Bay Area region, with job growth highest in three counties: San Francisco (35%), Santa Clara (31%), and San Mateo (30%) (California Employment Development Department, Labor Market Information, 2022).[1] While overall employment continued to decentralize, there also was significant job growth in existing employment centers, including downtown San Francisco (Heider & Siedentop, 2020). The increase in employment greatly exceeded housing production by a ratio of more than four to one (U.S. Census Bureau, Population Division, 2012, 2020), driving up housing prices (Joint Center for Housing Studies, 2022).

Previous research suggests that these changes ought to be associated with significant increases in commute distance. In this study, therefore, we examine the relationship between the spatial location of regional employment and commute distance, with a focus on the role of downtown employment growth. We draw on data from the 2002 and 2015 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) for the nine-county San Francisco Bay Area region and use ordinary least squares and spatial lag models to predict commute distance as a function of job location, controlling for other factors including the availability of housing.

We find that commute distances increased slightly over time, with the greatest increase among workers in job centers located in outlying parts of the region. However, unlike the findings of previous studies, growing commute distances likely were moderated by job growth in downtown San Francisco where, all else equal, workers traveled shorter distances relative to other workers. This relationship may have been due to the changing demographic composition of San Francisco residents: an increase over time in higher-wage, young, single workers who were able to afford high-priced housing near downtown. Finally, while the mismatch between jobs and housing was associated with longer commute distances, the strength of this relationship did not change over our study period. In the conclusion, we discuss the significance of our findings for other high-cost metropolitan areas and cities as they move beyond the immediate health crisis associated with the COVID-19 pandemic.

2 Commute distance: The Bay Area and beyond

2.1 Commute distance and urban form

The study of commuting behavior often begins with Alonso's monocentric city model as an explanation for housing choices, commute distance, and the costs associated with both (Alonso, 1964). The monocentric city model holds that cities radiate in decreasing levels of density from a singular large high-density city center. This city center, known as

[1] The nine-county region includes the following counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, Sonoma.

the central business district (CBD), has substantial gravitational pull from outlying areas, with household wealth increasing with distance from the city center, as households with higher incomes trade off longer commutes for reduced expenditures on housing.

Some scholars have questioned the relevance of the monocentric city model, arguing that many of the basic assumptions no longer apply (Berry & Kim, 1993). One key assumption of the model was the dominant role of the central business district. However, over the past several decades scholarship has pivoted toward a model of polycentric cities to capture the evolution of urban form (Arribas-Bel & Sanz-Gracia, 2014; Garreau, 1992; Giuliano et al., 2007). Most metropolitan areas remain monocentric (i.e., one major city center); however, there is modest evidence of an increase in the number of polycentric cities (i.e., multiple major city centers), particularly in large, dense, and higher-income regions (Arribas-Bel & Sanz-Gracia, 2014). While the CBD still influences commute and residential location behavior, its influence appears to have waned over time (Dubin & Sung, 1987).

At the same time, employment has continued to disperse and decentralize (Glaeser et al., 2001), such that job dispersion is the dominant characteristic in nearly 70 percent of all metropolitan statistical areas in the U.S. (Hajrasouliha & Hamidi, 2017). By 2000, only one in 12 people worked and lived in the same community, only one in nine jobs was located in a CBD, and only one out of seven jobs was located in an employment center outside of the CBD (Angel & Blei, 2016).[2] Although jobs have dispersed, they have not dispersed closer to the typical worker. Indeed, Kneebone and Holmes (2016) find that between 2000 and 2012, the number of jobs in proximity to most workers fell across the U.S., with poor and minority access falling faster than wealthy and white access. Resolving the issues of long commutes for low-wage workers may be challenging to address, as service employment—the realm of many low-wage workers (Ross & Bateman, 2019)—tends to be more decentralized than other sectors (Modarres, 2011).

2.2 Commuting over time in the Bay Area

Over the past several decades, a number of scholars have examined changes in commuting distance in the San Francisco Bay Area, expressing alarm at the growing separation between workers' homes and workplaces. Cervero (1989) attributes increasing commute distance to demographic trends, exclusionary zoning, and high housing costs; using data from the 1980s, he drew these conclusions prior to the explosive growth in the high technology sector. In a reexamination of this issue roughly a decade later, Cervero (1996) again attributes growing commute distances to high housing costs in the Bay Area. Subsequent studies also point to the increasing difficulty of finding housing at an appropriate price for a worker's wage level as an obstacle in finding a job, which can lead to expanded job searches and corresponding increased commute distances (Benner & Karner, 2016; Blumenberg & Wander, 2022; Cervero & Duncan, 2006).

Cervero and Wu (1997, 1998) twice examine the relationship between commutes and the clustering of jobs in the Bay Area. Accounting for job clusters and changes in travel mode and occupancy, they find that employment decentralization did not bring jobs

[2] Angel and Blei (2016) use a Mosaic of Live-Work Communities model to reach these conclusions. Their definition of the model is: "The metropolitan area is a mosaic of discrete live-work communities, where workers' homes and their jobs are all within walking or bicycling distance of each other" (p. 22). Thus, their definition of community varies between metro areas, but is consistently a spatial unit of residents who largely work within that same unit.

closer to workers. Commute distances to employment centers were longer than to secondary job areas (Cervero & Wu, 1998), a finding similar to other studies (Giuliano, 1991; Hu & Schneider, 2017; Manaugh et al., 2010). Further, Cervero and Wu (1998) find that overall regional growth in the Bay Area was associated with increases in commute distance and vehicle miles of travel per worker.

Since the 1990s the Bay Area has experienced significant change. The consolidation of information technology leadership, emergence of venture capital, and rise of the Internet all collided to give rise to an agglomeration of the high-technology industry along Route 101 from downtown San Francisco to downtown San Jose through what we now call Silicon Valley. This progression began with the proliferation of semiconductors in the 1970s, personal computers in the 1980s, the Internet in the 1990s, early mobile communications in the 2000s, and cloud-based computing in the 2010s. It likely contributed to the increase in employment concentrated in the densest spatial entities of the metropolitan area (Heider & Siedentop, 2020).

