# The Equity and Policy Implications of Long-Distance Commuting in the Greater Los Angeles Region

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A Research Report from the Pacific Southwest Region University Transportation Center

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#### 16. Abstract

The phenomenon of very long commutes, or "super-commutes," has long interested the public, planners, elected officials, and researchers. US researchers define super-commuting as one-way commutes over 50 miles or 90 minutes. We draw on multiple data sources to examine the prevalence, characteristics, and location of super-commuters in the greater Los Angeles region. We then use individual and household data to examine super-commuting and housing and transportation (H+T) expenditure burdens in California.

We find that super-commuters are a relatively small, albeit growing, share of workers in the greater Los Angeles region who are more likely to be higher-income than other workers. Low-income super-commuters are about six times as likely as higher-income super-commuters to travel by bus. Across all income groups, super-commuter households have slightly higher H+T burdens than non-super-commuter households. However, the contribution of super-commuting to the H+T expenditure burden is modest compared to other factors.

Public policy efforts to reduce commute times would almost certainly lower the number of super-commuters. So too would interventions to increase incomes or reduce housing and/or transportation expenditures. Possible policy interventions include: low-income auto access and ownership subsidies, programs to assist modest-income, first-time home buyers, zoning for and entitling additional housing, and improved transit service in transit-friendly neighborhoods.

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## **Table of Contents**

About	the Pacific Southwest Region University Transportation Center	1
U.S. De	epartment of Transportation (USDOT) Disclaimer	2
Califor	nia Department of Transportation (CALTRANS) Disclaimer	2
Disclos	ure	3
Abstra	ct	4
Execut	ive Summary	5
1. In	troduction	10
2. Tł	ne Long Road Home—A Review of the Research on Long Commutes	12
2.1.	The extent of super-commuting	12
2.2.	Why do people commute long distances or durations?	14
2.3.	Who tends to commute long distances or durations?	16
2.4.	The costs of long commutes	20
2.5.	Conclusion – Equity implications of super-commuting	21
3. D	ata and Methods	23
4. Sı	per-Commuting Trends 2005 to 2023	25
5. Cl	naracteristics of Super-Commuters in the Los Angeles Region	31
6. Supe	er-Commuting Hotspot Analysis	41
5.1.	Super-commuter hotspots	41
6.2	Super-commuters by wages	47
6.3	Job centers	48
6.4	Top job centers for workers in super-commuting hotspots	50
6.5	Commute distance	54
6.6	Commute duration	55
7. H	ousing and Transportation Expenditures in Super-Commuting Hotspots and Job Centers	57
7.1	Housing and transportation cost estimates for super-commuting hotspots	57
7.2	Housing and transportation cost estimates for Los Angeles job centers	63
8. H	ousing and Transportation Expenditures and Worker Households in California	68
8.1	Methodology	68
8.2	Characteristics of super-commuting households	70
8.3	Housing and transportation burden and costs	73
8.4	Predicting H+T expenditures and the H+T expenditure burden	82
8.5	Scenarios	89



9.	Conclusion:	Equity and Policy Implications of Super-Commuting	. 94
Refe	rences		.97
Арре	endices		102



## Table of Figures

Figure 1. Mean One-Way Commute Duration in the Greater Los Angeles Region, by Year	25
Figure 2. Percent and Number of Super-Commuters by Year, Los Angeles Region	26
Figure 3. The Share of Super-Commuters by Mode in the Greater Los Angeles Region	28
Figure 4. Share of Super-Commuters in the Most Populous Counties in the Greater Los Angeles Region	on
	30
Figure 5. Mean Commute Duration in the Greater Los Angeles Region and by County	31
Figure 6. Super-Commuting Rates in the Greater Los Angeles Region and its Component Counties	33
Figure 7. Distribution of Super-Commuters by Counties in the Greater Los Angeles Region	34
Figure 8. Modal Distribution of Super-Commuters, Counties in the Greater Los Angeles Region	34
Figure 9. Super-Commuting Rates by Worker Characteristics, Greater Los Angeles Region	37
Figure 10. Super-Commuters by Household Income and Transit Use, Greater Los Angeles Region	38
Figure 11. Visual Plot of the Two Types of Greater Los Angeles Region Super-Commuters	40
Figure 12. Distribution of Super-Commuters Across Top Hotspots, Greater Los Angeles Region	46
Figure 13. Super-Commuting Rates, by Super-Commuting Hotspots in Greater Los Angeles Region	46
Figure 14. Distribution of Super-Commuters by Wages, Super-Commuting Hot Spots in Greater Los	
Angeles Region	47
Figure 15. Percentage of Workers Working in Job Centers – Super-Commuter Hotspots and the Grea	at
Los Angeles Region	53
Figure 16. Annual Housing and Transportation Costs by Super-Commuting Hotspots	60
Figure 17. Housing and Transportation Cost Burden by Super-Commuting Hotspots	60
Figure 18. Housing and Transportation Cost Burden by Household Income Quintile (U.S.)	63
Figure 19. Comparison of Annual Housing and Transportation Costs across Places	64
Figure 20. Comparison of Home Ownership Costs across Places	66
Figure 21. Comparison of the Housing and Transportation (H+T) Expenditure Burden Between the 20	017-
18 Consumer Expenditure Survey (CES) and the NHTS/PUMS Estimates	70
Figure 22. Characteristics of 1+-Worker and Super-Commuter Households	71
Figure 23. Distribution of Households by Income Quintile	73
Figure 24. Median Housing and Transportation Expenditure Burden – Super-Commuter and 1+- Wor	rker
Households	75
Figure 25. Median H+T Expenditure Burden by Household Type	78
Figure 26. Median H+T Expenditure Burden – Super-Commuter Households by Income Quintile	
Figure 27. Median Expenditures Super-Commuting Households: Housing, Transportation, and H+T b	οу
ncome Quintile	-
Figure 28. Schematic: Variables in H+T Regression Models	84
Figure 29. Predicted H+T Burden by Scenario (Outward Movement)	92



## Table of Tables

Table 1.	Commute Duration and Mean Earnings by Mode – All Workers (Greater Los Angeles Region).	28
Table 2.	Variables Used to Identify Super-Commuter Types in the Greater Los Angeles Region	39
Table 3.	Results of the Super-Commuter Cluster Analysis for the Greater Los Angeles Region	39
Table 4.	Top Super-Commuting Hotspots, Greater Los Angeles Region	44
Table 5.	Top Five Job Centers—All Super-Commuters and Super-Commuters in Top Hotspots	54
Table 6.	Average Commute Distance for Workers in Top Super-Commuting Hotspots	55
Table 7.	Housing and Transportation Cost Estimates for Super-Commuting Hotspots and Job Centers	57
Table 8.	Summary of Household and Transportation (H+T) Expenditure Models	86
Table 9.	Summary of Household and Transportation (H+T) Burden Models	89
Table 10	Predicted Values for H+T Burden by Scenarios	91



## Table of Maps

Map 1. Top 10th Percentile of ZCTAs (based on total number of super-commuters), Great	er Los Angeles
Region	43
Map 2. Top Super-Commuting Hotspots, Greater Los Angeles Region	
Map 3. Major Job Centers in the Greater Los Angeles Region	49
Map 4. Job Centers and Super-Commuting Hotspots in the Greater Los Angeles Region	50



## **Appendices**

Appendix 1. Data Sources	102
Appendix 2. Strengths and Weaknesses of Data Sources	103
Appendix 3. Super-Commuting Rates (90+ minutes) by Individual and Household Charac	cteristics and
County	104
Appendix 4. Composition of Super-Commuters (90+ minutes) for Counties in the Greate	er Los Angeles
Region	106
Appendix 5. Detailed Methodology for Cluster Analysis	108
Appendix 6. Top Five Job Centers from Super-Commuting Hotspots	109
Appendix 7. Estimated Commute Duration from Super-Commuter Hotspots to Top-5 Er	nployment
Centers*	111
Appendix 8. Regression: Transportation Costs	113
Appendix 9. Expenditure Burdens by Household Characteristics and Type	114
Appendix 10. Regression: Household and Transportation Expenditures (logged), Califor	rnia Households
with 1+ Workers	115
Appendix 11. Regression: H+T Expenditures (logged) for Households with 1+ Workers b	oy Income 117
Appendix 12. Regression: Housing and Transportation Cost Burden – All Worker House	holds 119
Appendix 13. Regression: Housing and Transportation Cost Burden – Income Groups	121



# **About the Pacific Southwest Region University Transportation Center**

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region*. Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.



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## **Disclosure**

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## **Abstract**

The phenomenon of very long commutes, or "super-commutes," has long interested the public, planners, elected officials, and researchers. US researchers define super-commuting as one-way commutes over 50 miles or 90 minutes. We draw on multiple data sources to examine the prevalence, characteristics, and location of super-commuters in the greater Los Angeles region. We then use individual and household data to examine super-commuting and housing and transportation (H+T) expenditure burdens in California.

We find that super-commuters are a relatively small, albeit growing, share of workers in the greater Los Angeles region who are more likely to be higher-income than other workers. Low-income super-commuters are about six times as likely as higher-income super-commuters to travel by bus. Across all income groups, super-commuter households have slightly higher H+T burdens than non-super-commuter households. However, the contribution of super-commuting to the H+T expenditure burden is modest compared to other factors.

Public policy efforts to reduce commute times would almost certainly lower the number of super-commuters. So too would interventions to increase incomes or reduce housing and/or transportation expenditures. Possible policy interventions include: low-income auto access and ownership subsidies, programs to assist modest-income, first-time home buyers, zoning for and entitling additional housing, and improved transit service in transit-friendly neighborhoods.



# The Equity and Policy Implications of Long-Distance Commuting in the Greater Los Angeles Region

## **Executive Summary**

The phenomenon of very long commutes, or "super-commutes," has long drawn the attention of the general public, planners, elected officials, and researchers. In the US, super-commutes are typically defined as one-way journeys to work over 50 miles in distance and/or over 90 minutes in duration. The percentage of California workers who super-commuted gradually increased to just under five percent (4.7%) during the first two decades of the 21st century. While rates of super-commuting declined in the pandemic year of 2020, they have—once again—started to climb. Substantially increased rates of working from home during and since the pandemic have made commutes rarer for these workers, who may be willing to trade off longer, less frequent commutes for more spacious housing with home offices.

For the substantial majority of super-commutes made in cars and light-duty trucks, increased super-commuting can have negative effects on the environment. Super-commutes also can take a toll on the lives of workers and their families, as long periods of time spent commuting is time away from sleeping, parenting, socializing, and exercising. Finally, long commutes in automobiles can be expensive, which can strain household budgets.

So why would anyone choose to super-commute? It may be, as we note above, that more occasional long commutes may not entail more time or expense over the course of a week or month than the shorter, five-day-a-week commutes of the past. It may be in order to live in a highly desired (albeit distant from work) location. It may be to balance a spouse or partner's commute in another direction. It may just be temporary. Or it may be to "drive 'til you qualify" for home ownership on the suburban fringe. Indeed, the expenditure burden of long commutes may be offset by lower housing costs in outlying neighborhoods, especially if some household workers regularly work from home a few days a week.

The purpose of this study was to examine these possibilities and the equity implications of supercommuting. We address the latter primarily in terms of the housing and transportation (H+T) expenditure burdens of super-commuters, which we define here as the out-of-pocket costs of housing and transportation as a percentage of household income. Much of our analysis centers on the greater Los Angeles region, which is comprised of the six counties under the aegis of the Southern California Association of Governments: Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties.

In executing our analyses, we first drew on individual-level data to examine the prevalence of super-commuting and the characteristics of super-commuters in the greater LA region, with particular attention paid to variation across household income. We then used neighborhood-level data to identify super-commuting hot spots in the region, documenting differences in the housing and transportation expenditure burden of workers in these residential hotspots and in their top employment destinations. In the final analysis, we estimated the housing and transportation expenditure burden among all California households with at least one worker by household income as the basis for a set of scenarios



that highlight the association between the H+T expenditure burden, household income, and other factors of interest, such as remote work, travel mode, and residential location.

The following are the major findings from these analyses:

#### The Prevalence and Worker Characteristics of Super-Commuting in the Los Angeles Region

- Similar to nationwide trends, the percentage of super-commuters increased leading up to the COVID-19 pandemic, dropped sharply during the pandemic, and has started to increase again postpandemic.
- Super-commuting is comparatively rare. Fewer than one in 20 (4.5%) workers in the greater Los Angeles region super-commutes, although this share of super-commuters is higher than among U.S. workers as a whole.
- Higher-income workers are more likely to super-commute than lower-income workers.
- Super-commuting is correlated with a variety of worker and household characteristics. For example, age (up to 60) and education are positively related to super-commuting. Super- commuters are more likely to be male and Black.
- Super-commuting is more common among public transit commuters, particularly with respect to
  commute duration (of 90 minutes or more). Such transit commutes include both relatively long
  commuter rail trips (often by higher-income workers) to and from major job centers, particularly
  downtown Los Angeles, as well long duration commutes (often by lower-income workers) on
  relatively slow bus service that may entail multiple transfers.
- There are two distinct clusters of super-commuters based on socio-demographic characteristics.
   The first type of super-commuter tends to be younger, non-white, lower-income, and less educated; this cluster is more likely to commute on public transit and rent their homes. The second cluster tends to be older, white, higher income, and more educated, with higher rates of homeownership and automobile commuting.

#### **Super-Commuter Residential Hotspots in the Los Angeles Region**

- One in four super-commuters in the Los Angeles region (175,707 out of 701,751) live in seven hotspot areas located in the urban periphery of the region – Fontana-Rialto (San Bernardino County), Jurupa Valley (Riverside County), Lancaster-Palmdale (Los Angeles County), Moreno Valley (Riverside County), Oxnard (Ventura County), Perris-Elsinore-Temecula (Riverside County), and Victor Valley (San Bernardino County).
- The two largest concentrations of super-commuters in the greater LA region are in Lancaster-Palmdale in north Los Angeles County and Perris-Lake Elsinore-Temecula in southwestern Riverside County.



- A majority (57%) of super-commuters in the seven super-commuter residential hotspots work outside of major regional job centers. However, super-commuters in these hotspot areas are more likely to work in major job centers than other workers living in these hotspots.
- The two largest employment concentrations of super-commuters are in Downtown Los Angeles (DTLA) and the Wilshire Corridor (which is comprised of neighborhoods adjacent to Wilshire Boulevard running from west of DTLA to the Pacific Coast in Santa Monica).

## Housing and Transportation (H+T) Expenditure Burdens in Super-Commuter Residential Hotspots and Employment Destinations

- In almost all of the super-commuting hotspots, the average H+T expenditure burden is greater than the burden that is typically deemed to be affordable (45%) largely due to higher than average transportation (rather than housing) expenditure burdens.
- Total housing costs (both ownership and rent expenditures) in Downtown Los Angeles and along the
  Wilshire Corridor (the top two workplace destinations for super-commuters) are slightly (but not
  substantially) higher than in the super-commuting hotspots or in the greater Los Angeles region
  broadly; however, transportation costs in these areas are substantially lower.
- Setting aside rental housing costs, home ownership costs in all but one of the top super-commuting job centers are significantly higher than in any of the super-commuting residential hotspots, suggesting that at least some super-commuters trade off shorter commutes for home ownership.

#### **Super-Commuter Households in California**

- Super-commuter households tend to have higher incomes than both non-super-commuter households and households as a whole.
- Across all income groups, super-commuter households have higher housing and transportation
  expenditure burdens than California worker households as a whole. This pattern remains even
  when controlling for other factors associated with the H+T expenditure burden, such as
  race/ethnicity, household size and composition, household income and assets, household travel,
  and residential location.
- The H+T expenditure burden is highest among low-income worker households of all types both super-commuter and otherwise. Among super-commuter households in the bottom two income quintiles, the H+T burden is higher than 45 percent, which is the percentage typically viewed as affordable.
- The association between super-commuting and the H+T expenditure burden for worker households across low-, medium-, and high-income groups is relatively modest compared to the influence of other characteristics, such as the number of household vehicles and household size.
- Across all income groups, homeowners tend to have lower H+T expenditure burdens, all else equal, though this effect is strongest among middle-income worker households.



- Regardless of the mix of assumptions employed in our scenario analysis, lower-income households tend to have significantly higher H+T burdens compared to other households.
  - Among all lower-income households, the H+T burden tends to be slightly *lower* in households whose members: do not super-commute, are suburban homeowners, do not work-from-home, and commute to work by car.
  - Conversely, the H+T burden across all lower-income California households tends to be comparatively *higher* among urban renter households whose members commute to work by car.

Across all of these analyses, we find that—outside of a few neighborhoods—super-commuters are a relatively small, albeit growing, share of all workers in the greater Los Angeles region. And again, super-commuters are more likely than other workers to live in higher-income households. This is because many lower-income workers are unlikely to have the resources to sustain these types of commutes or the types of jobs that require them. When they do super-commute, low-income workers are almost six times as likely to travel by bus than higher-income super-commuters. Consequently, long commute durations among workers in this group are likely due to the comparatively slow travel speeds on one or more buses rather than long travel distances.