These changes resulted in a transformation in the Bay Area, which is now home to many of the world's most valuable companies that sit atop an ecosystem of startups, acquired companies, and collaborators all centered on the development of high-technology. Equally important, these sectors employ some of the region's highest-paid workers (Storper et al., 2015), who have contributed to increases in Bay Area housing prices (Chapple et al., 2004; Chapple & Jeon, 2021).

3 Means and methods

We hypothesize that commute distances in the San Francisco Bay Area continued to grow, in part, due to job growth in downtown San Francisco, combined with the effect of limited housing supply on the viability of residential selection near job centers. We test this relationship among workers *working* in the nine-county San Francisco Bay Area.

3.1 Data construction and limitations

Our primary dataset is the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) (U.S. Census Bureau, 2019). To measure change over time, we use the 2002 vintage (the earliest year available) for a base point and the 2015 vintage as the change point.[3] The data include information on individual workers' origin (home) and destination (work) census blocks, as well as aggregated tract-level information on worker traits and workplace area characteristics. As we note above, we focus on the census tracts where workers work.

Mean commute distance in each workplace census tract is not directly included in the LODES. To calculate this measure, we used the Open-Source Routing Machine (OSRM) to measure the shortest possible road network distance between each worker's origin (home) census block and destination (workplace) census block. Using road network distance in the Bay Area is particularly important, as it accounts for variations in topography like mountains and the San Francisco Bay itself.

Similar to Cervero and Wu (1998), we consider the relationship between job clusters and commute distance. To identify job clusters, we relied on the methods put forth by Giuliano and Small (1991) and Giuliano et al. (2007). We count any tract as being in an

[3] While LODES data are available through 2021, the dramatic changes wrought on by the COVID-19 pandemic had hardly settled by 2021, so we limit our analysis to pre-pandemic data.

employment cluster if it meets three criteria: 1) it is in a set of contiguous tracts, 2) it has a minimum of 10 employees per acre, and 3) combined with the other tracts in the cluster it has at least 10,000 employees. We then define a mega-cluster by expanding their method to have a minimum of 20 census tracts in the cluster, so that we can account for possible differences across cluster types (Cervero & Wu, 1998). In the Bay Area, there are two very large clusters (mega-clusters): downtown San Francisco (83 tracts) and downtown San Jose (22 tracts), which we treat separately in our analysis.

As Table 1 shows, the number of clusters grew only slightly, from 21 in 2002 to 22 in 2015. All three cluster types saw moderate increases in land area, but the story based on the number of census tracts was not quite so similar. Both peripheral clusters and downtown San Jose saw the swapping of former clustered tracts for newly clustered tracts; peripheral clusters netted a three-tract gain, while San Jose actually lost two net tracts in its cluster. Meanwhile, San Francisco gained a net of 16 tracts, an expansion of more than 25 percent. In sum, with only one exception, growth in employment concentration was a product of the expansion of existing clusters rather than the formation of new clusters, and specifically, nearly all of that expansion occurred in San Francisco. In both years, however, almost 90 percent of the region's census tracts were located outside of an employment cluster.

Table 1. Employment clusters in the San Francisco Bay Area, 2002 and 2015

Clusters	**Number of Tracts**					**Land Area (sq. mi.)**	
	2002	**Lost**	**Added**	**Net Δ**	**2015**	**2002**	**2015**
Peripheral Clusters*	70	15	18	+3	71	46.1	49.3
San Francisco Mega-Cluster**	65	1	17	+16	83	11.0	13.5
San Jose Mega-Cluster**	24	5	3	–2	22	30.6	31.9
Not Within Clusters	1,413			–17	1,396	5,749	5,742
Regional Total (tracts w/ employment)			1,572			5,837	

Data sources: LEHD Origin-Destination Employment Statistics (LODES) Dataset (2002, 2015), (2) Employment cluster calculations method from Giuliano and Small (1991) applied to LODES data (2002, 2015)

*** Peripheral cluster =** a set of 19 or fewer contiguous tracts that has a minimum of 10 employees per acre in each tract and at least 10,000 total employees

**** Mega-cluster =** a set of 20 or greater contiguous tracts that has a minimum of 10 employees per acre in each tract and at least 10,000 total employees

We derived five other measures: distance to the nearest employment cluster, a spatially weighted jobs-to-residents ratio, an industrial jobs ratio, a measure of job type concentration, and an estimate of the mean home neighborhood household incomes of workers in a tract. We analyze the first to assess the proximity of workers' jobs in a tract that is not job-dense to the nearest cluster of jobs. We analyze the second to assess the relative difficulty that workers may have living near their jobs and the competition for jobs among those workers. This measure is a ratio of the number of workers within an eight-mile buffer of a census tract's boundary to the number of employed residents within that same buffer. Several studies have used these or similar measures (Hu & Schneider, 2017; Schleith & Horner, 2014; Wang, 2001).

We calculate the ratio of jobs in the goods producing, trade, transportation, and utilities sectors to all other jobs in services; in short, a ratio of blue collar to white color jobs. We also include a measure of occupational concentration, the Herfindahl-Hirschmann Index (HHI) which is the percentage of jobs among each of the twenty available North American Industry Classification System (NAICS) sector codes (Rhoades, 1993). A higher HHI means that a tract's jobs are concentrated in relatively fewer sectors; a lower HHI means the jobs are spread more evenly across the sectors. The vast literature on the journey to work suggests that income is an important consideration (Hu & Schneider, 2017). The LODES include data on workers by three wage categories; however, the Census Bureau does not adjust these thresholds for inflation and thus do not allow us to follow income over time.[4] Thus, we turn to the 2000 U.S. Census (the closest year to our data) and the 2017 American Community Survey 5-year estimates (the midpoint matches our data) to bridge this gap (U.S. Census Bureau, 2000, 2017). We use the commute origin-destination file to assign the median household income of their home census tract to each worker, and then we take the tract mean of those values for workers at the workplace area. We set all values to 2015 US dollars using the California Consumer Price Index (California Department of Industrial Relations, 2022) and express them in units of $1,000. Finally, we include two workplace census-tract traits: the proximity of the tract to rail transit and neighborhood type of the tract. We construct proximity to rail transit as separate dummy variables for 2002 and 2015 for whether or not the tract is within a half-mile of a rail station as the network existed in each of those years. We also identify neighborhoods as urban or not urban, using the Voulgaris et al. (2017) typology of neighborhoods across the United States; here we define as urban census tracts that are located in any of their following three categories: "urban residential," "old urban," and "mixed-use."

There are a few additional limitations to the data and our analysis. Our data include tract-level characteristics and, therefore, cannot explain the individual behavior of neighborhood workers or the variations among them. There also are drawbacks to the LODES data. The data are drawn from unemployment insurance records, so while those records include 95 percent of private sector wage and salary employment, they exclude some workers (Graham et al., 2014). Additionally, some large employers assign all unemployment insurance records to their headquarters rather than to the individual's actual work location; geocoding improvements may have shifted the assignment of workers across small-area locations (Manduca, 2018). We speculate that the disconnect between administrative record work location and actual work location presents the biggest issue with remote workers, especially in the high technology industry. But, rates of remote work changed surprisingly little during our study period: 4.0 percent of Bay Area workers were remote in 2000 (again the closest year to our data) (U.S. Census Bureau, 2000), which increased to just to just 5.8 percent by 2015 (U.S. Census Bureau, 2017). To account for this limitation and because the share of Bay Area remote workers was so small throughout the study period, we restrict our analysis to commutes of less than 100 miles.

Finally, we are limited by the available data to measuring commute distance; while travel mode, tracked or reported travel distance, trip duration, workplace departure/arrival

[4] The LODES use monthly wages cutoffs of $1,250 and $3,333. There are two issues with this approach. First, the wages from a worker's one job are not necessarily the wages from all a worker's jobs. Second, $3,333 in 2002 dollars would be roughly $5,000 in 2015 dollars. Neither presents a clear picture of workers' income levels.

times, frequency of commuting, and traffic congestion would be beneficial measures, our data do not include those.[5] While some of those measures are available in travel surveys, survey data do not provide the universe of workers included in the LODES data, which is what enables us to draw conclusions about the relationship between employment, land use and commute distance.

3.2 Descriptive statistics

Table 2 includes descriptive statistics for the model variables. The average mean commute distance among all tracts increased just over a half-mile, but the distance to the nearest employment cluster decreased by about two-thirds of a mile. As expected, the number of workers grew, but the percentage of young workers declined. So too did the ratio of industrial jobs relative to other jobs, likely attributable to the continued growth in white-collar employment. Data for the categorical variables are not shown in the table. First, there is a set of variables related to Bay Area job clusters; the clusters are mapped in Figure 1. Second, the dummy variable for proximity to rail transit increased from 36 percent in 2002 to 39 percent in 2015. Finally, 42 percent of the tracts were located in urban areas.

3.3 Model

We developed a pooled ordinary least squares (OLS) regression model predicting the relationship between workplace area factors and commute distance in 2002 and 2015. Because mean commute distance is positively skewed, we transformed the dependent variable using the natural logarithm. We employed cluster-robust standard errors and an interaction term for the year across all other variables to estimate both the single-year effects for 2002 and the change in the slope of the predictors by 2015. Next, we estimated the marginal effects of the year to obtain single-year effects for 2015. The models take the following form shown in Equation 1:

$$\mathbf{ln\ (Commute\ Distance\ to\ Workplace\ Census\ Tract) =} \boldsymbol{f\,(L, W, T, I\,)} \quad (1)$$

where L denotes a vector of locational characteristics (employment cluster status, distance to nearest employment cluster, proximity to rail transit, and urban form), W denotes a vector of work characteristics (number of workers, weighted ratio of jobs-to-residents, percent of workers ages 29 and younger, the industrial ratio, and the HHI job type concentration measure), T denotes a dummy variable indicating the year 2015 time period, and I denotes the interaction term for the year 2015 with all other independent

[5] Data on commute duration, commute mode, and congestion in the Bay Area show some change over this period, but in keeping with the theme of this analysis, perhaps less change than one might have predicted. First, Census and ACS estimates place the average commute duration in the San Francisco Bay Area at 29 minutes in 2000 and 32 minutes in 2015, a modest but not stunning increase (U.S. Census Bureau, 2000, 2017). Second, Census and ACS data also suggest that Bay Area commute mode was relatively constant over this time, with slight (1 to 3 percentage points) increases in transit and walking/biking (U.S. Census Bureau, 2000, 2017). And third, Texas A&M Transportation Institute's congestion data suggest that delay per auto commuter in the area increased 24 percent from 2002 to 2015 — which amounts to a total 13-year increase of only about 2 minutes on each one-way commute trip (Texas A&M Transportation Institute, 2021). While such a percentage increase is undoubtedly meaningful, the minutes per trip increase across the region suggests that the effects would be minimal on balance and difficult to capture at the individual level. In short, while congestion in the area increased during the study period, it was already quite congested at the beginning of our study period.

variables. Because the number of jobs is also positively skewed, we use the natural log of the number of jobs in the model.

Table 2. Employment clusters in the San Francisco Bay Area, 2002 and 2015

Variable Name	2002				2015			
	Mean	**St. Dev.**	**Min.**	**Max.**	**Mean**	**St. Dev.**	**Min.**	**Max.**
Mean commute distance *(miles, within tract)**	17.2	5.4	5.5	43.2	17.8	5.3	5.6	46.2
Work Characteristics								
Number of Workers	2,026	4,768	2	77,412	2,362	6,123	27	125,749
Weighted Jobs-to-Residents Ratio	1.05	0.91	0.04	11.88	1.01	0.85	0.07	16.25
% Workers ≤29 years old	28%	0.08	0%	68%	21%	0.07	6%	68%
Industrial Ratio**	0.91	2.9	0	92.9	0.53	0.9	0	13.2
HHI for Job Type Concentration***	2,450	1,429	828	10,000	2,494	1,394	816	9,493
Median Household Income *(in $1,000s of 2015$USD)*	97.0	13.4	61.6	159.2	89.2	13.1	56.2	132.8
Neighborhood Characteristics								
Distance to Nearest Job Cluster *(miles)*	4.2	5.9	0	26.1	3.5	5.0	0	27.1
Number of census tracts	1,572				1,572			

All variables are calculated at the tract level.