Across all income groups, including low-income households, super-commuter households have slightly higher H+T burdens than non-super-commuter households. However, the contribution of super-commuting to the H+T expenditure burden is relatively small compared to other factors. Therefore, concerns about the growth in super-commuting may be warranted on a variety of grounds (environmental, congestion, time burden, etc.) but perhaps less so on equity grounds. However, our analysis suggests two equity issues with respect to super-commuting—long travel times on buses and high H+T burdens—issues that also affect low-income workers more broadly. As we note above, a high percentage of (the relatively few) low-income super-commuters endure long commutes on comparatively slow-moving buses. Moreover, lower-income super-commuter households have significantly higher H+T expenditure burdens than higher-income households, on average, which impose disproportionate financial pressures on these households.

Public policy efforts to reduce commute times would almost certainly lower the number of super-commuters. In addition, interventions to increase incomes or reduce housing and/or transportation out-of-pocket costs would lower household H+T burdens. Overall, our findings suggest four potential points of intervention in this regard:

1. Expand policy efforts to offset the costs of automobile access and ownership. Automobiles provide travelers with tremendous accessibility to opportunities, particularly in suburban and non-metropolitan areas where motor vehicle travel is ubiquitous and where most California households live. Because low-income households often struggle to afford the costs of automobile ownership, California has a number of programs to subsidize the purchase of cleanfuel vehicles and offset the costs of auto insurance and maintenance for low-income households. These programs could be expanded.



- 2. Expand programs to assist low-income, first-time home buyers. Homeownership is associated with a lower H+T burden for all income groups, likely related to residential location in outlying neighborhoods where housing values are lowest. But regardless of location, homeownership tends to be out of reach for most lower-income households. Thus, the expansion of programs to assist low-income, first-time home buyers could help reduce their H+T burdens.
- 3. Expand state efforts to motivate local governments to zone for and entitle more housing, particularly multi-unit housing in central areas. Housing growth in California across all price levels has lagged employment growth for many years. This has contributed significantly to a housing affordability crisis, which has motivated increasing numbers of residents and employers to move to other states; it has also increased super-commuting for households moving to the fringes of metropolitan areas in search of home ownership. Over the past decade the California Legislature has passed and the Governor has signed a number of bills to streamline housing production broadly, and near transit stops and stations in particular. Increasing such efforts could meaningfully enhance the housing supply in urban areas and weaken at least one motivation for super-commuting.
- 4. Enhance public transit in neighborhoods where transit works best. From the perspective of travelers, public transit is relatively cheap compared to the costs of automobile ownership. Targeted transit investments (and other complementary policies) in areas where transit provides good access to jobs within a reasonable travel time could serve multiple purposes: it could reduce travel times among current transit users, decrease the number of low-income super-commuters, and—assuming these investments promote transit use—lower the H+T burden.

While we have shown that the H+T *burdens* tend to be higher among lower-income households, *total expenditures* on housing and transportation in such households tend to be very low overall. On average, low-income households spend less than half of the expenditures of households in the top income quintile – suggesting the presence of unmet transportation and housing needs among lower-income Californians. Transportation and housing interventions of the sorts outlined above could ease the H+T expenditure burden without compromising households' access to needed destinations and the opportunity to live in decent housing in high-quality neighborhoods without the need to endure brutally long commutes to and from work.



## 1. Introduction

The journey to and from work, often called "the commute," is a critically important component of household travel. While not the most frequent regular household trip purpose, it is most often the longest in distance and duration. It is also (at least it was before the COVID-19 pandemic) the household trip most fixed in time and space, and thus has an outsized effect on both household activity patterns and transportation system operations. Commuting is a big reason for why we have morning and afternoon rush hours; commuters also comprise a disproportionate share of public transit riders. In recent years, the phenomenon of very long commutes, or "super-commutes," has drawn the attention of the general public, planners, elected officials, and researchers. Researchers usually define super-commuting either in distance or duration by a threshold that differs from country to country, or across places within a country, due to different land use and transportation systems that stretch or shrink average commute lengths. In the US, researchers often define super-commuting as one-way journeys to work over 50 miles in distance and/or over 90 minutes in duration (Bai et al., 2020; Boarnet et al., 2021). Recent news coverage of workers who wake before dawn and spend hours on freeways or public transit to travel from their more affordable homes in Stockton (or Riverside) to their workplaces in San Francisco (or Los Angeles) has helped make super-commuting a popular topic(Dougherty & Burton, 2017; McPhate, 2017; Straight, 2024).

Underlying this extreme phenomenon is a less eye-catching, but nonetheless important, issue: commutes have been growing longer for quite a while. Census data show that commute times in the US increased from 1990 to 2000, particularly in metropolitan areas (Burd et al., 2021; Levinson & Wu, 2005). More specifically, the national average commute time increased from 25.0 minutes in 2006 to 27.6 minutes in 2019, representing an overall rise of about 10 percent over 14 years. Moreover, between 2006 and 2019, long commutes became more common as workers reporting a 60-minute-orlonger commute increased from 7.9 percent to 9.8 percent; at the same time, short commutes became less common as workers reporting a less-than-ten-minute commute declined from 14.8 percent to 11.9 percent. In 2019, commute times were also longest in duration for transit commuters and workers in the largest metropolitan areas, where traffic congestion is common. But while commutes were lengthening leading up to the pandemic, super-commuting remained relatively rare: those traveling 90 minutes or more one-way for work accounted for just 3.1 percent of all commuters in 2019 (Burd et al., 2021).

The COVID-19 pandemic complicated this picture, as average commute durations declined during the pandemic (Ruggles et al., 2024). While commute times have gradually increased post-pandemic, they have not (yet) returned to pre-pandemic levels (Ruggles et al., 2024). Moreover, the increased adoption of remote work (sometimes called "telework") during and since the pandemic has had important effects on residential location choices (Bloom & Ramani, 2021) and commute patterns (Speroni et al., 2024). Although research on these effects is still underway, there is a growing body of evidence that remote work, both full- and part-time, is considerably more prevalent than before the pandemic despite many workers returning to the office post-pandemic (Barrero et al., 2023; Ilham et al., 2024). The increase in remote work, together with increases in other forms of virtual access to healthcare, shopping, streaming, and so on, has led people to spend more time at home and make proportionally fewer trips to work and other destinations (E. Morris et al., forthcoming). This trend has in turn increased the demand for larger housing in areas with more green space, which are typically in suburban and exurban areas away from dense city centers (Ilham et al., 2024; Moser et al., 2022).



The purpose of this study is to examine super-commuting characteristics and trends in the larger Los Angeles region, which we define to include Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties. We then draw on individual-, household-, and neighborhood-level data to examine the equity implications of super-commuting. For the purposes of this study, equity is measured as the housing and transportation (H+T) expenditure burden – the out-of-pocket costs of housing and transportation as a percentage of household income. Using these data, we develop a set of statistical models to test the relationship between various factors and the H+T expenditure burden. We then draw on these models as the basis for a set of scenarios, highlighting the association between the H+T expenditure burden and other variables of interest—remote work, residential location, and travel mode—among households in three income groups (low-, medium-, and high-income).

The report proceeds as follows. In Section 2 we review the research on long commutes, with special attention to its connection to the commutes of low-wage workers. In Section 3, we turn to a description of our data and methods. Because our analyses draw on a diverse set of approaches, when necessary, we include detailed descriptions of our methodology in the analytical sections as well. Sections 4-6 include our analysis of super-commuters – trends over time (Section 4), characteristics (Section 5), and spatial location in the Los Angeles Region (Section 6). The succeeding two sections focus on the housing and transportation expenditure burden, first at the neighborhood level (Section 7) and then across households by income (Sections 8). In the concluding section (Section 9), we review our findings and their implications for policy and planning intervention, and offer suggestions for future research as well.



# 2. The Long Road Home—A Review of the Research on Long Commutes

In the context of a shift toward longer, and perhaps less frequent, commutes post-pandemic, this literature review summarizes the research and empirical evidence on the extent of super-commuting and the demographic characteristics of workers with very long commutes in order to understand the causes, consequences, and costs of long journeys to work. We conclude with a discussion of the equity implications of super-commuting.

### 2.1. The extent of super-commuting

As we note above, the definition of super-commuting is rather fluid, because what is considered extreme can vary depending on regional development and commuting patterns across cities, regions, and countries around the world. Researchers have also used other terms such as "extreme commuting" and "mega commuting" to denote commutes that are very long and which can exact extraordinary tolls (pecuniary and otherwise) on the workers making them (Bai et al., 2020; Rapino & Fields, 2013). Some studies also examine very long commutes that are essentially super-commutes (over 50 miles in distance or 90 minutes in duration) without labeling them as such (Andersson et al., 2018; Dargay & Clark, 2012). Overall, these studies find that super-commuters as a group typically account for a small share of all commuters, and tend to reside on the periphery of large metropolitan areas.

One study of super-commuting in the US did not define it based on a distance threshold. Moss and Qing (2012) used 2010 LODES (Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics) data to identify peripheral super-commuters as workers who work in a core CSA (combined statistical area) and live in peripheral counties, and long-distance super-commuters as workers who work in a core CSA and live in counties beyond the peripheral counties. Their analysis found that both types of super-commuting increased between 2002 and 2009 and continued to increase from 2009 to 2010 despite significant job losses during the Great Recession period.

Drawing on data from the 5-year 2006-2010 American Community Survey of the US Census from around the same time period, Rapino and Fields (2013) identified workers who commute over 50 miles one-way in distance and those who commute over 90 minutes in duration. They used the term "mega commuter" for workers whose commutes meet both the distance and duration thresholds. Their estimates showed that about five percent of US workers commuted over 90 minutes or over 50 miles to work; about 2.4 percent of workers commuted over 90 minutes; about 3.2 percent commuted over 50 miles; but only about 0.8 percent were mega commuters who commuted over 90 minutes and over 50 miles. Their regional estimates also showed higher rates of super- and mega- commuting in Southern California compared with the national average: about 1.25 percent of workers were mega commuters in the Los Angeles-Long Beach-Santa Ana region, while San Bernardino-Los Angeles, Riverside-Los Angeles, and Riverside-San Diego were the top, 2nd, and 7th ranked cross-county mega commuting flows (by frequency) in the US. The mean commute durations of these three commuter flows were 104, 109, and 102 minutes, and mean commute distances were 68, 77, 76 miles, respectively. The other metropolitan areas with the highest rates of mega commuters were in the San Francisco Bay Area, New York metropolitan area, and Washington, DC. In the five counties that had the most super-commuter flows into Washington DC, they found higher shares of mega commuters among workers who carpooled and rode public transit to work, compared to those who drove alone. These five counties (Spotsylvania and



Stafford Counties in Virginia, Frederick and Baltimore Counties in Maryland, and Berkeley County in West Virginia) are not directly adjacent to Washington D.C., so the transit commuters most likely traveled by commuter rail.

Researchers at the University of Southern California studied super-commuting, again defined as oneway commutes over 50 miles or 90 minutes, in California's San Francisco Bay Area/Sacramento megaregion using multiple data sources including LODES, StreetLight, and travel surveys (Boarnet et al., 2021; Wang et al., 2022). They found that the share of super-commuters in these areas' counties grew by three to nine percentage points between 2002 and 2018. They also found a spatially clustered pattern of super-commuting, especially in the Central Valley east of the Bay Area where Sacramento and several rapidly suburbanizing agricultural counties are located. Specifically, counties nearest to the Bay Area and in and around the Sacramento area had super-commuting rates of up to eight percent, more than double the national average and generally two to four times more than more urban Bay Area counties. In Canada, where the land use and transportation systems are similar to (though somewhat less autooriented than in) the US, an analysis of census data showed that about nine percent of commuters had commutes over 60 minutes in 2016, of which 57 percent were car commuters and 40 percent were transit commuters. Moreover, among car commuters, about seven percent had commutes over 60 minutes, but just 1.6 percent had commutes over 90 minutes (Government of Canada, 2019). A more recent Canadian study estimated that three percent of male workers and less than two percent of female workers had commutes over 90 minutes (Allen et al., 2022).

These studies collectively show that super-commuters as a group, while growing prior to the pandemic, account for a rather small share of all commuters, and they tend to be more concentrated in the peripheral parts of the largest metropolitan areas. Data outside North America tell a similar story. In the UK, workers with one-way commutes over 50 km (~31 miles) increased from 2.7 percent to 3.5 percent 2001, and about 11 percent of workers spent over two hours per day commuting (Lyons & Chatterjee, 2008). In Sweden, rural-urban commuters (with one-way commute distances over 100 km (~62 miles) increased 29 percent between 1990 and 2000; however as a whole they still accounted for less than three percent of the working population residing in rural areas (Andersson et al., 2018). Moreover, according to UK data, not only do super-commuters account for a small share of all commuters, but also commute trips account for a much smaller share (10%) of all long-distance trips (over 50 miles) than trips for non-work purposes such as visiting friends and relatives, holiday trips, leisure trips, and business trips (Dargay & Clark, 2012).



### 2.2. Why do people commute long distances or durations?

According to classical economic theories, residential location choice is primarily the outcome of a tradeoff between housing costs and transportation costs to and from work (Alonso, 1964; Mills, 1967). Giuliano and Small's (1993) study of commuting in Los Angeles challenged this assumption by showing that commuters had much longer commute times than they would have if their residential location choices were primarily based on the housing-commute tradeoff, yet shorter than they would have if their residential location choices were completely random. Thus, when choosing where to live, households also consider factors beyond the housing-commuting tradeoff. This finding then means that workers may endure longer commutes to consume cheaper housing (or myriad other factors, such as high-quality public schools), but they also may choose not to relocate closer to work due to certain qualities of or constraints on where they live. Research on commuting and well-being also shows that longer commutes are not associated with life satisfaction overall, indicating that workers may choose longer commutes if there are compensating benefits, such as more desirable jobs, higher wages, and better quality housing and/or neighborhood amenities (Chatterjee et al., 2020).

Housing is indeed a major determinant of long commutes. Islam and Saphores' (2022) Los Angeles County study found that living in neighborhoods with higher housing prices is associated with shorter commute distances, while working in a high-housing-cost neighborhood is associated with longer commute distances, all else equal – reflecting the tradeoff between housing and commute costs. Relatedly, the lack of housing, particularly affordable housing, near jobs helps to explain longer average commutes. Islam and Saphores (2022) found that a higher jobs-housing ratio at workplaces is associated with longer commute distance, and that a higher jobs-housing ratio at residences is associated with (slightly) shorter commute distance. Blumenberg and Wander (2023) found that a worse "fit" between the number of low-wage jobs and affordable housing rentals in an area is associated with longer commute distances in the Los Angeles-Orange Metropolitan Statistical Area (MSA) (which is higher cost, coastal, mostly developed in the mid-20th century, and more urban), but that association is not statistically significant in the Riverside-San Bernardino MSA (which is lower cost, suburban inland area that was mostly developed in the late-20th and early-21st centuries).

The lack of jobs near residences may also explain long commutes. Using data from Canada, Maoh and Tang (2012) found that lower land use diversity and levels of job concentration at worker's place of residence help to explain long-distance commutes more than socio-demographic factors such as sex, age, occupation etc. For low-income workers, the lack of jobs near where they can afford housing can lead to longer commutes as well (Allen et al., 2022; Huang et al., 2018).

But even if there are jobs nearby, workers may still be willing to commute longer to get better ones. A study of Beijing's transit smartcard data over seven years found that transit commuters with shorter (less than 45 minutes) commutes tend to increase their commute durations over time, likely for better jobs, or better housing, or both (Huang et al., 2018). A similar pattern was also observed among UK commuters (Lyons & Chatterjee, 2008). Moreover, there appears to be a threshold (which varies across urban contexts) beyond which the commute becomes too long and workers tend to either relocate or find a new job to shorten their commute (Huang et al., 2018; Lyons & Chatterjee, 2008; Wachs et al., 1993). In the US, where home ownership is comparatively common, this may manifest in the axiom "drive [away from the expensive central city] until you qualify [for a home mortgage you can afford]." Wachs et al. (1993) found that workers in metropolitan Los Angeles who moved into rental housing tended to shorten their commutes, while those who moved to a home or condominium they owned



tended to lengthen their commutes, and those who moved from renting to owning tended to lengthen their commutes most of all.

The tendency to relocate or find a new job when commutes become too long also indicates the temporary nature of many long commutes. Studies based on UK data found that more than half of commuters with one-way commutes over one hour in one year decreased their commute time by at least five minutes the following year, on average, and that people tend to tolerate long commutes (over one hour) for a short period of time (one to two years) before finding a new job or relocating their housing (Lyons & Chatterjee, 2008).

However, some other studies suggest that long-distance commuting may be a longer-term strategic mobility choice for at least some workers, rather than a temporary solution. A Swedish study found that workers with comparatively long commutes in a Swedish context (over 30 km or ~18.6 miles one-way) are likely to endure these commutes for extended durations if they have prior long commuting experience and higher wages or better income growth at their job (Sandow & Westin, 2010). A German study found that some families are firmly settled in a location and perceived long-distance commuting (over 60 minutes one-way) as the best option to preserve the integration of the family unit within a familiar social environment. Another European study using longitudinal data found that people's willingness to commute long distances may adapt and adjust to current commuting practices. Specifically, this study found that whether or not a worker is willing to commute long distances is not associated with the decision to start or stop long-distance commuting; rather, workers' willingness to commute long distances tends to increase after starting long-distance commuting, and decrease after stopping (Rüger et al., 2021). It is possible though, that people are willing to tolerate these moderately long commutes for extended durations because they are not long enough (i.e., below their personal threshold) to trigger a change in job or home locations.