Data sources: (1) LEHD Origin-Destination Employment Statistics (LODES) Dataset (2002, 2015), (2) OSRM Route Modeling, (3) Employment center calculations method from Giuliano and Small (1991) applied to LODES data (2002, 2015), (4) Neighborhood Type Analysis (Voulgaris et al. 2017), (5) Rail transit stop locations via 2002 and 2015 GTFS data

* We exclude OSRM commute distances in LODES data of 100+ miles

** Industrial Ratio = no. jobs in goods producing, trade, transportation, and utilities sectors / no. all other jobs

*** HHI = Herfindahl-Hirschmann Index (HHI)

Finally, because analyses like these are prone to spatial autocorrelation—strong associations between proximate observations such as census tracts—we also developed a spatial lag model. Spatial associations would violate the assumption of independence of residuals, which would compromise the validity of our OLS model (Golgher & Voss, 2016; StataCorp, 2021). While a spatial lag equivalent cannot be estimated on a model such as ours that contains multiple observations of the same geographic units over time, we estimated a spatial lag using the 2015 data only and find no evidence of significant indirect effects, meaning all significant model effects are those a tract has on itself (direct effects). Results of the spatial lag model are available from the authors upon request.

4 Changing commute in the Bay Area

Between 2002 and 2015, jobs grew substantially across the entire San Francisco Bay Area. However, unlike prior decades that saw the most growth in Silicon Valley, peripheral areas, and suburban job clusters (Cervero & Wu, 1998) but only minimal growth in San Francisco, job growth in downtown San Francisco exploded from 2002 to 2015. Table 3 shows job growth by type of job cluster. Specifically, the San Francisco mega-cluster experienced a 44-percent increase in total jobs, while the other clusters saw roughly 10 percent growth and the outlying areas 13 percent. Put another way, of the roughly half-million jobs that the Bay Area added between 2002 and 2015, 35 percent of them were in *downtown* San Francisco. (The tracts outside of the mega-cluster in San Francisco added another 27,719 jobs.) In 2002, 58 percent of all Bay Area jobs were located outside of an employment cluster. While job growth in these areas was slower relative to downtown San Francisco, areas outside of job clusters accounted for 47 percent of all additional jobs.

Both in 2002 and 2015, workers in the San Francisco mega-cluster had the shortest commute distances, relative to the other clusters and to outlying areas not within a cluster. But the commutes of workers in this cluster increased from 14.4 to 15.4 miles, which is a noticeable change when multiplied by more than a half-million workers by 2015. In a departure from earlier studies (Cervero & Wu, 1997), workers in the peripheral clusters had the longest commutes at 19.1 miles and 20.8 miles in 2002 and 2015 respectively. This finding may be the culmination of a trend Cervero and Wu (1998) identified—the fastest growth in commute distances in the most outlying employment clusters. Indeed, while Cervero and Wu found that workers in urban San Francisco had the longest commute distances in 1990; in contrast in both 2002 and 2015 we find them to be the shortest, with continued and rapid commute distance growth in outlying clusters and less-but-still-significant growth in San Jose from 1990 to 2002.

Table 3. Job growth and commute distance based on cluster status

Cluster Type	Employment (total jobs)				Commute Distance (mi.)*			
	2002	**2015**	**Δ**	**% Δ**	**2002**	**2015**	**Δ**	**% Δ**
San Francisco Mega-cluster	424,364	611,718	187,354	44.1%	14.4	15.4	1.0	7.0%
San Jose Mega-cluster	326,806	359,844	33,038	10.1%	18.1	18.6	0.5	2.8%
Peripheral Cluster	596,609	654,672	58,063	9.7%	19.1	20.8	1.6	8.4%
Not Within Clusters	1,837,692	2,087,047	249,355	13.1%	17.2	17.8	0.6	3.3%
Region Total	3,185,471	3,713,281	527,810	16.6%	17.2	17.8	0.6	3.7%

*Mean of the means across census tracts

Data sources: (1) LEHD Origin-Destination Employment Statistics (LODES) Dataset (2002, 2015), (2) Employment center calculations method based on Giuliano and Small (1991)

We shift now to the more granular analysis across census tracts. The maps in Figure 1 show each tract's mean commute distance in 2002 (left map) and 2015 (right map), shaded by 2015 quintiles of miles. Overlaid on top of these are that year's employment clusters. In 2002, mean commute distances in the downtowns of San Francisco and San Jose were shorter than the areas north of San Francisco and between these two central business districts, while the areas adjacent to these mega-clusters have mean commute distances largely in the lowest or second-lowest quintiles. Of note, Oakland exhibits similar traits, but its cluster contains only 14 tracts and thus falls short of our mega-cluster definition. The maps for 2015 show similar relative trends as 2002 for these areas, with some slight increases to commute distances in the San Francisco mega-cluster, some growth in employment clusters, and additional outlying tracts moving into the highest quintile.

Figure 2 more precisely describes these changes, depicting percentage change for jobs (left panel) and mean commute distances (right panel). Tracts in which the number of jobs grew are colored in increasing shades of green, with yellow as neutral and dark green as growth that more than doubled. Nearly 70 percent of tracts saw job growth of some amount; over 15 percent of those more than doubled. Accordingly, nearly the entire map is some shade of yellow to green. As we might expect based on our above analysis of growth within the cluster types, the map shows particularly evident growth in San Francisco, where nearly the entire city is green. There is further notable growth in the northern and northeastern areas of the region, particularly in areas near Napa, Vacaville, Concord, and Antioch. There are very few pockets of job loss (shaded increasingly in red); only the areas north of the Golden Gate Bridge in Marin County show any sort of spatially consistent reduction in jobs.

There also were widespread increases in commute distance, but the change was more modest than the growth in jobs. The right panel in Figure 2 shows areas in yellow where there was no change, with commute distance in increasingly red tracts growing up to 50+ percent and commute distance in increasingly blue tracts decreasing up to 50+ percent. Roughly a third of tracts saw minimal change in commute distance between a 10-percent decrease to 10-percent increase. There were concentrations of census tracts with higher growth in commute distances in outlying areas outside of clusters that had experienced substantial increases in jobs. Commutes also grew in Silicon Valley and downtown San Francisco, both within and adjacent to the mega-cluster. Notably, we find substantially lengthening commutes in those same outlying areas with job growth —those near Napa, Vacaville, Concord, and Antioch—all of which are generally near freeways. There are some pockets of strongly-decreasing commutes, particularly in the southern parts of San Francisco and the northern part of neighboring San Mateo County, as well as in the southern neighborhoods of Oakland. In all, commute distances declined in 38 percent of tracts, nearly two-thirds of which were located in those two areas.

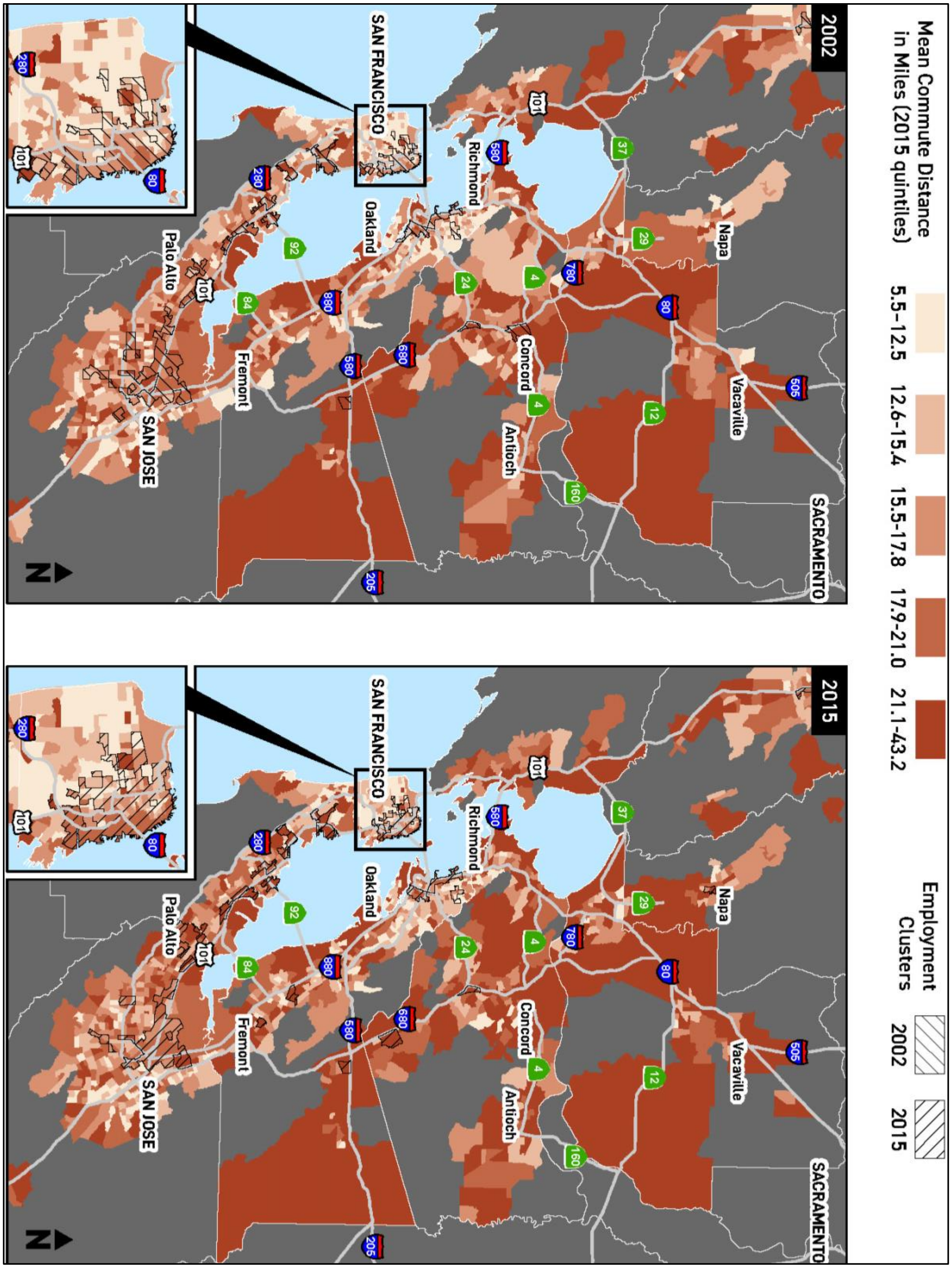

Figure 1. Mean commute distances and job clusters in the Bay Area, 2002 (left) and 2015 (right)
Sources: 2002 and 2015 LEHD LODES, OSRM, Census TIGER/Lines