Fewer studies have examined the determinants of super-commuting, but some evidence suggests that housing costs and jobs-housing balance (a measure of job accessibility) are major factors, but that other factors also play a role. Mitra and Saphores' (2019) study of super-commuters (over 50 miles one-way) in California found that higher housing prices near workplaces are associated with higher odds of super-commuting while higher housing prices near home are associated with lower odds of super-commuting. This suggests that super-commuters may live farther away from work to have more affordable housing in the periphery of metropolitan areas – the "drive until you qualify" phenomenon. This is consistent with findings from other studies: in Washington state's Central Puget Sound (greater Seattle) region, workers who live far from regional growth centers are more likely to super-commute (Bai et al., 2020); in California's San Francisco Bay Area and Sacramento area, districts (zip codes) that have lower shares of renters and higher shares of in-migration from the Bay Area also have higher super-commuting rates (Boarnet et al., 2021; Wang et al., 2022).

Jobs-housing balance – indicating greater job accessibility – appears to play a smaller, but not inconsequential, role in commuting. Bai et al. (2020) found that neighborhoods (census tracts) with greater jobs-housing balance have lower rates of super-commuting. Similarly, Mitra and Saphores (2019) found that higher jobs-housing ratios around a worker's home are associated with lower odds of super-commuting, but only modestly, which reflects a limited role for commute distances and durations in people's residential location choices than classical urban location theory would suggest.



The above evidence is consistent with the idea that super-commuters trade off higher commuting costs for cheaper housing on the urban periphery. However, in California's San Francisco Bay Area and Sacramento area, districts (zip codes) with higher shares of transit riders have higher rates of super-commuters (again, defined as one-way commutes over 50 miles or 90 minutes) (Boarnet et al., 2021; Wang et al., 2022). There are two different but not mutually exclusive explanations here. First, transit commuting tends to be much longer in duration than driving, though not necessarily long in distance, because transit typically runs slower, requires walking and waiting, and often transfers as well. While most transit riders in the US are low-income, the second factor concerns the commuter rail riders whose income is higher on average than drivers, and much higher than bus riders. Commuter rail trips tend to be used for commuting into and out of downtowns and other major job centers, and they are often very long in distance.

Consistent with evidence discussed above on the often temporary nature of long commutes, Mitra and Saphores (2019) found that longer housing tenure lowers the odds of super-commuting. This finding suggests that super-commuting may also be temporary – workers may find jobs closer to home, or homes closer to their jobs, over time.

Beyond the US, a European survey of super-commuters (spending over two hours per day on two-way commute) in Brussels, Geneva, and Lyon found that super-commuters tend to be highly specialized workers whose job opportunities are less geographically ubiquitous (think a cardiologist relative to a grocery clerk). For some workers, super-commuting results from a tradeoff between job insecurity and residential stability. Part of this tradeoff may be due to workers' strong attachment to their home locations' environment, schools, activities, culture, and/or social/family networks. In addition, family constraints, such as the need to care for older family members, may influence job and home location decisions as well. Besides, flexible working hours, being able to work remotely or work during the commute – rail is the preferred mode among surveyed super-commuters – are also important factors (Vincent-Geslin & Ravalet, 2016).

## 2.3. Who tends to commute long distances or durations?

While most research on super-commuting is relatively recent, there is a larger body of literature on long commutes, if not "super" ones. We synthesize both literatures to understand who tends to make long commute trips, who tends to super-commute, and whether super-commuters are different from the larger group of longer-distance/duration commuters. Overall, the literature presents a rather complex picture of the associations between socio-demographic and job-related characteristics and commute distances and/or the likelihood of super-commuting.

McLafferty and Preston (2019) studied workers with long commutes, which they defined as over 45 minutes one-way, in the transit-rich New York region between 2000 and 2010. While they did not control for commute mode (drive alone, carpool, public transit, etc.), they found that male and female workers of color were more likely than White male workers to hold low-wage, long-commute jobs while Asian and White male workers had similar odds of having high-wage, long-commute jobs. They also found that, from 2000 to 2010, Asian male and female workers, on average, shifted from low-wage, long-commute jobs to higher-wage, long-commute jobs, whereas Black and Hispanic male and female workers, on average, remained concentrated in low-wage, long-commute jobs.



Islam and Saphores (2022) studied commute patterns in Los Angeles County using the 2012 California Household Travel Survey. Their analysis found that Hispanic workers, regardless of race, commuted longer distances than non-Hispanic workers, and Black and Asian workers commuted longer distances than White workers, all else equal. In contrast, college educated workers had shorter (distance) commutes, on average, by self-selecting into neighborhoods with higher housing prices. Moreover, higher income commuters and female commuters had faster commutes (shorter duration but not distance).

An analysis of 2016 Canadian Census data showed that higher-income workers had a higher rate of long commutes (over 60 minutes one-way), indicating that workers are willing to commute longer for higher paying jobs, all else equal. Workers in the natural resources, agriculture, and related sectors also had a higher rate of long commutes, likely because they need to commute to spatially dispersed job sites that are typically located on the urban periphery or in rural areas. While workers without a fixed work location had a higher rate of long commutes, about 60 percent of long commuters (by car) with a fixed work location worked in Toronto, Vancouver, or Montreal metropolitan areas, the three largest in Canada (Government of Canada, 2019).

Two other commuting studies using the Canadian Census data focused on immigrants. They found that immigrants generally commute shorter distances than native-born workers, all else equal, but they are more likely to use public transit for commuting, which likely lengthens their commute durations. Further, immigrants' commute distances tend to increase as their time living in Canada increases (Harun et al., 2022; Newbold et al., 2017).

UK data show that men's commutes on average are significantly longer in distance, but only slightly longer in duration, than women's commutes, suggesting that men are more likely than women to commute by faster modes, like solo driving. Also, long-distance commuters are mostly in London and other metropolitan areas and are disproportionately managers and senior officials, while long-duration commuters (who are neither the same as nor mutually exclusive from long-distance commuters) are more likely to own homes, work at large offices or plants, and have higher levels of post-secondary education (Lyons & Chatterjee, 2008). Other European studies similarly have found that higher income, male, and highly-educated workers are more likely to commute long distances or durations than other workers (Cassel et al., 2013; Limtanakool et al., 2006).

These studies collectively show that socio-demographic factors including income, sex, race/ethnicity, education, marital status, homeownership, age, and immigrant status may all influence workers' commute distance and/or duration in complex ways. Workers' industry, occupation, and work location also play a role. In general, higher-income workers tend to have longer commutes. This is because lower-paying jobs tend to be more spatially dispersed and ubiquitous, whereas higher-paying jobs tend to be rarer, more spatially clustered, and specialized. Thus it is usually easier for lower-income workers to find a job closer to home. It is also more difficult to justify the (time and monetary) costs of longer commutes to a low-paying job. Higher-income workers, on the contrary, may be willing to commute longer to even high-paying jobs. Moreover, a longer commute distance does not necessarily equal a longer commute duration, due to the travel speed differentials among cars, trains, and buses. Given this, are super-commuters consistently different from longer distance commuters in any ways? We turn to this question below.



Marion and Horner (2007) used US Census Public Use Microdata (PUMS) to examine the socio-demographic characteristics of super-commuters (one-way commutes over 90 minutes) in Atlanta, Baltimore, Houston, and Tampa. Broadly, they found that when focusing on commute times rather than distances, super-commuters in these cities tended to be lower income and less educated than was found in the studies above focused on commute distances. Using logistic regression models, they found that, in central and suburban areas of these metropolitan areas, the odds of super-commuting are higher for workers who are male, less educated, in households with children (except in Baltimore), in a lower income household (except in Baltimore), Black (Atlanta and Baltimore only), a homeowner (Atlanta and Houston only). In addition, workers who carpool, depart for work before 12 pm (Atlanta and Baltimore), and work more hours are also more likely to super-commute. In central areas, fewer such characteristics are significant: less educated (Tampa and Houston only), Black (Atlanta and Baltimore only), lower household income (except in Baltimore), owning home (Atlanta only), and carpoolers (Atlanta only). They also found that women in central areas are more likely than their suburban counterparts to super-commute.

The analysis of "mega commuters" (discussed above) found some similar characteristics: mega commuters are more likely to be male, older, married, and depart for work before 6 am, earn a higher salary, and have a spouse who does not work (Rapino & Fields, 2013). The USC study (also discussed above) of super-commuting in the Bay Area and Sacramento area found that having more children in the household is associated with higher likelihood of one adult super-commuting, all else equal (Boarnet et al., 2021; Wang et al., 2022). They also found that workers in manufacturing, construction, maintenance, and farm jobs are more likely to super-commute.

Bai et al. (2020) used census and travel survey data to study super-commuters (commute duration over 90 minutes) in Washington state's Central Puget Sound (greater Seattle) region. Their analysis showed that commute mode differentiates super-commuters: higher household income is associated with higher odds of super-commuting among car commuters but not transit commuters; having a graduate degree or higher is associated with lower odds of super-commuting among car commuters but not transit (likely commuter rail) commuters, all else equal. Factors associated with higher odds of super-commuting among transit commuters are being older and having more workers in a household. Observing mixed associations between demographic factors and super-commuting rates across different parts of the region, they argued that, in areas with higher income and education levels, super-commuters are likely to have a higher demand for housing quality and can absorb higher transportation costs, while in areas with higher shares of rental units, super-commuting may be a constrained choice due to socioeconomic disadvantage.

A study of Canadian super-commuters (commuting over 90 minutes one-way) found that immigrant workers who have arrived before 2010, workers living in substandard housing, and minority workers have higher odds of super-commuting durations, all else equal (Allen et al., 2022). Higher education is also associated with higher odds of super-commuting. Transit commuters have higher odds of super-commuting than car commuters, likely due to the slower average travel speeds on transit. While workers in large metropolitan areas have higher odds of super-commuting than those in smaller metropolitan areas, rural workers have higher odds than non-rural workers, all else equal. Some results are consistent with the idea that super-commuters trade off higher commute costs for more or cheaper housing. Workers living in single family homes have higher odds of super-commuting than those living in apartments, and homeowners have higher odds than renters. Workers who moved homes in the last



year have higher odds of super-commuting, which may also reflect the temporary nature of super-commuting.

Outside of North America, one Swedish study of rural to urban long-distance commuting (home and work locations over 100 km (~62 miles) apart in straight line distance) found that rural residents working in large cities constitute a highly selected group of workers who tend to be young, well paid, highly educated, and work in advanced knowledge-intensive occupations (Andersson et al., 2018). The vast majority of these rural-urban long-distance commuters already lived in rural areas before starting to commute to urban areas, while only about 30 percent had moved from urban areas to rural areas (ibid.). Another Swedish study of extremely long-distance commuters focused on those whose work and home locations were over 200 km (~124 miles) apart in straight line distance (Öhman & Lindgren, 2003). These extreme long distance commuters are more likely to be male and younger, and have at least three years of university education, previous experience with long-distance commuting, either a very low or a very high income, a spouse with a university degree, no children, and are less likely to live in a detached house. They are also more likely to live in a larger city or its hinterland and work in occupational sectors with flexible work schedules and/or locations (ibid.). Both of these studies identified long-distance commuting using home and work locations, thus do not differentiate between frequent commuters and telecommuters. The large commute distance thresholds they used also means that a significant share of the long-distance commuters in these studies are likely remote workers.

These studies collectively present mixed and complex associations between demographic factors, job-related characteristics, and the likelihood of super-commuting. The evidence above can appear contradictory: super-commuters are more likely to be high income and low income, highly educated and less educated, etc. Broadly, studies of super-commuters defined by distance tend to find them to be better educated, higher income, older, White, homeowners, and drivers, while those defining super-commuters in terms of duration tend to find them to be relatively less educated, lower income, younger, people of color, renters, and a non-trivial share are transit riders. But even transit super-commuters are split between generally higher-income commuter rail riders and lower-income urban transit (bus and rail) riders. A large part of this complexity is because super-commuters as a group, being arbitrarily identified by some commute distance or duration thresholds based on cross sectional data, are heterogeneous. In other words, the super-commuting label may mask underlying differences among different types of commuters that, likely for very different reasons, commute extremely long distances and/or durations at some point in their lives.

Where they live and what commute mode they use help to explain this complexity. A higher income worker who drives over 90 minutes from an outer-ring suburban house to a downtown office; a lower income worker who makes a 90-or-more-minute transit trip involving multiple transfers on congested urban roads; and a farm or construction worker who lives in cheap housing on the ex-urban periphery and spends over 90 minutes traveling to different parts of the region for work on different days – all would have been captured by these studies as super-commuters, but their rationales for making such long commutes and their ability to absorb their high time and monetary costs likely vary substantially. Nonetheless, a common finding across these studies is that super-commuters tend to own homes and/or likely demand larger housing (due to larger numbers of children and/or workers in the household and in some cases the need to work from home). This could reflect the tradeoff between cheaper or larger housing located in outlying areas and higher transportation costs.



### 2.4. The costs of long commutes

There are costs – pecuniary and otherwise – associated with commuting, the most straightforward of which are the monetary and time costs borne by the commuter. But research has shown that long commutes can negatively affect the commuter's physical and mental health too (Chatterjee et al., 2020; Lyons & Chatterjee, 2008). Society also bears costs from environmental externalities associated with extensive motor vehicle travel (which is beyond the scope of this review). This section reviews research on the various costs of long commutes.

In addition to the per mile monetary and time costs associated with travel, long commutes may have other costs because these trips are more likely to incur congestion and delays (Lyons & Chatterjee, 2008) and the relative effects of these delays are more substantial than for those with shorter commutes. For low-wage workers, there may be additional uncertainty, because they tend to own older and unreliable vehicles (Bhat et al., 2009; Ong & Lee, 2007). Longer commutes also represent opportunity costs as they reduce the time available for other activities: family, exercise, social activities, paid work, and sleeping (Chatterjee et al., 2020). Long commutes also can negatively affect commuters' physical and mental health by increasing fatigue and stress, which may then lead to lower productivity and job satisfaction (Lyons & Chatterjee, 2008). Long commutes can negatively affect employers in terms of higher rates of employee absenteeism, tardiness, and staff turnover (ibid.). One study also found a correlation between long commutes and higher mortality rates among women, particularly those with lower education levels and incomes (but not men), which may be explained by stress associated with long commutes as well as the added household burden for female, especially lesseducated and lower-income, long distance commuters (Sandow et al., 2014). Long commutes may also negatively affect family relationships, causing higher separation and divorce rates and very uneven distributions of family duties (Landesman & Seward, 2013; Sandow, 2014; Stenpaß & Kley, 2020).

Despite the costs associated with long commutes, research on commuting and well-being has found little to no association between longer commutes and overall life satisfaction (Chatterjee et al., 2020). Some research did find lower life satisfaction associated with longer commutes, which is likely due to people underestimating the costs of commuting and overestimating their ability to adapt. Moreover, this negative association appears to be non-linear – stronger when commuting is extreme (ibid.).

That long commutes generally do not lead to lower life satisfaction may be partly due to benefits associated with jobs and housing that commuters tradeoff for higher commuting costs. These could include higher wages, desired suburban living, and homeownership (Morris & Zhou, 2018). Some research shows that long commutes may not be all bad. This finding may be due to commuters' productive use of travel time – largely aided by technology – during the commute, which also tends to be higher if workers commute by rail (Lyons & Chatterjee, 2008). Qualitative evidence also suggests that long commutes can offer an opportunity for the commuter to transition and get some time out between different life roles and tasks (ibid.). An analysis of social media data also found that an above-median commuting distance is linked to more diverse individual social networks, suggesting that longer commuters may facilitate social mixing (Bokányi et al., 2021).

The evidence reviewed here suggests that while there are costs associated with long commutes, they may be offset to some degree by benefits associated with more desirable jobs, housing, and even satisfaction with activities (work, relaxation, etc.) during the long commute. However, when commuting becomes extremely long, these costs and benefits may not net out, resulting in lower life satisfaction.



### 2.5. Conclusion – Equity implications of super-commuting

Our review of the literature yields several main findings regarding super-commuting. First, super-commuters account for a very small share of all workers, despite the popular attention given to them. Second, housing costs and, to a lesser extent, job accessibility appear to be important determinants of super-commuting. Third, there are costs associated with super-commuting, which for some workers may not be fully compensated by the benefits associated with jobs, housing, and the commute, and hence result in lower life satisfaction. However, most long distance commuters do not have lower life satisfaction, likely due to the ability to marry desirable job and home environments. Fourth, super-commuting may be a temporary strategy – workers may tolerate super-commuting for a relatively short duration due to various circumstances (such as a spouse finishing a college degree) before finding a new job or moving to a new home with shorter commutes. Finally, super-commuters are heterogeneous and super-commute for widely varying reasons.

The last finding makes it challenging to consider the equity implications of super-commuting. Some super-commuters may be more able than others to absorb the costs of the commutes and also better able to get out of super-commuting by changing jobs or moving homes, switching their commute mode from bus, light rail, or subway to car, from car to commuter rail, or by switching to partially or fully remote work. For example, some super-commuters may be higher income, educated workers trading higher commuting costs for owning a larger home in more affordable (and often also more peripheral) parts of the metropolitan area. Depending on their occupation and industry, it may or may not be easy for them to find a job closer to home, because some of them may work in very specialized jobs that are not dispersed throughout the metropolitan area. But an increasing share of these workers postpandemic have more flexible work schedules and have the option to telework for some days of the week, which would lessen their commuting burden.