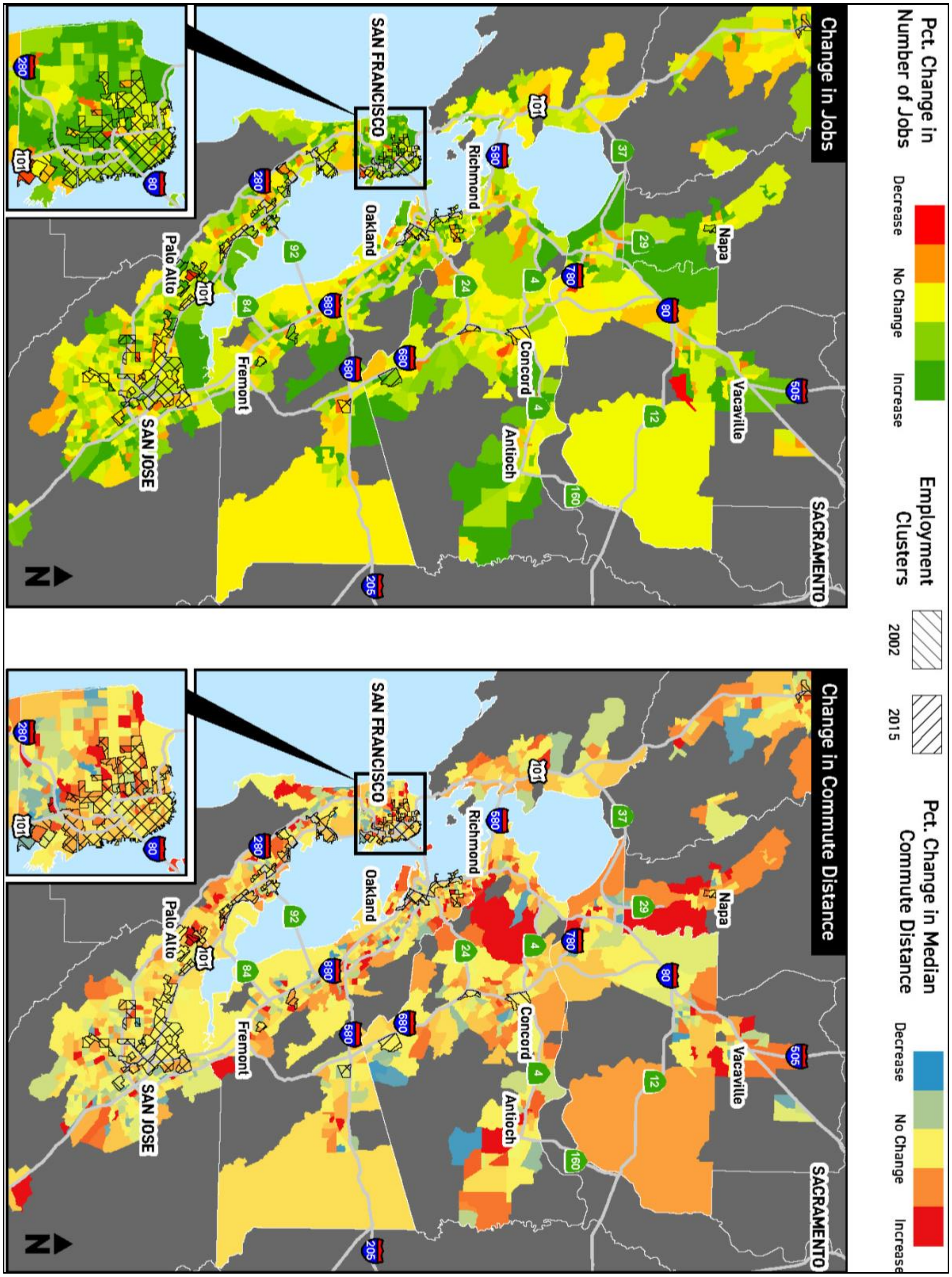

Figure 2. Changes in Employment (Left) and Mean Commute Distance (Right) in the Bay Area between 2002 and 2015
Sources: 2002 and 2015 LEHD LODES, OSRM, Census TIGER/Lines

5 Explaining commute distance in the Bay Area

While commute distance in the Bay Area nominally increased over time, the factors that explained commute distance remained relatively stable over the study period. Table 4 shows the results of the pooled OLS regression model, with 2002 on the left, 2015 in the middle, and the change effects on the right. The pooled model explains roughly 38 percent of the variation in commute distances.[6]

In both 2002 and 2015, work characteristics were associated with commute distance in anticipated ways. The number of workers in a tract was the single biggest predictor of commute distance. In both years it was positively related to commute distance. The ratio of jobs to residents—a proxy for jobs-housing balance—was also statistically significant but had less of an effect in both years compared to the job count. Further, areas with a higher percentage of workers below age 30 and/or a higher ratio of industrial jobs to other jobs were also associated with longer commutes. Finally, in 2015, greater homogeneity by employment sector was associated with shorter commutes.

Also, for the individual years and controlling for the total number of workers, workers in a mega-cluster (downtown San Francisco or downtown San Jose) had shorter commutes.[7] Similarly, proximity to rail transit was also associated with shorter commute distances. Notably, being in an urban tract was not significant, indicating that rail was not serving as an inadvertent proxy for urbanicity; rather, living near rail appears to be genuinely associated with shorter commutes in both years. Conversely, as job distance from an employment cluster increased, so too did commute distance in both years.

Examining the change between the two years indicates that all of the neighborhood characteristics and workplace area variables kept the same sign in both 2002 and 2015 and all maintained some level of significance at the $\alpha = 0.05$ level across both years (and most at the $\alpha = 0.01$ level), with one exception: job type concentration. The biggest change was in the effect of the total number of jobs, also the strongest predictor for each year. The number of jobs was more strongly associated with commute distance in 2015 than 2002. Changes in the effect of two other workplace characteristics also are noteworthy. The association between the industrial ratio and commute distance strengthened: as the ratio of blue collar to white collar jobs increased, so too did its positive effect on commute distances. Meanwhile, increasing homogeneity of job types within a tract was slightly less associated with increasing commute distances in 2015 than it was in 2002.

At the neighborhood level, two associations strengthened over time. The negative relationship between being located in the San Jose mega-cluster and commute distance became stronger. So too did the positive relationship between commute distance and distance to the nearest job cluster. In other words, the spatial dispersion of employment still has not brought jobs closer to workers; workers continue to drive further to jobs that are not collocated with other jobs, meaning that the trend Cervero and Wu (1998) uncovered persisted. Although tracts in downtown San Francisco remain strongly associated with shorter commutes in both 2002 and 2015, there was no significant change between the two years. Finally, we note that although the jobs-housing balance measure

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[6] We also estimated OLS models for individual years in 2002 and 2015. The 2002 model yielded an adjusted R-squared of 0.32, while the 2015 model's adjusted R-squared was 0.44.

[7] We tested whether this relationship was statistically significant if we did not control for the total number of workers. The San Francisco mega-cluster remained significant and negative. The peripheral cluster variable became significant and positive, while the San Jose mega-cluster variable was no longer statistically significant.

is statistically significant in both years, the change between the two years is not significant.