Some super-commuters may be lower-income workers who lack access to a car and commute by transit. Their commutes may not be long in distance, but long in duration because public transit tends to be considerably slower than driving and the trip may involve multiple transfers. These workers tend to work in lower-skilled jobs in the service sector, which could mean lower job security. As we noted earlier, super-commuting could be the outcome of a tradeoff between job insecurity and residential stability. In other words, these workers may super-commute to a job far away from home rather than move close to that job if they believe that they may need to switch jobs in the near future. But lower-skilled jobs tend to be dispersed across metropolitan areas, which could mean a higher probability that these workers eventually find jobs closer to home, and hence shift out of super-commuting. Yet, research also shows that those without access to a car have a lower likelihood of finding and keeping a job (Blumenberg & Pierce, 2014; P. M. Ong, 2002), which means that these transit super-commuters may face additional barriers in the job market.

Some super-commuters may also be lower income workers in sectors like construction and agriculture, which means that they tend not to have a fixed work location. They may live in the more affordable neighborhoods in the urban periphery and commute long distances by driving alone or carpooling (which can be long duration as well), and probably less by public transit, to different parts of the metropolitan area on different days. It is likely that the work locations of these workers change periodically, which means that whether they super-commute or not may change from week to week, or even day to day.



There is almost certainly even more heterogeneity among super-commuters than we discuss here. But this review of the research literature is an attempt to illustrate the complexity of considering equity implications of super-commuting due to the heterogeneity. The existing literature focuses mostly on describing the extent of super-commuting, identifying the socio-demographic characteristics of super-commuters, and exploring the causes of super-commuting, but not on analyzing the equity implications of super-commuting, the principal objective of our study.



## 3. Data and Methods

Our analysis draws on multiple data sources to examine the equity implications of super-commuting. The spatial analysis focuses on the greater Los Angeles region. We define this region as the six counties under the aegis of the Southern California Association of Governments (SCAG), which is the metropolitan planning organization (MPO) for most of Southern California.¹. The counties in the SCAG region consist of Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. The region is home to just under 19 million people, more than half (10.1 million) of whom live in Los Angeles County and seven out of ten of whom are a race-ethnicity other than non-Hispanic White (Ruggles et al., 2024; Southern California Association of Governments, 2021). The region's population is spread over 38,000 square miles and includes a diverse array of neighborhood types and land uses, including large swathes of lightly populated mountains and desert areas. It is, by almost any measure, an enormous and remarkably diverse region.

Each of the data sources available to study the equity implications of super-commuting are limited in some way, which required us to draw from and analyze multiple datasets to:

- 1. quantify changes in the super-commuting numbers and rates over time (specifically, from 2005 through 2023);
- 2. characterize super-commuters in terms of their sociodemographic, household, and travel profiles;
- 3. identify super-commuting hotspots in the region and the travel by workers in these residential hotspots to major employment destinations; and
- 4. analyze the housing and transportation (H+T) expenditure burdens in super-commuting hotspots and job centers.

Given the constraints of our data, the final equity scenario analysis also draws on multiple sources of data for California households to:

- 5. estimate the housing and transportation (H+T) expenditure burden of worker households by income group, with particular attention to the effect of super-commuting
- 6. use the results of the H+T burden models to develop a set of scenarios estimating the effect of super-commuting alone and in combination with remote work, transit use, and suburban location—on the H+T burden.

Depending on the data source, we define super-commuters as workers whose commutes are 50-100 miles or 90+ minutes one way. The equity focus centers on the extent and financial burden of long commutes particularly for low-income or low-wage travelers who face the greatest financial constraints.

<sup>&</sup>lt;sup>1</sup> The parts of Southern California not in the SCAG region are San Diego County to the southwest, Santa Barbara and San Luis Obispo Counties to the northwest, and Kern County to the north. The SCAG region extends all of the way from the Pacific Ocean in Los Angeles, Orange, and Ventura Counties in the west to the Arizona and Nevada borders to the east.



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Given the limitations of existing data, as we note above, this final component of the analysis rests on household-level data for all California households.

The analysis draws from publicly-available data sources such as the Public Use Microdata Samples of the American Community Surveys, the Longitudinal Employer Household Dynamics (LEHD) Origin and Destination Employment Statistics (LODES), and the California add-on of the 2017 National Household Travel Survey. We supplement these data with mobile-device-derived data from StreetLight, Inc., neighborhood-level data on housing and transportation costs from the Center for Neighborhood Technology, and auto ownership and operating costs data from the American Automobile Association (AAA).

The table in Appendix 1 summarizes our data sources and variables of interest. In Appendix 2, we highlight the strengths and weaknesses of each of these sources. We provide more detailed descriptions of our data and methodology in each analytical section of the report.



## 4. Super-Commuting Trends -- 2005 to 2023

We use the one-year American Community Survey (ACS) Public Use Microdata Samples (PUMS) to analyze super-commuting trends over time in the greater Los Angeles region. The U.S. Census Bureau collects these data daily and then pools them over the calendar year; the one-year samples include records for approximately one percent of the U.S. population and are weighted to represent the total population (U.S. Census Bureau, 2021). The U.S. Census Bureau encourages users to be cautious about using data collected during the COVID-19 pandemic; therefore, we omit the 2020 data, which explains the dotted lines in the graphs from 2019 to 2021.

Figure 1 shows commute duration in the SCAG region from 2005 to 2023. There was a steady increase in commute duration leading up to the COVID-19 pandemic, a decline during the pandemic year, and then a steady increase in commute duration coming out of the pandemic. Commute duration rose by six percent between 2021 and 2023; however, as of 2023 it remained slightly lower than in 2019.

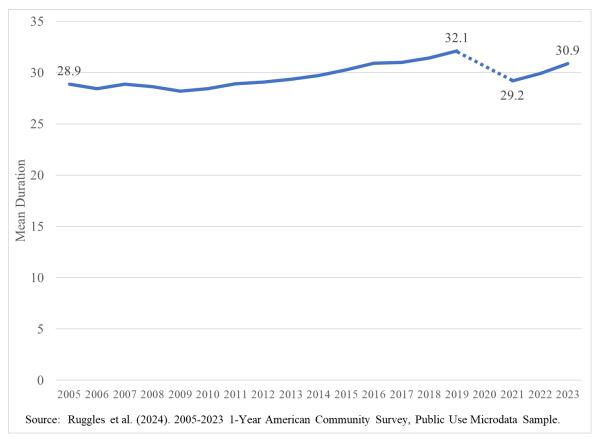


Figure 1. Mean One-Way Commute Duration in the Greater Los Angeles Region, by Year

Figure 2 shows both the number and the percentage of super-commuters in the region based on commute durations of 90+ minutes. The trend is similar to that in Figure 1. The number and percent of super-commuters increased leading up to the pandemic, declined significantly during the pandemic, and then increased through 2023. Both the numbers and the percentages of super-commuters remain lower in 2023 than in 2019.



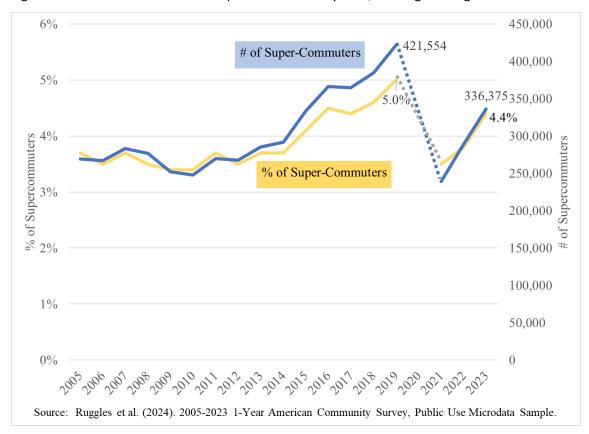


Figure 2. Percent and Number of Super-Commuters by Year, Los Angeles Region



Figure 3 shows trends in super-commuting by mode of travel. Rates of public transit super-commuting are, on average, almost five times as high as rates of auto super-commuting. Transit trips can be long because they require numerous stops and/or, in some cases, because commuters rely on commuter rail systems to travel long distances from outlying areas into urban job centers. For example, the average commute duration by transit in the greater Los Angeles region is 1.7 times greater than the average commute duration by automobile (**Table 1**). Travel times are longest for relatively high-wage workers who use commuter rail, although in the greater Los Angeles region these travelers comprise a small share of all transit commuters.

Despite the differences in super-commuting rates, trends through the pandemic by mode were generally similar—slow annual increases in super-commuting rates leading up to the pandemic and a significant decline during the pandemic. While super-commuting by automobile started to increase in 2021, transit super-commuting rates continued to fall through 2022 and have only recently started to climb again.



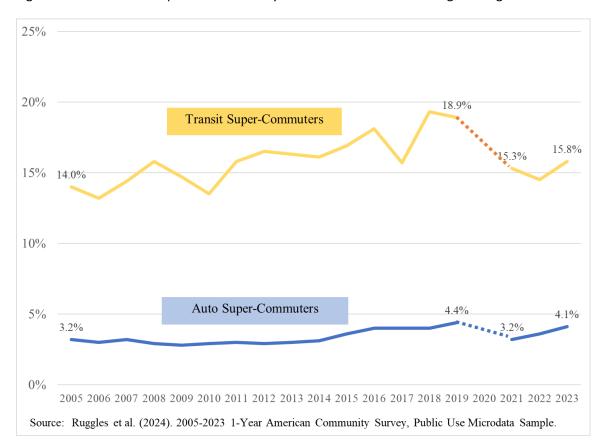


Figure 3. The Share of Super-Commuters by Mode in the Greater Los Angeles Region

Table 1. Commute Duration and Mean Earnings by Mode – All Workers (Greater Los Angeles Region)

Mode	Commute Duration		Modal Distribution	
Private Automobile	30.7	\$56,697	91.3%	
Bus	50.5	\$28,592	3.4%	
Rail	65.4	\$66,666	0.7%	

Source: Ruggles et al. (2024), data from the 2015-2019 5-Year American Community Survey Public Use Microdata Sample.



Figure 4 presents the trends in super-commuting rates for the four most populous SCAG-region counties. These are the counties whose sample sizes are large enough to produce reliable estimates. Super-commuting rates were highest in the region's two most outlying counties, Riverside and San Bernardino, and substantially lower in the most centrally located Los Angeles and Orange Counties. Super-commuting rates were higher in Los Angeles compared to Orange County, likely due to higher rates of transit commuting. In all four counties, super-commuting rates started to climb in the post-COVID years.



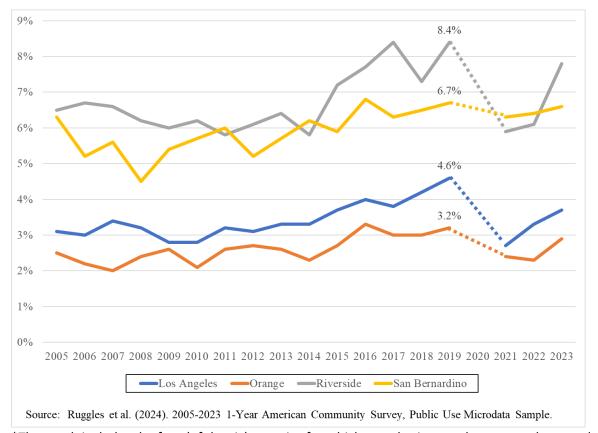


Figure 4. Share of Super-Commuters in the Most Populous Counties in the Greater Los Angeles Region



<sup>\*</sup>The graph includes the four (of the six) counties for which sample sizes are large enough to produce reliable estimates.

# 5. Characteristics of Super-Commuters in the Los Angeles Region

We draw on the 5-Year 2015-2019 ACS PUMS data to analyze (1) the frequency and characteristics of super-commuters in the Los Angeles region and (2) how these characteristics broadly sort into two general types of super-commuters . Similar to the 1-year ACS PUMS data, the 5-Year data are an aggregation of daily data collection, in this case, over the five years. The five-year file includes observations for approximately five percent of the population. Unlike the one-year data, these data provide a large enough sample to reliably estimate a range of super-commuter characteristics.<sup>2</sup> Further, they align with the data year (2019) of the hot spot analysis in the next section. A final advantage of these data is that they exclude the potentially biased 2020 data.

Figure 5 shows mean commute duration for the region and by county. On average workers travel about 30 minutes. Travel times are slightly longer in Los Angeles where transit ridership is highest and in Riverside where land use densities are relatively dispersed.

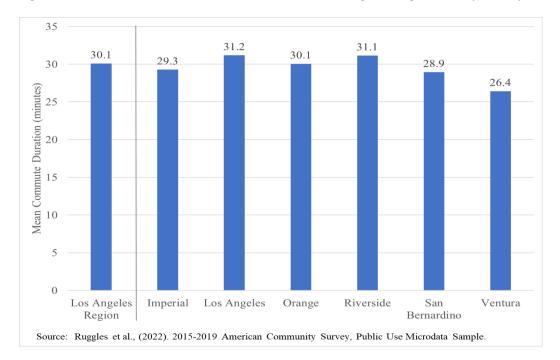


Figure 5. Mean Commute Duration in the Greater Los Angeles Region and by County

<sup>&</sup>lt;sup>2</sup> The California add-on of the National Household Travel Survey (NHTS) also includes individual- and household-level data and extensive information on travel behavior. However, this sample is too small for our purposes and is stratified to be used for statewide analysis. We take advantage of the 2019 LEHD Origin-Destination Employment Statistics (LODES) for the hotspot analysis in our subsequent analysis. These data also are not suitable for this analysis; they are aggregated by neighborhood and include very few worker characteristics.



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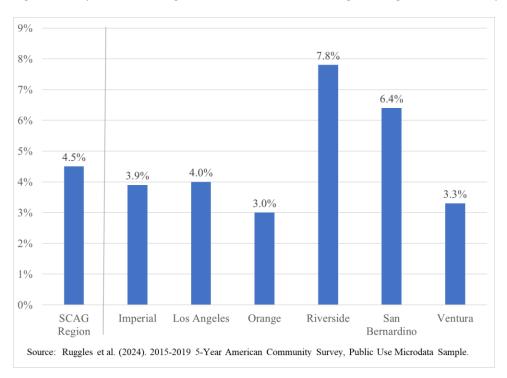
As Figure 6 shows, 4.5 percent of all workers in the region are super-commuters, defined as having one-way commutes of 90 minutes or more. Super-commuting rates are highest in both Riverside and San Bernardino counties, the two large Inland Empire, mountain, and desert region counties with the lowest residential densities.<sup>3</sup> However, half of all super-commuters in the region live in Los Angeles County, which is also home to more than half of the SCAG-region residents (

<sup>&</sup>lt;sup>3</sup> The PUMS data include the mean population-weighted geometric mean of the census tract population densities in each PUMA. Excluding largely rural Imperial County, the lowest mean population densities of respondents in the region are in Riverside County (2,735/mile<sup>2</sup>), followed by San Bernardino County (3,810/mile<sup>2</sup>) and Ventura County (4,213/mile<sup>2</sup>). The densities in more urbanized Orange (7,511/mile<sup>2</sup>) and Los Angeles (11,437/mile<sup>2</sup>) are considerably higher (Ruggles et al., 2022).



Figure 7). Owing to its central location in the region, Figure 8 shows that fully a quarter of Los Angeles County super-commuters are transit super-commuters.

Figure 6. Super-Commuting Rates in the Greater Los Angeles Region and its Component Counties





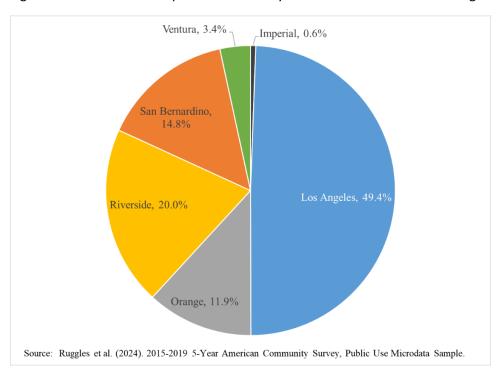


Figure 7. Distribution of Super-Commuters by Counties in the Greater Los Angeles Region

Figure 8. Modal Distribution of Super-Commuters, Counties in the Greater Los Angeles Region



<sup>\*</sup>The graph includes the four (of the six) counties for which sample sizes are large enough to produce reliable estimates.



Characteristics of Super-Commuters in the Greater Los Angeles Region

We analyzed the characteristics of 90+ minute duration super-commuters in the Los Angeles region and by county within the region. The detailed data for this portion of the analysis are in Appendix 3 and Appendix 4. We summarize the principal findings for the greater Los Angeles region here and in



Figure 9. The data show some clear trends, many of which are apparent in the county-level data. The characteristic most strongly associated with super-commuting is public transit use, for the reasons that we discussed previously. Workers who carpool are also more likely to super-commute than other workers, perhaps motivated by the opportunity to share travel costs. Finally, super-commuting is higher among workers who depart for work outside of the traditional morning peak period.

The associations between super-commuting by duration and other worker characteristics are present as well, but their effects are more muted. Male workers are more likely to super-commute than female workers. In general, women's commutes tend to be shorter than men's (Crane, 2007), in part a response to their dual responsibility for both paid and household labor (Gimenez-Nadal & Molina, 2016; Turner & Niemeier, 1997). Black workers are more likely to be super-commuters than workers from all other racial-ethnic groups. This finding is likely due to their higher rates of transit commuting primarily, but also to the need to travel further than other workers to locate jobs, all else equal (Bunten et al., 2024). Finally, age and income are positively associated with super-commuting. Both of these characteristics likely function as proxies for worker skills and wages. Higher-wage workers are more likely than lower-wage workers to trade off better neighborhoods for longer commutes; they also have the incomes to support the high out-of-pocket costs associated with long travel times.



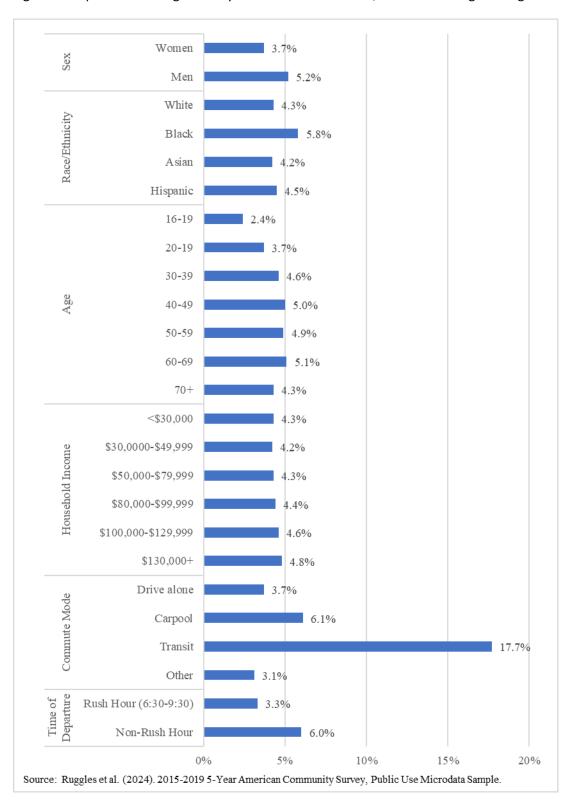


Figure 9. Super-Commuting Rates by Worker Characteristics, Greater Los Angeles Region



As we note above, transit commuters are much more likely to be super-commuters (particularly with respect to commute duration) than other commuters. However, super-commuters' reliance on public transit varies significantly across income and by mode. As Figure 10 shows, about a third of all super-commuters in the bottom income quintile commute by public transit, almost exclusively by bus. In other words, long bus travel times strongly influence rates of super-commuting among this income group. By contrast, 10 percent of high-income super-commuters—households in the top income quintile—commute on public transit; however, among this group of transit users, half travel by rail.

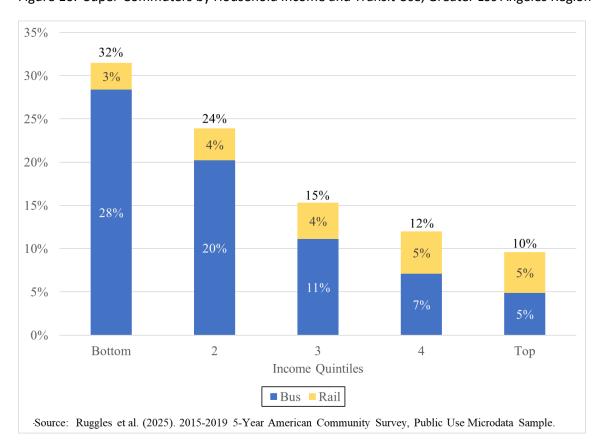


Figure 10. Super-Commuters by Household Income and Transit Use, Greater Los Angeles Region

#### Cluster Analysis of Super-Commuter Types

We have thus far described the association of various characteristics (e.g. income, sex, home ownership, etc.) and the likelihood of super-commuting. But do these characteristics tend to group with one another to create "types" of super-commuters? To examine this question, we performed a cluster analysis, also using the 2019 5-year American Community Survey (ACS) Public Use Microdata Series (IPUMS) for the greater Los Angeles region, using ACS sample weights, resulting in an estimated sample of 428,966 super-commuters in the region. **Table 2** below lists and describes the variables used and Table 3 shows the results of the cluster analysis. Additional methodological details for this cluster analysis can be found in Appendix 5.



Table 2. Variables Used to Identify Super-Commuter Types in the Greater Los Angeles Region

Variable	Description	
Age	A respondent's age in years	
Ethnicity	Whether one identifies as Hispanic or Latino	
Marital status	Whether one is married or single	
Usual means of transportation to and	Driving or public transit	
from work		
Number of children age < 5	Number of children under age 5 living in the household	
Home ownership status	Whether one owns or rents	
Race	Whether one identifies as non-Hispanic white	
Sex	Male or female	
Wage	A respondent's total pre-tax wage and salary income	
Years of education	A respondents' educational attainment, as measured by the	
	highest year of school	

Table 3. Results of the Super-Commuter Cluster Analysis for the Greater Los Angeles Region

Variable	Cluster 1: Lower-income Latino/as who both drive and	Cluster 2: Higher-income homeowners who mostly drive		
	ride transit to work	to work		
Age (years)	40.7	47.3		
Ethnicity (% Hispanic)	87%	1%		
Marital status (% married)	48%	63%		
Commute mode (% public	22%	9%		
transit)				
Mean # of children age < 5	0.16	0.13		
Ownership (% homeowners)	56%	75%		
Race (% non-white)	99%	34%		
Sex (% female)	36%	37%		
Annual wage	\$38,614	\$82,271		
Years of education	11.6	14.9		

Note: Data are reported as unscaled mean values for each cluster.

While we tested 2, 3, and 4 cluster solutions, a 2-cluster solution proved to best fit the data. Table 3 presents the unscaled average values for each cluster, and reveals two distinct profiles. Cluster 1 comprises individuals who are on average younger (about 40 years old), overwhelmingly Hispanic (87%) and almost exclusively not non-Hispanic-White (99%), with lower pre-tax wages (approximately \$38,614/year) and a high-school education or less (11.6 years). More than one in five (22%) of the super-commuters in this cluster travel to and from work on public transit, and more than 2 in 5 (44%) are renters.

In contrast, Cluster 2 is characterized by somewhat older commuters (average age 47), two-thirds (66%) of whom are non-Hispanic White. Cluster 2 super-commuters have much higher wages (roughly \$82,000/year), more education (nearly 15 years on average); 3 in 4 (75%) own their home and few (9%) commute on public transit.



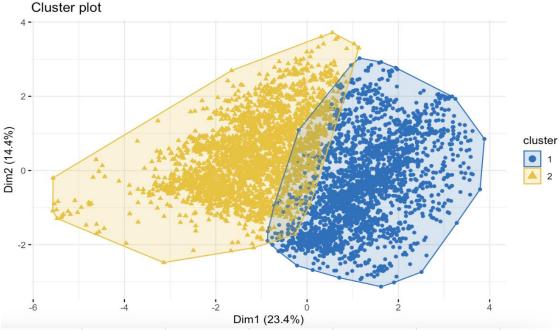


Figure 11. Visual Plot of the Two Types of Greater Los Angeles Region Super-Commuters

Figure 11 presents a visualization of the differences between the two super-commuter clusters. The plot graphically displays the level separation between the two groups, showing both the level of similarity within each of the two clusters, as well the differences between them. As the figure suggests, these two clusters of super-commuters are quite distinct. The within-cluster sum-of-squares (WCSS) for this cluster model is 17.2 percent, which means that just 17.2 percent of the total variation in the data is due to differences within the clusters, while the remaining 82.8 percent of the variation is explained by differences between the two clusters.



## 6. Super-Commuting Hotspot Analysis

In this section, we identify super-commuting residential hot spots and top super-commuting employment destinations in the Los Angeles region drawing on data from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). We then provide basic descriptive data for the region as well as for super-commuters in seven hotspot areas.

## 5.1. Super-commuter hotspots

We first estimated the commute distances for California workers in the LODES dataset by calculating the distance, through the street network, between each worker's home census block and work census block for their primary job.<sup>4</sup> We then defined super-commuters as workers whose home-to-work distance (proxy for the driving distance of a one-way commute) is 50 or more miles, while excluding those with an over-100-mile home-to-work distance because they are likely remote workers (Blumenberg & Speroni, 2024).

To identify super-commuting hotspots in the greater Los Angeles region, we first calculated the number of super-commuters in each zip code tabulation area (ZCTA). We then identified the top decile of ZCTAs by number of super-commuters. These ZCTAs are highlighted in the map below (

<sup>&</sup>lt;sup>4</sup> We obtained the street networks data from the <u>OpenStreetMap</u> project, and the calculation was performed using the <u>Open Source Routing Machine</u> software. We estimated the network distance between the centroids of each census block home and work pairing present in the LODES. We then counted the number of commutes in each home census block that fit our super-commuting threshold of 50 miles, and subsequently, we aggregated these to our other geographic units of analysis.

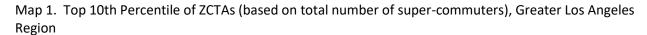


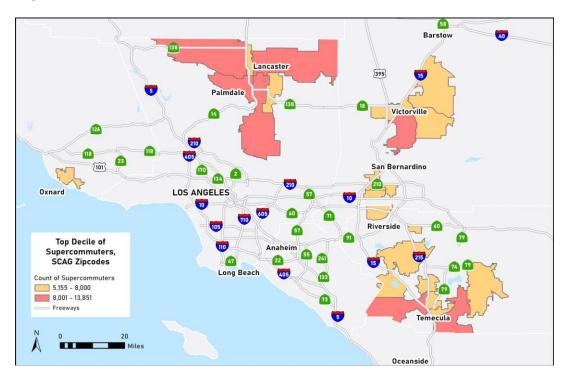
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Map 1), with the 90-94th percentile ZCTAs shown in orange and the 95th-100th percentile ZCTAs in pink. We then combined contiguous ZCTAs into a total of seven residential hotspots. Finally, we numbered and named the seven hotspots, and also identified the county in which each hotspot is located (see

Map 2 and Table 4).







Map 2. Top Super-Commuting Hotspots, Greater Los Angeles Region





Table 4. Top Super-Commuting Hotspots, Greater Los Angeles Region

Hotspot Number	County	Name
1	Riverside	Perris - Lake Elsinore - Temecula
2	Riverside	Moreno Valley
3	Riverside	Jurupa Valley
4	Ventura	Oxnard
5	San Bernardino	Fontana - Rialto
6	San Bernardino	Victor Valley
7	Los Angeles	Lancaster - Palmdale

Super-commuters are located throughout the greater Los Angeles region. However, one in four (175,707 out of 701,751) live in the seven hotspots that we identify in

Map 2. These areas do not simply reflect the location of all workers since only approximately one out of 20 non-super-commuters live in these hotspots. The seven hotspots vary in size as well as the number and percentage of super-commuters (see



## Figure 12 and

Figure 13). Some hotspots have significantly more super-commuters than others. Lancaster - Palmdale in northern Los Angeles County, Perris - Elsinore - Temecula in Riverside County, and Victor Valley in San Bernardino County are the three largest hotspots in terms of the number of super-commuters. While these three hotspots also have the highest rates of super-commuters (out of all workers), Moreno Valley in Riverside County, despite having the lowest number of super-commuters, has the fourth highest rate of super-commuters.



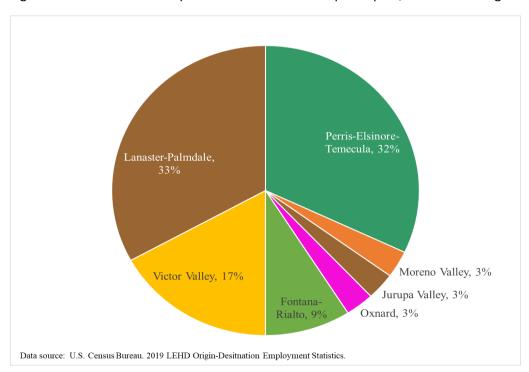
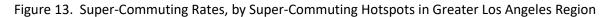
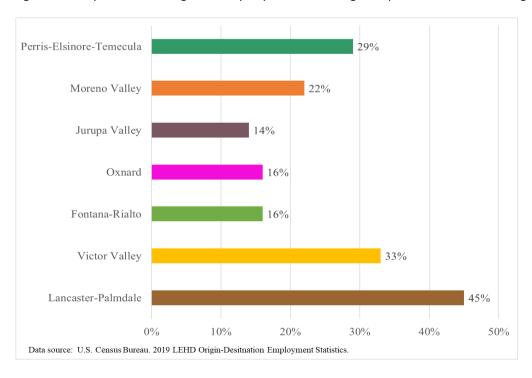


Figure 12. Distribution of Super-Commuters Across Top Hotspots, Greater Los Angeles Region

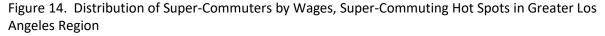


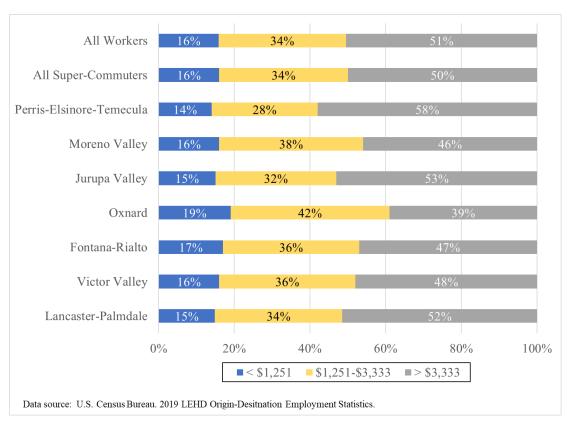




## 6.2 Super-commuters by wages

Worker wage categories are defined in the LODES dataset as monthly earnings less than \$1,251, between \$1,251 and \$3,333, and more than \$3,333.<sup>5</sup> With one exception, there is a dominant trend across the hotspots in terms of the wage distribution of super-commuters (Figure 14). For all hotspots but Oxnard (in Ventura County), the highest wage super-commuters form the largest category, between 46 percent and 58 percent of super-commuters in the hotspot. In Oxnard, super-commuters earning the LODES middle-level wages are the largest category (42%). In all cases, super-commuters earning the lowest wages are a small share of all super-commuters in all seven hotspots, accounting for between 14 percent and 19 percent of all super-commuters. For reference, 16 percent of all super-commuters and all workers in the greater Los Angeles region are in the lowest earnings group.





<sup>&</sup>lt;sup>5</sup> Some workers hold multiple jobs. For this analysis, we use workers' primary jobs. The LODES do not allow for matching of jobs to individuals, so we are unable to sum wages from different jobs together.



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## 6.3 Job centers

The City of Los Angeles is large, relatively dense, home to large numbers of jobs and, therefore, the destination of most super-commuters in the region. So rather than focus our analysis on destination *cities*, we examine the top *job centers* to which super-commuters travel.

To identify job centers, we drew from the methodology of two studies: Giuliano and Small (1991) and Giuliano et al. (2015). We defined job centers as clusters of contiguous census tracts with high number and density of jobs—each tract within the clusters must contain 10,000 or more jobs, and 25 or more jobs per hectare. Based on this definition, two job clusters—a long stretch of census tracts running from Santa Monica along Wilshire Boulevard to Downtown Los Angeles (DTLA) and further east to the City of Commerce, and a large cluster of tracts that include Los Angeles International Airport (LAX) and Culver City southwest of DTLA—are particularly large and consist of distinct sub-clusters. Therefore, we divided them into sub-centers: the former into (1) Wilshire Corridor (west of DTLA), (2) DTLA, and (3) Commerce/Vernon/East LA Railyards (east of DTLA); and the latter into (4) Culver City - Mar Vista (north) and (5) LAX (south). Map 3 provides the location of all major job centers we defined in the greater Los Angeles region.



Map 4 includes both the job centers and the super-commuting hotspots. The map shows that most job centers are located toward the center of the metropolitan region, whereas the super-commuting hotspots are located on the periphery.



Map 3. Major Job Centers in the Greater Los Angeles Region





Map 4. Job Centers and Super-Commuting Hotspots in the Greater Los Angeles Region

## 6.4 Top job centers for workers in super-commuting hotspots

A majority (57%) of super-commuters from the top residential hotspots work outside of job centers, but super-commuters are more likely than non-super-commuters to work in job centers (see



Figure 15). Across the hotspots, between 34 and 48 percent of super-commuters work in a job center, compared to only six to 22 percent of non-super-commuters (and 14% to 25% of all workers). However, super-commuters in the greater LA region are less likely to work in job centers than non-super-commuters. In other words, super-commuters in the hotspots are more likely to work in job centers than their counterparts outside of the hotspots. The top five job centers for super-commuters from all seven hotspots combined are shown in



Table **5** below. DTLA and the Wilshire Corridor stand out as the two largest attractors of supercommuters.



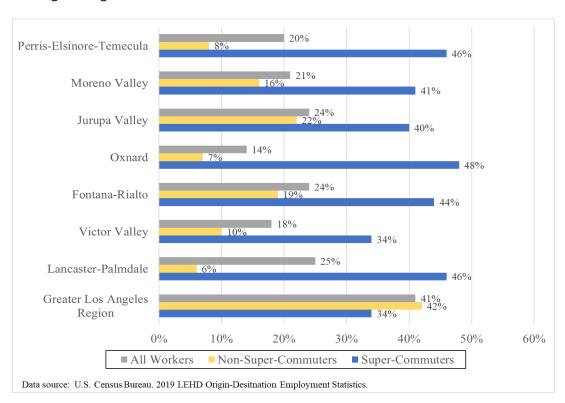


Figure 15. Percentage of Workers Working in Job Centers – Super-Commuter Hotspots and the Great Los Angeles Region

We also identified the top five job centers for each super-commuting hotspot (Appendix 6). DTLA and the Wilshire Corridor are the top two destination job centers for super-commuters from all of the top hotspots except for Perris - Elsinore - Temecula in Riverside County and Victor Valley in San Bernardino County. For Victor Valley super-commuters, the Costa Mesa/Irvine/Santa Ana job center in Orange County is the top employment destination, but DTLA and Wilshire Corridor are the second and third. For super-commuters in Perris - Elsinore - Temecula, the top destination job center is Costa Mesa/Irvine/Santa Ana in Orange County, followed by three job centers in San Diego County. For super-commuters in this hotspot, DTLA and the Wilshire Corridor are the fifth and sixth most frequented destinations.