Table 4. Log mean commute distance by work census tract – OLS model results

Independent Variables	2002 Coefficient (Std. Error)	2002 Beta Weight	2015 [a] Coefficient (Std. Error)	2015 [a] Beta Weight	Change Coefficient (Std. Error)	Change Beta Weight
Year Interaction (2015)	–0.111 (0.084)	–0.179				
Work Characteristics						
Log Number of Workers	0.086*** (0.007)	0.363	0.122*** (0.006)	0.515	0.036*** (0.008)	0.410
Weighted Jobs-to-Residents Ratio	0.037*** (0.010)	0.107	0.023** (0.009)	0.067	–0.014 (0.011)	–0.036
Percent of Workers ≤29 years old	0.010*** (0.001)	0.264	0.010*** (0.001)	0.261	–0.000 (0.001)	–0.004
Industrial Ratio	0.018** (0.007)	0.126	0.054*** (0.007)	0.374	0.036** (0.012)	0.080
HHI for Job Type Concentration	0.000 (0.000)	0.047	–0.000* (0.000)	–0.046	–0.000** (0.000)	–0.105
Median Household Income *(in 1000s of 2015$)*	0.002*** (0.001)	0.103	0.003*** (0.001)	0.117	0.000 (0.001)	0.046
Neighborhood Characteristics						
In Job Cluster (non-mega)	0.001 (0.032)	0.001	0.000 (0.033)	0.000	–0.001 (0.033)	–0.000
In San Francisco Mega-Cluster	–0.193*** (0.031)	–0.132	–0.196*** (0.032)	–0.134	–0.003 (0.036)	–0.002
In San Jose Mega-Cluster	–0.137** (0.040)	–0.054	–0.223*** (0.056)	–0.087	–0.086* (0.037)	–0.023
Distance to Nearest Job Cluster (mi.)	0.013*** (0.001)	0.226	0.018*** (0.001)	0.319	0.005** (0.002)	0.067
Near Rail Transit (within 0.5 mi.)	–0.057*** (0.015)	–0.088	–0.068*** (0.014)	–0.106	–0.011 (0.015)	–0.015
Constant Term	1.634*** (0.076)	—		–0.024	0.000 (0.015)	0.000

n = 1,572 R^2 = 0.381   Probability > F = 0.000   *All variables are calculated at the tract level with cluster-robust standard errors.*

* p < 0.10; ** p < 0.05; *** p < 0.01.

[a] All values for 2015 calculated as marginal effects in main model.

Data sources: (1) LEHD Origin-Destination Employment Statistics (LODES) Dataset (2002, 2015), (2) OSRM Route Modeling, (3) Employment center calculations method from Giuliano and Small (1991) applied to LODES data (2002, 2015), (4) Neighborhood Type Analysis (Voulgaris et al. 2017), (5) Rail transit stop locations via 2002 and 2015 GTFS data

6 Discussion

The data show that commute distances in the Bay Area have grown over time, although perhaps not as much as observers had expected. Certainly, some workers—like Sheila James—moved outward in search of cheaper housing and traveled long distances back to their places of employment. However, for other workers—particularly lower-skilled workers—moves to outlying neighborhoods likely motivated changes in employment to jobs located closer to workers' new homes. Among other factors, this process is facilitated by the ongoing dispersion of low-skilled jobs. Therefore, while these workers may commute longer distances than they had previously, their commutes may not have increased as much as some proclaim. Moreover, if workers in outlying areas travel by car on less congested roads and highways, they may even experience a decline in travel time (but potentially higher transportation expenditures if they previously had traveled by public transit).

The data do not allow us to follow individual workers over time. However, the results of the statistical models are suggestive of some of these trends. The number of jobs is associated with longer distance commutes, indicating that some workers travel from far away to access places with concentrated employment, a finding consistent with the larger theoretical and empirical literature. This relationship has strengthened over time; indeed, its slope changed by a magnitude four times greater than of any other predictor. At the same time, the model predicts longer commutes to dispersed jobs—jobs that are located away from job centers; this relationship also strengthened over time.

However, we find that commutes into downtown San Francisco (the focus of our analysis) are shorter relative to commutes to other areas, controlling for other determinants of commute distance. This anomaly may be due to the characteristics of the San Francisco workforce: higher-wage workers who can afford to live close to downtown San Francisco. There is a growing gap in median wages between workers living in San Francisco relative to workers in the region (Ruggles et al., 2021). While median wages of Bay Area workers declined slightly (-3%) from 2000 to 2015, workers in San Francisco experienced a 17 percent increase in wages (Ruggles et al., 2021). The wage gap continued to grow through 2019. Hu et al. (2017) find a convex relationship between worker wages and commute distance in Baton Rouge. They argue that when mean wages reach some threshold, workers experience a high opportunity cost to commuting; their high incomes enable them to purchase or rent homes close to their places of employment. Finally, our jobs-to-residents variable is statistically significant in both years. Not all workers want to live close to their workplaces, selecting neighborhoods based on other characteristics (e.g., quality of schools, safety, etc.) (Giuliano, 1991). However, the findings suggest that at the margins, some households might choose to live closer to their jobs if there were greater opportunities to do so.

While mean commute distances may not have grown as much as pundits expected, total person commute miles *did* grow substantially. In 2002, the nine-county region's workers amassed 57.8 million one-way miles of commute distance; by 2015, that number had grown to 68.7 million miles, an increase of nearly 19 percent. Comparing this with only a three-percent increase in mean work tract commute distance further suggests that the story has more to do with the dramatic increase in jobs rather than the increase in commute distance.

Figure 3 shows the increase in commute miles by job cluster type. In particular, we see substantial growth in aggregate commute miles for all workers in downtown San Francisco, where the dramatic increase in workers combined with the modest increase in mean commute miles led to a 49-percent increase in aggregate commute miles. Although only holding 17 percent of the region's jobs, workers in San Francisco accounted for 30 percent of the region's aggregate growth in commute miles. The remaining growth in commute miles came half from workers outside of clusters (where most jobs are located), 14 percent from peripheral clusters, and only five percent from downtown San Jose.