Table 5. Top Five Job Centers—All Super-Commuters and Super-Commuters in Top Hotspots

	From H	otspots	From Anywhere (including hotspots)		
	# of	% of	# of	% of	
Job Center Name	super-commuters	super-commuters	super-commuters	super-commuters	
Downtown Los					
Angeles (DTLA)	11,607	7%	23,666	3%	
Wilshire Corridor	10,384	6%	31,728	5%	
Costa					
Mesa/Irvine/Santa					
Ana	6,868	4%	25,003	4%	
LAX	4,810	3%	14,336	2%	
Disneyland/Platinum					
Triangle	2,913	2%			
Sorrento Valley/UC					
San Diego			11,381	2%	

### 6.5 Commute distance

The average commute distance for super-commuters from each hotspot area is two to three times longer than those for non-super-commuters (see **Table 6**). Super-commuters from hotspot areas that are farther out on the fringe of the metropolitan area (Oxnard, Victor Valley, Lancaster - Palmdale) commute longer distances on average than their counterparts from other hotspot areas (Perris - Elsinore - Temecula, Moreno Valley, Jurupa Valley, Fontana - Rialto). But this trend does not hold for non-super-commuters from the same hotspots. For example, non-super-commuters from Oxnard have shorter commutes on average than those from Perris - Elsinore - Temecula, even though super-commuters from Oxnard have longer commutes on average than those from Perris - Elsinore - Temecula. This is because super-commuters are more likely than non-super-commuters to work in highly-skilled and specialized jobs that tend to cluster in job centers (such as Downtown Los Angeles) which are mostly located in the core areas of the metropolitan region.



Table 6. Average Commute Distance for Workers in Top Super-Commuting Hotspots

#	Hotspot Name	Mean commute distance (miles)			
		Super- Non-Super-		All workers	
		Commuters	Commuters		
1	Perris - Elsinore - Temecula	67.1	21.0	35.3	
2	Moreno Valley	67.6	18.9	30.0	
3	Jurupa Valley	65.8	19.9	26.7	
4	Oxnard	72.8	11.0	21.9	
5	Fontana - Rialto	62.6	18.0	25.6	
6	Victor Valley	75.2	21.4	41.4	
7	Lancaster - Palmdale	71.1	15.8	43.6	
	Greater LA Region	69.2	15.2	20.7	

## 6.6 Commute duration

We used Streetlight Data to estimate travel durations between our top super-commuting hotspots and 44 employment centers in the greater Los Angeles region. Streetlight (prior to 2022) aggregated location-based services (LBS) data. Prior research suggests that in 2019 Streetlight captured about ten percent of mobile phones in its sample (Speroni et al., 2024), which it used to derive estimates for travel volume and duration between a customizable set of destinations.

In our case, we estimated average travel duration in minutes across five time periods: two peak periods, morning and afternoon, and three off-peak periods, which we combined into one set of off-peak metrics using weighted means. Streetlight counts all mobile devices traveling among our geographies and is not capable of counting only those devices in its sample that are commuting from home to work. However, these calculations do reveal the roadway conditions that such super-commuters experience.

Appendix 7 details the mean travel duration estimates between the seven super-commuter hotspots and each hotspot's top-five destination employment centers at a super-commute distance (50 to 100 miles) across five commuting directions and hours:

- Morning Peak-period, Peak-direction (6:00 to 9:59 AM, travel from super-commuter hotspots to employment centers)
- Evening Peak-period, Peak-direction (3:00 to 6:59 PM, travel from employment centers to super-commuter hotspots)
- Morning Peak-period, Off-direction (6:00 to 9:59 AM, travel from employment centers to super-commuter hotspots)
- Evening Peak-period, Off-direction (3:00 to 6:59 PM, travel from super-commuter hotspots to employment centers)
- Off-peak (12:00 to 5:59 AM, 10:00 AM to 2:59 PM, and 7:00 to 11:59 PM, all directions, with means from each time period and direction weighted by the average daily number of trips)

Overall, we find expected patterns: peak-period, peak-direction trips took longer than off-peak trips, with peak-period, off-direction trips lying in the middle. More specifically, routes traveled by super-commuters take approximately 124 minutes during the peak-hour, peak-direction periods, on average; 100 minutes during the peak-hour, off-direction periods; and 99 minutes during the off-peak periods.



While on its face the roughly 25 percent peak-period, peak-direction time penalty is substantial, we find it somewhat surprising that the difference is not even greater. However, we suspect that the relatively narrow peak/off-peak travel time difference is influenced by a substantial majority of the off-peak trips being taken during the middle of the day, when congestion delays may still be moderate, compared with the delay-free middle of the night.

There are two limitations to our approach here. First, some employment center destinations are excluded from the analysis. Because some hotspots—especially Perris - Elsinore - Temecula—are so close to urbanized San Diego, we allowed employment centers there to count toward the top five. However, our StreetLight license provided data for the SCAG region only, so we are unable to include super-commuters from this greater Los Angeles sub-region into San Diego County job centers.

Second, there are three hotspot/employment center combinations that do not have available duration data. StreetLight requires a minimum sample of device trips to reach a proprietary significance threshold before the platform will report data for that given time period and geography. Because supercommuting is, in fact, relatively rare, some trips between smaller geographies—like Oxnard to Costa Mesa/Irvine/Santa Ana—did not meet their threshold. We find that this threshold appears to be approximately 200 super-commuters.



# 7. Housing and Transportation Expenditures in Super-Commuting Hotspots and Job Centers

## 7.1 Housing and transportation cost estimates for super-commuting hotspots

The top half of **Table 7** below shows the estimates for monthly housing costs, annual transportation costs, as well as H+T cost burdens for the seven super-commuting hotspots. All estimates were based on census tract level data from the 2022 H+T Affordability Index database on neighborhood characteristics. The housing cost estimates are weighted averages of median owner costs and median gross rents by tenure type; transportation costs are the sums of auto ownership costs, auto use costs, and transit use costs. To obtain estimates for super-commuting hotspot areas (defined based on ZCTAs), we took the average of estimates of census tracts that overlap with the hotspot areas.

Table 7. Housing and Transportation Cost Estimates for Super-Commuting Hotspots and Job Centers

	Median monthly homeownership cost	Median monthly gross rent	Average monthly housing cost	Average annual transportation cost	Housing + transportation cost burden	Housing cost	Transportation cost burden
Supercommuting Hotspot							
Perris - Elsinore - Temecula	\$2,048	\$1,594	\$1,938	\$17,643	63%	36%	27%
Moreno Valley	\$1,334	\$1,408	\$1,385	\$16,393	51%	26%	25%
Jurupa Valley	\$1,660	\$1,325	\$1,594	\$17,597	56%	29%	27%
Oxnard	\$1,862	\$1,555	\$1,748	\$19,056	46%	24%	22%
Fontana - Rialto	\$1,697	\$1,382	\$1,611	\$16,728	55%	30%	26%
Victor Valley	\$1,441	\$1,142	\$1,371	\$16,778	51%	25%	26%
Lancaster - Palmdale	\$1,704	\$1,313	\$1,586	\$17,116	50%	26%	24%
Job Center Name							
DTLA	\$2,228	\$1,421	\$1,493	\$9,406	37%	25%	13%
Wilshire Corridor	\$2,544	\$1,648	\$1,853	\$9,429	43%	30%	13%
Costa Mesa /Irvine/Santa Ana	\$2,042	\$1,974	\$2,110	\$14,678	55%	35%	20%
LAX	\$2,901	\$1,816	\$2,365	\$13,000	57%	39%	18%
Disneyland/Platinum Triangle *	\$1,440	\$1,772	\$1,777	\$14,970	50%	29%	21%
Sorento Valley/UC San Diego *	\$2,112	\$1,974	\$2,180	\$13,692	51%	33%	17%

Notes: Disneyland/Platinum Triangle is the top 5th job center for supercommuters from the seven hotspots; Sorento Valley/UC San Diego is the top 5th job center for all supercommuters in the SCAG region.

Note that the transportation cost estimates are modelled for a typical household in the region, which is defined as a household with median income, average household size, and average number of commuters per household in the Core Based Statistical Area (CBSA). Cost burdens are also calculated based on the median household income in a CBSA. This means that transportation costs and cost burdens for five of the seven hotspots (excluding Oxnard and Lancaster - Palmdale) are calculated based on the same household parameters because those five hotspots are all in the Riverside - San Bernardino - Ontario CBSA. Also, using regional median household parameters means that these estimates are unlikely to accurately represent the particular costs and cost burdens borne by individual super-

<sup>&</sup>lt;sup>6</sup> The 2022 update of the H+T Index relies on data from the 2019 American Community Survey, the 2019 Longitudinal Employer-Household Dynamics Program, and 2018 to 2019 transit schedules.



.

commuters (or low-wage workers) or their variability across all super-commuters in a given geography, since such commuters are both heterogeneous and likely to differ from the median household in a given sub-region.



Figure 16 show that estimated levels of housing and transportation costs vary meaningfully across the seven super-commuting hotspot areas. Among the seven hotspots, housing cost is highest in Perris - Elsinore - Temecula and Oxnard, while lowest in Moreno Valley and the Victor Valley. Oxnard households also have the highest average transportation cost. The estimated variation in housing costs is larger than the variation in transportation costs across the sub-regions, thus Perris - Elsinore - Temecula and Oxnard – the two hotspots with the highest housing cost – also have the highest housing and transportation costs combined.

Figure 17 shows the estimated average cost burden for each of the hotspots. As noted earlier, many scholars and organizations view housing typically as "affordable" if it comprises no more than 30 percent of household income (Center for Neighborhood Technology, 2022). According to the Center for Neighborhood Technology (CNT), transportation is affordable at no more than 15 percent of the Area Median Income (Center for Neighborhood Technology, 2022). Therefore, they estimate that the H + T is affordable if it consumes no more than 45 percent of income. While these are perhaps arbitrary thresholds, they are widely used. As a point of comparison, in 2019 the mean housing and transportation burden (relative to pre-tax income) in the U.S. was 38 percent with housing comprising 25 percent and transportation 13 percent of this figure (Bureau of Labor Statistics, 2020b).

In all but one of the super-commuting hotspots, the H+T expenditure burden was over the 45 percent threshold. The H+T expenditure burden was elevated largely due to higher than average transportation expenditure burdens; households in all of the hotspots had transportation expenditure burdens greater than 20 percent. The H+T burden was highest in Perris - Elsinore - Temecula. It was lowest in Oxnard even though housing costs there were second highest; this was a function of the higher median household income in the Oxnard CBSA compared to the other hotspot areas studied.



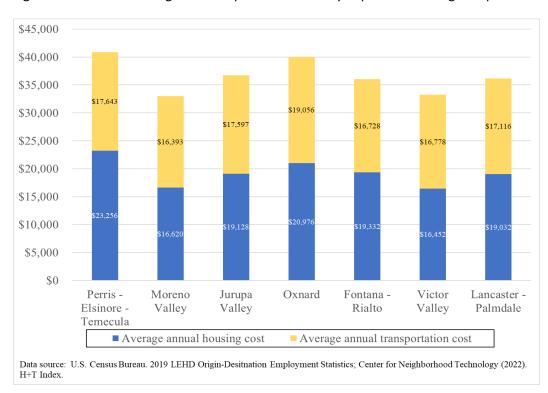
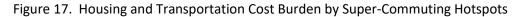
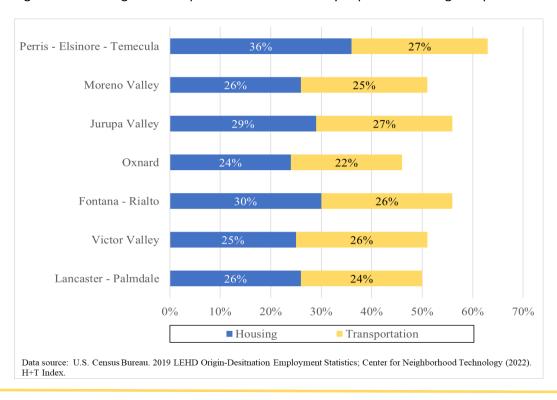


Figure 16. Annual Housing and Transportation Costs by Super-Commuting Hotspots







As we noted previously, these data do not allow us to disaggregate the H+T expenditure burden by household income for households in each hotspot. However, national data from the 2019 Consumer Expenditure Survey show that when household pre-tax income is used as the basis for calculating the expenditure burden, the H+T expenditure burden declines significantly as household income rises. The left side of



Figure 18 below shows that households in the lowest income quintile have a H + T expenditure burden of 134 percent of income, not even counting all other non-housing, non-transportation household expenses.<sup>7</sup> It is difficult to imagine that low-income households could sustain this type of substantial and mounting debt on an ongoing basis.

What explains this glaring discrepancy between income and expenditures in the lowest income households? The most obvious explanation is that the lowest income households are more likely to receive various forms of public assistance that may not be fully reported as income. In addition, they may earn income through casual employment that is not reported, and they perhaps receive ongoing extended-family financial assistance as well – all in addition to reported earned income. Because of this, calculating H + T expenditures as a share of all household *expenditures*, rather than reported *income*, is more of an apples-to-apples comparison across poorer and wealthier households (Blumenberg, 2003).

Indeed, when total expenditures, rather than reported income, are used as the denominator, the H + T expenditure burden across poorer and wealthier households looks very different. Households in the bottom income quintile have the highest housing expenditure burden (40%). However, their transportation expenditure burden is *slightly less* than households in the other income categories (16%), likely due to lower automobile ownership rates, higher rates of transit use, the purchase of less expensive vehicles, and less overall travel.

<sup>&</sup>lt;sup>7</sup> Mean total household expenditures for households in the bottom income quintile are 2.4 times their mean pre-tax incomes.



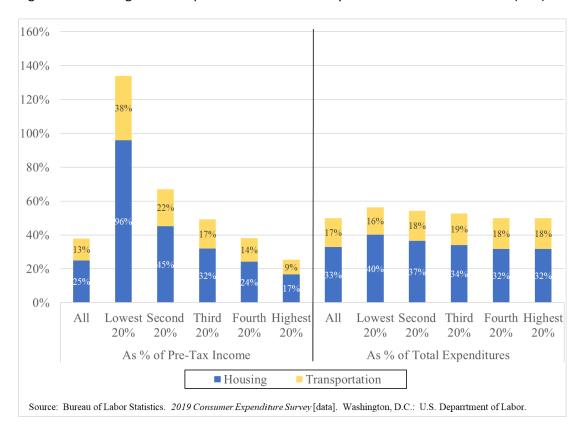


Figure 18. Housing and Transportation Cost Burden by Household Income Quintile (U.S.)

### 7.2 Housing and transportation cost estimates for Los Angeles job centers

The bottom half of **Table 7** shows housing and transportation cost estimates for the top five greater Los Angeles job centers for super-commuters from hotspots and for all super-commuters. All job centers in the table but one (Sorento Valley/UC San Diego) are in the Los Angeles - Long Beach - Anaheim CBSA, meaning the transportation costs and cost burdens are estimated based on the same household parameters. Housing costs are highest in the LAX job center and lowest in DTLA. Variation in housing cost estimates is a function of variations in home ownership cost, rent, and the shares of owner-occupied and rental housing units across places. Transportation costs are lowest in DTLA and along the Wilshire Corridor, where both density and transit supply are the highest in the region.



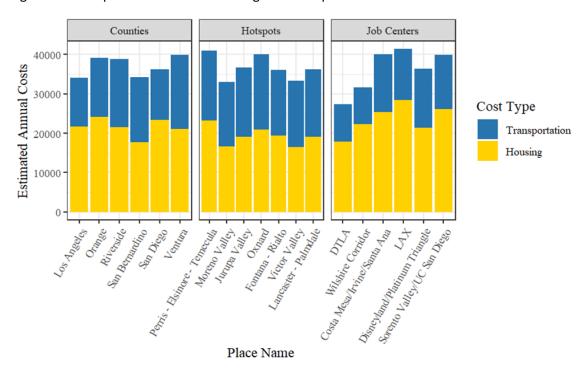


Figure 19. Comparison of Annual Housing and Transportation Costs across Places



Figure 19 above compares annual housing and transportation costs of the seven hotspots, top job centers, and the counties in which these hotspots and job centers are located. This comparison shows some variation in combined housing and transportation costs across super-commuting hotspots and top super-commuting job centers. However, the variation is not substantial, with a few notable exceptions. As noted earlier, Perris - Elsinore - Temecula has the highest housing cost and combined housing and transportation costs among the hotspots; higher than nearby Moreno Valley and Jurupa Valley (the other two hotspots in the Riverside County), Fontana - Rialto and Victor Valley (the remaining two hotspots in the Riverside - San Bernardino - Ontario CBSA), and the Riverside County average. This finding suggests that super-commuters who live in Perris - Elsinore - Temecula may be different from their counterparts in the other hotspots in the same county or the larger CBSA area in terms of income and occupation. Recall that Perris - Elsinore - Temecula also has the lowest share of lower-wage super-commuters across all seven hotspots. Similar differences also exist between Fontana - Rialto and Victor Valley, the two hotspots located in San Bernardino County.

Moreover, two job centers stand out in the comparison – DTLA and the Wilshire Corridor (

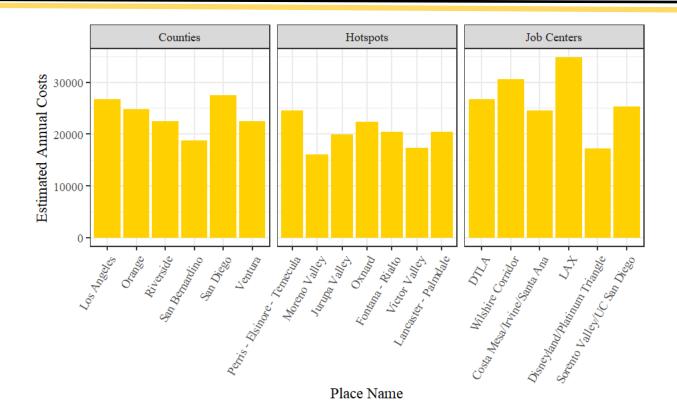


Figure 19). They are the top two destinations for super-commuters from the super-commuting hotspots and for the SCAG region as a whole, but housing costs in DTLA and the Wilshire Corridor are not substantially higher than in the hotspot areas or in the region as a whole, while transportation costs in those two huge centrally-located job centers are substantially lower than elsewhere. This would appear to contradict the theory that people tradeoff housing and transportation costs in choosing where to live and work, especially given that the transportation costs borne by super-commuters are likely even higher than these hotspot averages would suggest. However, recall that housing costs are the weighted average of home ownership costs and gross rent by tenure type. Given this, a comparison of home ownership costs tells a different story (see Figure 20).

Home ownership costs in all top job centers but one (Disneyland/Platinum Triangle) are higher than Perris - Elsinore - Temecula (the hotspot with the highest housing and home ownership costs), and substantially higher than in the other hotspots. In fact, the biggest job centers in Los Angeles County (DTLA, Wilshire Corridor, and LAX) have the highest home ownership costs. Moreover, not only do super-commuting hotspots have lower home ownership costs than in most other major greater Los Angeles job center destinations, most of them (Moreno Valley, Jurupa Valley, Victor Valley, and Lancaster - Palmdale) also have lower home ownership costs than their respective counties (Riverside [the former two], San Bernardino, and Los Angeles) as a whole. Thus, it does appear plausible that at least some super-commuters may be trading away shorter commutes and relatively affordable rental housing, for much longer commutes and home ownership. They may be, in other words, "driving until they qualify." The lower home ownership cost in Disneyland/Platinum Triangle may seem like an exception, but its share of owner-occupied units (34%) is substantially lower than the super-commuting hotspots (ranging from 53% to 71% with a combined average of about 63%).

Figure 20. Comparison of Home Ownership Costs across Places







# 8. Housing and Transportation Expenditures and Worker Households in California

In this section, we provide housing and transportation (H+T) cost and burden estimates for super-commuting households by income. Again, H+T costs refer conceptually to all household expenditures on housing (rents, mortgage expenses, utilities, etc.) and transportation (car payments, insurance, fuel, transit fares, etc.):

H+T burdens = H+T costs / household incomes

However, as we explain below, assembling the data to estimate these costs and burdens by income is no simple matter. These estimates are based on data from the California Add-on to the 2017 National Household Travel Survey and California data from the 2015-2019 American Community Survey, Public Use Microdata Sample. We then develop a set of models to predict the household and transportation burden of worker households in California by income. The models serve as the basis for a set of scenarios that we present in the conclusion of this section.

### 8.1 Methodology

There are three significant challenges to developing equity scenarios based on the super-commuting hotspot data infrastructure that we developed and report in Section 7. The housing + transportation (H+T) burden by census tract is a weighted average of transportation costs and, therefore, does not reflect the individual transportation cost burden of super-commuters. That said, the measure we develop is useful for understanding the H+T burden of all households in a given neighborhood and in making comparisons across neighborhoods.

The LODES data allow us to calculate the commute distance for workers by three pre-selected wage categories included in the dataset. However, the H+T expenditure burden is not based on individual workers but rather on households. For example, it is possible that a lower-wage worker lives in a household with a high-wage worker or multiple middle-wage earners. In other words, there is a mismatch in the units of analysis. Finally, the transportation data (from the H+T dataset) are estimated for all travel, and not just commuting to and from work; but we only have commuting data in the LODES dataset. This is another data mismatch.

Therefore, to reasonably estimate the housing and transportation costs for super-commuting households across various characteristics, including income, we took the following steps. We relied on two data sets for this process: the California add-on of the 2017 National Household Travel Survey (NHTS), which contains detailed household travel information but not housing costs information, and the 2015-2019 Public Use Microdata Sample (PUMS) of the American Community Survey (ACS) data, which contains detailed housing costs information but has no household travel information. Both data sets contain socio-demographic and geographic information. These data allow us to train a model for household transportation costs based on the 2017 NHTS California add-on data set, using only variables that also are present in the PUMS ACS data, and then use this model to predict household transportation costs using the PUMS ACS data.



Because the 2017 NHTS data contain household travel information but not transportation cost information, we attached per-mile cost of driving in 2017 (the year of our California NHTS Add-on data) based on American Automobile Association (AAA) cost estimates—which include costs of fuel, maintenance, repair and tires, license, registration and taxes, insurance, depreciation, and finance, for different types of vehicles—to each household vehicle and calculated total annual household transportation costs (American Automobile Association, 2017).

As we note earlier, the AAA cost estimates are based on the national average of each cost component, and the finance costs are based on a five-year loan with ten percent down payment. The per-mile driving costs in 2017 were estimated for three levels of annual mileage: 10,000, 15,000, and 20,000. We used estimates based on 15,000 annual miles driven—the basis of per-mile estimates adopted by AAA in subsequent years. We matched the AAA estimates to each household vehicle based on the vehicle types (sedan, SUV, pickup, hybrid, electric, and other vehicles). The AAA estimates for sedans and SUVs were broken down into different sizes, so we calculated the average costs for those two types. We used the overall average estimate for other vehicles.

We then estimated household transportation costs for households with at least one worker ("1+ worker households"). This model only uses variables that also are present in the PUMS ACS data. See the table in Appendix 8 for the model results. We then applied this model to impute household transportation costs for California households among 1+ worker households in the PUMS ACS data. Based on this imputation, we then calculated the H+T total expenditures and H+T expenditure burdens for worker households by income and other select characteristics. We focus on income for this analysis but include the H+T expenditure burdens for other household types in Appendix 9.

For the scenario analysis, we model the housing and transportation expenditure burden for all 1+-worker households and for all 1+-worker households by income – low-income (bottom income quintile), middle income (2<sup>nd</sup>, 3<sup>rd</sup>, and 4<sup>th</sup> quintiles), and high-income (top income quintile). These models allow us to assess the relationships between super-commuting, income, and other factors of interest, such as work from home, mode use, and residential location.

The Consumer Expenditure Survey (CES) administered by the U.S. Bureau of Labor Statistics provides summary data on mean consumer expenditures for all "consumer units" (roughly equivalent to households) in California by income quintile (Bureau of Labor Statistics, 2020a). To check the reliability of our estimates, Figure 21 compares our results to those from the CES data.

Across all the income groups, the H+T expenditure burden is higher for households in the CES data than our estimates, likely due to systematic differences in the two samples. The CES data include mean expenditures for a sample of all consumer units in California. In contrast, the data we have analyzed in this report include a sample of only 1+ worker households and their median (not mean) expenditure burdens. Given this, the observed discrepancies make sense because non-working households tend to have lower incomes than households with workers, and thus higher expenditure burdens as a result. Moreover, our use of median values minimizes the influence of outliers. As



Figure 18Figure 21 shows, however, the results are similar, with the biggest gap among the lowest income households; as expected, the H+T expenditure burden declines significantly and similarly by income quintile in both sources of data.

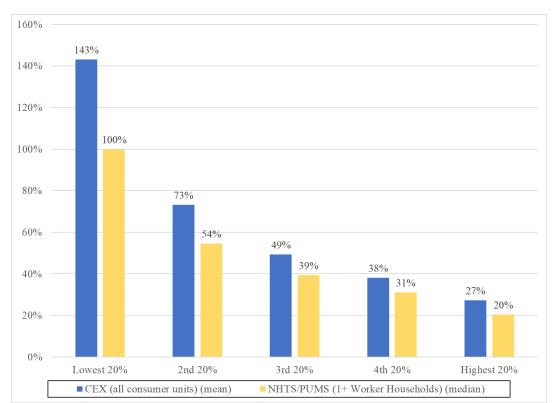


Figure 21. Comparison of the Housing and Transportation (H+T) Expenditure Burden Between the 2017-18 Consumer Expenditure Survey (CES) and the NHTS/PUMS Estimates

### 8.2 Characteristics of super-commuting households

The data used for this analysis are different from the PUMS data that we analyzed and presented in earlier sections of this report, since the unit of analysis for this portion of the study is households with workers, and not individual commuters. Accordingly, Figure 22 compares all 1+ worker households with households with at least one super-commuter—defined as a worker who commutes at least 90 minutes one-way. It shows that, compared to all 1+ worker households, workers in super-commuter households are much more likely to commute by public transit, less likely to have a worker who works from home, and more likely to live in metro-noncity areas.<sup>8</sup>

<sup>&</sup>lt;sup>8</sup> At first blush, "Metro-noncity" would seem an oxymoronic term. In this case, "Metro" indicates that the household resides in a metropolitan area. For such residents, they either live within ("city") or outside of the central/principal city ("noncity"). So generally, metro-noncity households can be thought of as being located in the suburbs of a given metropolitan area. However, in some cases the



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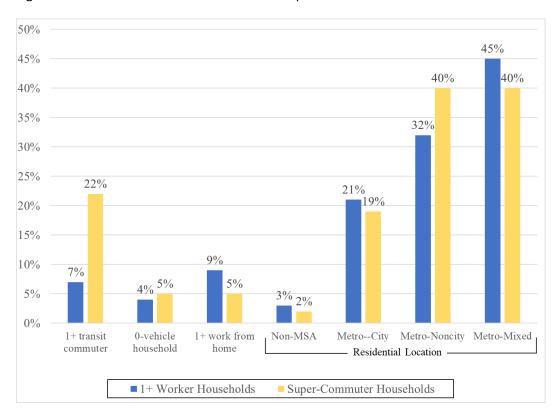


Figure 22. Characteristics of 1+-Worker and Super-Commuter Households

metropolitan and central/principal-city status are not directly identified. In these instances, IPUMS derives "metro" status based on other available geographic information, including location within a Public Use Microdata Area (PUMA). If a county group or PUMA lies only partially within a central/principal city, then the household residential designation is "mixed," likely a neighborhood located in a higher-density, inner-ring suburb.



Figure 23 presents the distribution of worker and super-commuter households across income quintiles; the income quintiles are calculated based on all California households, including those without workers. As we would expect, households with 1+ workers tend to have higher incomes than all households and, therefore, are particularly underrepresented among households in the bottom income quintile. This distribution is further skewed for super-commuter households; only eight percent are in the bottom income quintile, while 57 percent are in the top two income quintiles.



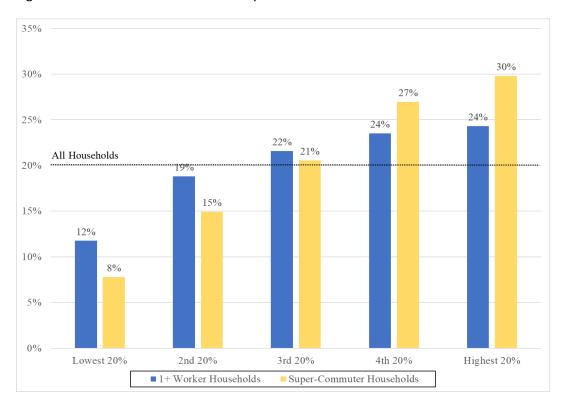


Figure 23. Distribution of Households by Income Quintile

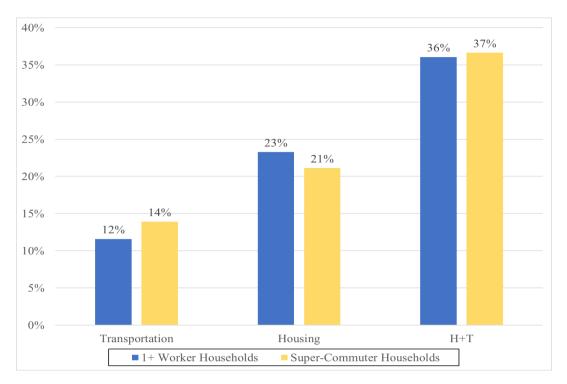
8.3 Housing and transportation burden and costs



Figure 24 shows the difference in the median H+T expenditure burden for the two household types. The combined H+T burden does not vary significantly between all worker households and super-commuting households. However, compared to all worker households, super-commuter households—as expected—tend to have slightly higher transportation expenditure burdens but slightly lower housing expenditure burdens. This finding comports with urban theory, which posits that households trade off higher transportation costs for lower-cost housing, often in more distant, peripheral neighborhoods.



Figure 24. Median Housing and Transportation Expenditure Burden – Super-Commuter and 1+- Worker Households



While the data show a positive relationship between income and super-commuter households (



Figure 23), the financial burden of housing and transportation costs falls more heavily on lower-income worker households (



Figure 25). However, across all income quintiles, super-commuter households have slightly higher H+T burdens compared to 1+ worker households. The overall difference in expenditure burdens between super-commuter households and 1+ worker households is less pronounced than differences observed in each income quintile. This finding is due to our use of medians and the larger number of super-commuters in the higher-income quintiles.

<sup>9</sup> As we note above, the very high reported H+T expenditures in the bottom quintile of households in

Figure 25 may raise some eyebrows, given that household members need to spend money on things other than housing and transportation, like food, clothing, and healthcare. What may explain this result? Note that these data compare reported income and expenditures, although income from informal sources may often be underreported in lower-income households. Further, not all revenues for expenditures in low-income households come from income, such as public subsidies and support from extended family members.



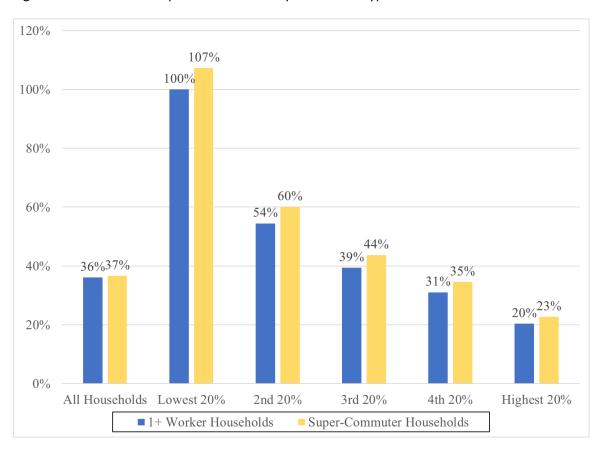


Figure 25. Median H+T Expenditure Burden by Household Type



Figure 26 shows the median housing and transportation expenditures for super-commuter households. As we discussed earlier in this report, housing is typically considered "affordable" if it comprises no more than 30 percent of household income. Our data show that housing is above the 30-percent threshold for households in the bottom two quintiles and significantly above this threshold for households in the bottom income quintile. As we note previously, in constructing their Housing and Transportation (H+T) neighborhood affordability index, the Center for Neighborhood Technology argues for the inclusion of transportation costs and sets the combined housing and transportation affordability threshold as no more than 45 percent of household income. Once again, households in the bottom two income quintiles exceed this percentage, on average.

<sup>&</sup>lt;sup>10</sup> Again, these and similar data from the national Consumer Expenditure Survey show that households in the bottom income quintile appear to spend more than 100 percent of their incomes on both housing and transportation for the reasons discussed above.



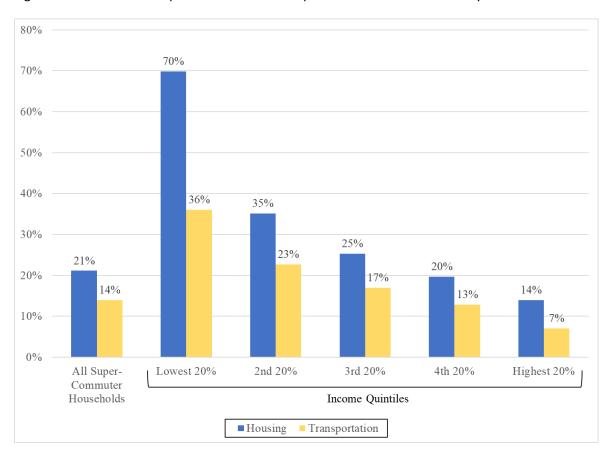


Figure 26. Median H+T Expenditure Burden – Super-Commuter Households by Income Quintile

Finally,



Figure 27 shows the median expenditures for housing, transportation, and H+T combined, by household income quintile. As expected, expenditures on both housing and transportation increase with income. Households in the top income quintile spend more than twice as much on both housing and transportation than households in the bottom quintile. With respect to transportation, lower-income households are more likely than higher-income households to rely on public transit, own fewer vehicles, and/or purchase less expensive vehicles. They also travel fewer miles than higher-income households. The data show that the relationship between income and transportation expenditures weakens at higher incomes, suggesting that there is a limit to how much higher-income households will spend on transportation. This decelerating growth in transportation expenditures as income rises does not appear to be the case for housing; in fact housing costs tend to accelerate with income.