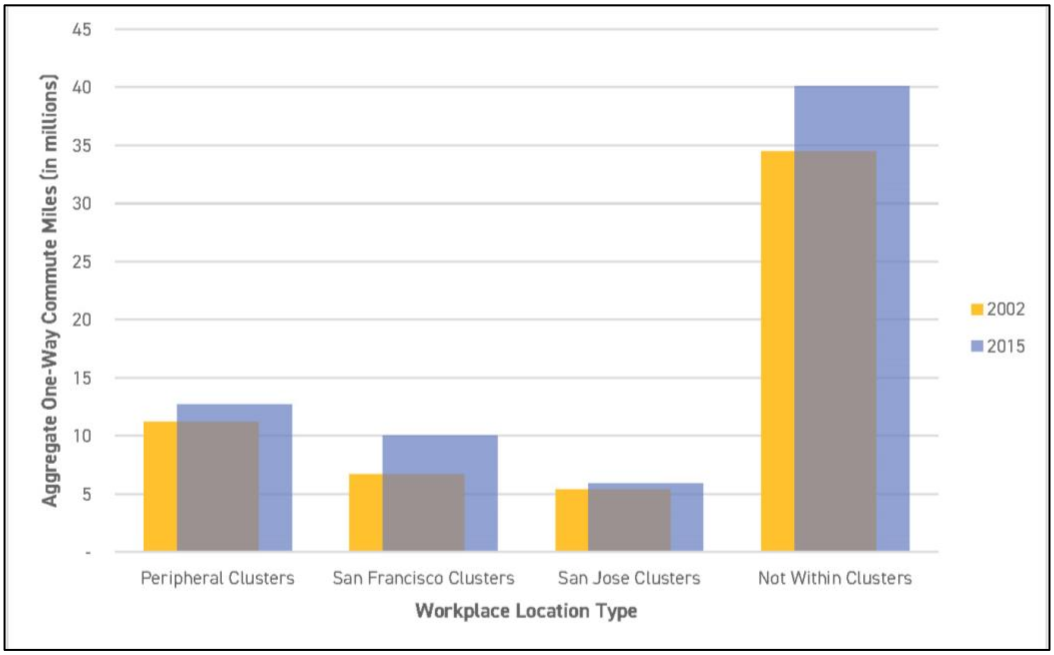

Figure 3. Aggregate commute miles (one-way) of Bay Area workers by workplace location type
Sources: 2002 and 2015 LEHD LODES, OSRM

7 Conclusion

From 2002 to 2015 the San Francisco Bay Area experienced an enormous increase in work-related travel due both to increases in commute distance and the substantial growth in the number of workers. These trends put tremendous pressure on the region—especially its infrastructure and population (Metropolitan Transportation Commission, 2016). Forty-four percent of job growth took place in areas outside of job centers, where destination access is predicated on having a car, the purchase of which can be a financial strain for some households. Low-wage workers living in these areas may benefit from policies to subsidize car use and ownership (Klein, 2020; Lucas & Nicholson, 2003).

About 38 percent of the employment growth occurred in downtown San Francisco where workers had the shortest commutes. We speculate that while commute distances are growing, they remain shorter than commutes to other jobs largely because higher-wage workers *do* self-select into these neighborhoods. If this speculation is valid, additional affordable housing in neighborhoods close to downtown San Francisco would give lower-wage workers the opportunity to live close to where they work, and potentially ease the financial burden of automobile travel.

Of course, since the time period of our study data, the COVID-19 pandemic also disrupted the journey to work—and the concept of work itself. In the early stages of the pandemic, many workers fled their offices in downtown San Francisco, and many of those also fled their residences chosen in part for commuting to those offices; however, many who relocated did so within the same metropolitan areas (Ramani & Bloom, 2021).

As of this writing, office visits have begun to rebound, albeit slowly (Weber et al., 2022). Based on employer and employee preferences, the future of remote work appears to be hybrid: a few days per week in-office and a few days remote (Bloom et al., 2022).

However, even in the Bay Area with its extraordinary agglomeration of high-technology industries, remote work is far from universal: less than half of jobs can be done remotely based on the nature of the work required (Dingel & Neiman, 2020). Though rates of remote work grew substantially from 5.8 percent of Bay Area workers in 2015 to 24.9 percent of workers in 2022 (U.S. Census Bureau, 2017, 2022), this leaves greater than three quarters of all Bay Area workers traveling to work at least some of the time. Further, as of Spring 2021, daily Bay Area toll bridge traffic averaged 85 percent of the levels recorded prior to the pandemic (Metropolitan Transportation Commission, 2021). Given this, we believe our findings remain relevant to the Bay Area. We limit our study to a pre-pandemic analysis, but as new data become available that are clearly in the post-pandemic era (2023 and beyond), future research should examine how both the administrative record location of jobs and the *observed* work locations of workers have changed, especially in regions with high shares of employment in sectors with strong propensities for remote work.

Is this just a Bay Area story? Perhaps. Among the largest 92 U.S. metropolitan areas San Francisco experienced the second largest increase in the number of downtown jobs from 2010 to 2018, second only to New York (Loh & Kim, 2021). At the same time, the rate of job growth in downtown San Francisco ranked eighth, behind numerous smaller metropolitan areas (Loh & Kim, 2021). The combination of large job numbers and rapid job growth may place San Francisco in a category of its own, an example from which other metropolitan areas can learn. However, coming out of the 2008 recession one-third of all downtowns experienced employment growth at a similar or faster pace than their regions (Loh & Kim, 2021), suggesting that some of these metropolitan areas—particularly high-housing cost areas such as New York or Seattle—face issues similar to those of the Bay Area. The pandemic may have accelerated the rates of dispersion—of both households and employment. Therefore, researchers should replicate the analysis with more recent data when they are available as well as test the generalizability of our findings to other high-cost regions with booming downtown business districts.[8]

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[8] The LODES data are not yet available for 2022, limiting our ability to test whether these relationships have shifted beyond the immediate effects of the pandemic. However, we also note that future vintages of the LODES will less accurately capture commuting as proxied by distance between home and administrative payroll work location, as a far greater share of workers are now fully remote from that recorded work location.

Author contribution

The authors confirm contribution to the paper as follows: Evelyn Blumenberg: study conception and design. Samuel Speroni: data assembly. Blumenberg and Speroni: analysis and interpretation of results; draft manuscript preparation.

All authors reviewed the results and approved the final version of the manuscript.

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