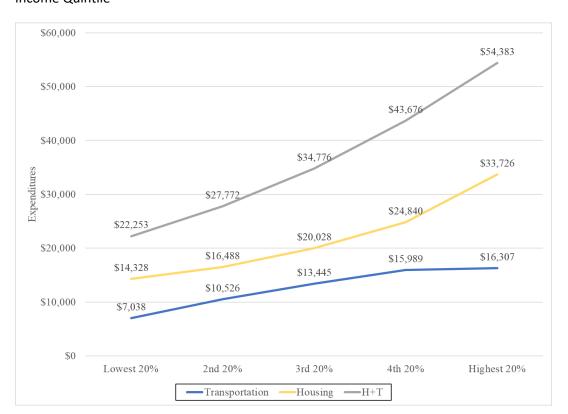


Figure 27. Median Expenditures Super-Commuting Households: Housing, Transportation, and H+T by Income Quintile

## 8.4 Predicting H+T expenditures and the H+T expenditure burden

We draw on data from the Public Use Microdata Sample (PUMS) and our imputed estimate of transportation expenditures to predict (a) total H+T expenditures and (b) the H+T expenditure burden (household housing and transportation expenditures relative to household income) for all California households in which there is at least one worker. Both outcomes (expenditures and burdens) are logged given the distribution of the variables. For both H+T expenditures and burden, we developed a model for all 1+ worker households and then constructed models for three income groups – low-income (bottom income quintile), middle-income (quintiles 2, 3, and 4), and high-income (top income quintile). The models include a set of control variables that we hypothesize may be associated with H+T expenditures. We also use a set of interaction terms to explore the relationship between supercommuting and our variables of interest: (a) work from home, (b) transit use, and (c) residential location. The schematic in



Figure 28 presents the variables that we include in our models.



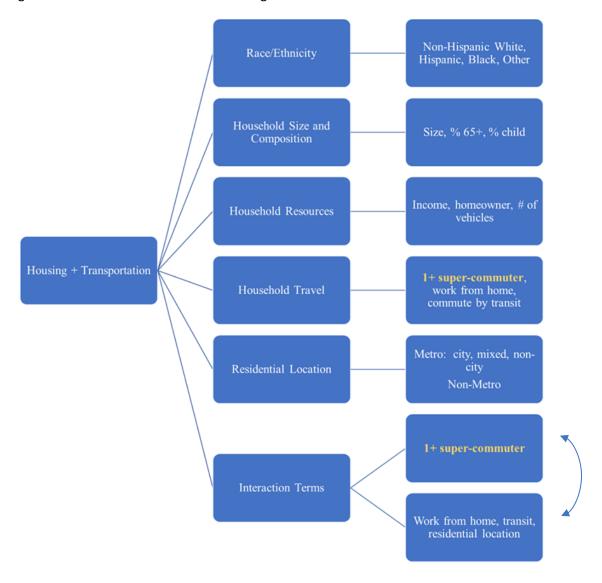


Figure 28. Schematic: Variables in H+T Regression Models

Model Results: Total Housing and Transportation Expenditures

We summarize our findings of the models by income in



**Table 8**, where "+" indicates a positive, statistically significant relationship between the independent or control variable and the outcome variable; "-" indicates a negative, statistically significant relationship between the two variables, and "NS" indicates a relationship that is not statistically significant. The blue font text in the table highlights our independent variables of interest. The full model results are located in Appendix 10 and Appendix 11.

Many of the independent variables operate similarly across the three income groups. For example, Non-Hispanic White households have lower H+T expenditures (controlling for other characteristics, including household income) compared to households of color. H+T expenditures also are lower in households with older adults and in neighborhoods located outside of urban areas. In contrast, H+T expenditures are positively related to household size, income, and the number of household vehicles. Finally, with one exception, in all three models the two variables with the strongest relationships to H+T expenditures are household income and the number of household vehicles. For middle-income households, household size also contributes significantly to H+T expenditures. Finally, the percentage of older adults is a relatively strong and negative predictor in all three models as well.

As we expected, with respect to super-commuting, the presence of at least one super-commuter in the household is related to higher transportation and housing expenditures, all else equal. Again, this is true for households in all three income groups. The presence of at least one worker who works from home is statistically significant and *positive* for all households on average, likely because this relationship is significant for middle-income households, the largest of the three income groups. The interaction between super-commuting households and work from home is not significant for households in any of the income groups, which suggests that the presence of one or more super-commuters and one or more remote workers in the same household does not further increase or decrease that household's H+T expenditures significantly.

The relationship between super-commuting and transit use varies across the various income groups. For low- and medium-income households, H+T expenditures are lower among households in which at least one worker uses transit, potentially a function of the typically lower costs of riding transit relative to driving. Among higher-income households, however, the relationship reverses; higher-income households that use transit have higher H+T expenditures, all else equal. For both middle- and high-income households, the interaction between transit and super-commuting is negative and significant, mediating these relationships. In both cases the sum of these coefficients is negative.

Finally, as we note above, across all income groups H+T expenditures are lower for households living in neighborhoods located outside of principal cities. Super-commuting affects these H+T expenditures by location differently across the income groups. For low-income households, the interaction term is positive and significant in suburban areas (both non-central-city and central city/suburban); the size of the coefficients indicates that super-commuters in these areas spend more on H+T, ceteris paribus. For middle-income households the findings are similar but also extend to non-metropolitan areas. Finally, for higher-income households, only one of the residential location interaction terms is significant and positive: location in a non-metropolitan area. But in all cases, the sum of the coefficients—the main effects and the interaction term—remains negative, which indicates that super-commuting tends to increase H+T expenditures for households living outside of principal city neighborhoods, but that increase does not fully erode the savings from living in these less central/more outlying areas.



Table 8. Summary of Household and Transportation (H+T) Expenditure Models

Variables	All 1+ Worker	Worker Ho	useholds by Inc	ome Group	
	Households	Low	Middle	High	
Race/ethnicity (excl. NH White)					
Hispanic	_	_			
Asian	_	_			
Black	_	_	_	_	
Other	_	_	_	_	
Household size and composition					
% household 65+	_	_	_	_	
% child	_	_	+	+	
Household size	+	+	+	+	
Household resources					
Household income	+	+	+	+	
Homeowner	+	_	_	+	
# of vehicles	+	+ +		+	
Household Travel					
Super-commuter (SC) household	+	+	+	+	
Work-from-home household	+	NS	+	NS	
Commute-by-transit household	_	_	_	+	
Residential location					
Non-metro	_	_	_	_	
Metro-noncity	_	_	_	_	
Metro-mixed	_	_	_	_	
Interaction terms					
SC*Work-from-home household	NS	NS	NS	NS	
SC*Transit household	-	NS	_	_	
SC*Non-metro	+	NS	+	+	
SC*Metro-noncity	+	+	+	NS	
SC*Metro-mixed	+	+	+	NS	
NS=not statistically significant	<u> </u>				

NS: not statistically significant

Data: 2015-2019 American Community Survey, Public Use Microdata Sample; 2017 National Household Travel Survey, California Add-On.



Model Results: Housing and Transportation Expenditure Burden

The full model results are located in Appendix 12 and Appendix 13. Like we did above, we summarize the model findings in



**Table 9**. Once again, some of the variables in the model operate similarly across the income groups, while others do not. Expenditure burden is positively related to the household size, number of household vehicles, and the presence of at least one super-commuter. It is negatively associated with the percent of older adults in the household and the presence of at least one transit commuter.

There are a few notable differences across the models by income. With but one exception, low-income households of color have lower H+T expenditure burdens relative to non-Hispanic White households, controlling for an array of factors. The relationships are more mixed among middle- and higher-income households. Middle-income black households have lower H+T expenditure burdens than middle-income White households. However, middle- and higher-income Hispanic and Asian households have higher expenditure burdens relative to non-Hispanic White households relative to other households in their income group.

Super-commuter households tend to have higher H+T expenditure burdens regardless of income. However, the contribution of super-commuting to the H+T expenditure burden is relatively modest in all three models. The variables that contribute the most to the H+T burden across income groups are the number of household vehicles (+), household size (+), and the percent of older adults (-). Particularly for middle-income households, homeownership also has a strong negative association with the H+T expenditure burden.

The relationships between super-commuting and our variables of interest (work from home, transit use, residential location) are largely insignificant. Most notably, none of these interactions are statistically significant for lower-income households.



Table 9. Summary of Household and Transportation (H+T) Burden Models

Variables	All 1+ Worker	Worker Households by Income Group			
	Households	Low	Middle	High	
Race/ethnicity (excl. NH White)					
Hispanic	+	_	+	+	
Asian	+	NS	+	+	
Black	+	_	_	NS	
Other	NS	_	_	_	
Household size and composition					
% household 65+	_	_	_	_	
% child	+	+	+	NS	
Household size	+	+	+	+	
Household resources					
Homeowner	_	_	_	+	
# of vehicles	+	+	+	+	
Household Travel					
Super-commuter (SC) household	+	+	+	+	
Work-from-home household	_	NS	_	_	
Transit household	_	_	_	_	
Residential location					
Non-metro	+	_	_	_	
Metro-noncity	+	_	NS	+	
Metro-mixed	+	_	NS	+	
Interaction terms					
SC*Work-from-home household	_	NS	_	NS	
SC*Transit household	+	NS	NS	_	
SC*Non-metro	NS	NS	+	+	
SC*Metro-noncity	NS	NS	NS	NS	
SC*Metro-mixed	_	NS	NS	NS	
NS=not statistically significant					

NS: not statistically significant

Data: 2015-2019 American Community Survey, Public Use Microdata Sample; 2017 National Household Travel Survey, California Add-On.

#### 8.5 Scenarios

Drawing on our models for the H+T Burden for all households and households by income group, we develop a set of scenarios to illustrate how the H+T burden might vary by several characteristics of interest. The scenarios are based on existing research on likely changes in residential location, homeownership status, and travel behavior that contribute to super-commuting.

Justification. Many households relocate to suburban and outlying metropolitan areas to take advantage of lower housing costs (Howell & and Timberlake, 2014), oftentimes enabling families to make a transition from being renters to homeowners (Dawkins, 2009). Although higher-income White households remain more likely to live in the suburbs compared to other groups, the decentralization of



the population has been widespread, cutting across all groups by income, nativity, and race (Farrell, 2016; Howell & and Timberlake, 2014; Massey & and Tannen, 2018).

Moves outward have been facilitated by the ability of some workers to work remotely and, therefore, forgo regular travel to their places of employment (Ramani et al., 2024). As of early 2024, almost 30 percent of U.S. workers engaged in some telework or work from home (Borkowski & Kaynas, 2025). Most remote workers (52%) followed a hybrid model, commuting on select days while working remotely the remainder of their week; the average weekly hours among all remote workers was just over 27 hours per week.

Dispersed suburban environments tend to be inhospitable to public transit, which performs best in areas where residents can easily walk to bus stops and stations and where origins and destinations are reasonably proximate. Suburban moves, therefore, are likely predicted on automobile ownership (Jeon et al., 2018). While some suburban workers take advantage of commuter rail (Nelson & O'Neil, 2019), most suburban residents commute by automobile (Ruggles et al., 2025). Eighty-one percent of California workers in the central city commute by automobile compared to 92 percent of workers in suburbs and non-metropolitan areas. Rates of automobile use for non-work travel are even higher. Moreover, even when suburban workers utilize commuter rail or transit for work commutes, they are likely to use personal vehicles for other trips.

Scenarios. Based on this research, we developed a set of scenarios which are included in the left side of **Table 10**. We start with two base cases. Both cases include households that live in urban areas, are renters, and do not have workers who super-commute or work from home. Base option A includes households in which workers commute by transit and Base option B includes workers who only commute by automobile.

We then develop a set of scenarios for households that live in the suburbs. We assume that one of the motivations for living or moving to locations outside of the central city is the opportunity for homeownership.<sup>11</sup> We also assume that if households live in the suburbs, they will be more likely to travel using a household vehicle.

In the first scenario (Step 1), the household is in the suburbs, owns a home, does not super-commute or work from home, and its workers commute by automobile. In the second scenario (Step 2), the same conditions apply but at least one worker in the household is a super-commuter. Finally, in the third scenario (Step 3) the same conditions apply but households include at least one worker who is a super-commuter and at least one worker who works from home. All of the other variables in our models are set at the mean; race/ethnicity is set as non-Hispanic White.

*Scenario findings*. The right side of **Table 10** shows the predicted H+T burden. These also are presented graphically in

<sup>&</sup>lt;sup>11</sup> Thirty-seven percent of California households who live in central cities are homeowners compared to 58 percent of households in the suburbs and 60 percent of households outside of metropolitan areas (Ruggles et al., 2025).



Figure 29. Regardless of the set of assumptions, lower-income households have significantly higher H+T burdens than other households. The H+T expenditure burden is lowest for low- and middle-income households in Step 1 who are (1) suburban homeowners, (2) have no super-commuters or those who work from home, and (3) have workers who commute by car. By contrast, the H+T burden is highest for both of these groups (Base B) in urban areas where they both rent and commute by automobile. Higher-income households have the lowest H+T burden as renters in urban areas who use transit, and neither super-commute nor work from home. For all three groups, super-commuting is associated with higher H+T burdens (as the models above also show), though working from home appears to mitigate this relationship. Finally, the figures suggest that the greatest variability in the H+T burden across these various scenarios is among lower-income households. However, in all but one case, these households spend very large shares of their incomes on housing and transportation.

Table 10. Predicted Values for H+T Burden by Scenarios

	Variables: (a) set at mean (b) constant – race/ethnicity=NH White				Predicted H+T Burden by Household Income Group				
	Res Loc	Home	SC	WFH	Mode	Low \$	Mid \$	High \$	All HH
Base A	Urban	Rent	No	No	Transit	1.02	0.38	0.17	0.32
Base B	Urban	Rent	No	No	Car	1.08	0.41	0.18	0.39
Step 1	Suburb	Own	No	No	Car	0.94	0.36	0.19	0.30
Step 2	Suburb	Own	Yes	No	Car	1.05	0.38	0.21	0.31
Step 3	Suburb	Own	Yes	Yes	Car	1	0.37	0.20	0.27

Res Loc = Residential Location; SC = Super-commuter household; WFH = Work-from-home household; Mode = Commute mode



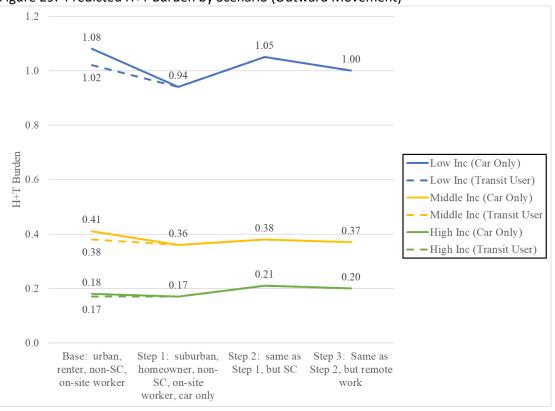


Figure 29. Predicted H+T Burden by Scenario (Outward Movement)

There are some weaknesses with this analysis that are important to note. As we have described, we imputed household transportation expenditures based on household vehicle miles of travel. This analysis required us to generalize about the costs of driving based on aggregate estimates from the Automobile Association of America, rather than relying on survey data as is the case with the Consumer Expenditure Survey. Our estimates also do not directly include the costs of using public transit. However, as of 2023 only four percent of workers in California commuted by transit (Ruggles et al., 2025). Further, transit costs tend to be minimal relative to other transportation costs. Data from the 2023 U.S. Consumer Expenditure Survey show that zero-vehicle households in the bottom income quintile spend \$889 per year on transportation, seven percent of their household income (Bureau of Transportation Statistics, U.S. Department of Transportation, 2023).

Finally, we based our transportation cost imputation on variables included in the two datasets – the NHTS and the ACS PUMS microdata. These datasets are limited in two important ways: the data on remote work and residential location. Remote work information in the NHTS and the ACS PUMS data is slightly different due to how the survey question was asked. The NHTS asked the survey respondent if they usually worked from home, while the ACS asked the respondent what their primary means of transportation to work was during the previous week, and the respondent could select that they primarily worked at home. Both are inaccurate measures of remote working because both can include people who worked in home-based businesses, which is different from those who worked remotely at home instead of going into an office. But the issue more relevant to our cost imputation is that the two measures are not entirely compatible because they are based on different time frames. More specifically, someone who primarily worked at home during the past week does not necessarily usually



work from home, and vice versa. As for residential location, for confidentiality reasons, the public version of the PUMS data includes limited geographic identifiers. We used the smallest unit of geography—Public Use Microdata Areas (PUMAs)—in our modeling; however, these areas are relatively large and, therefore, only coarse indicators of the built environment of the area. In our final set of models, we included differences across urban, suburban, and non-metropolitan areas, variables that appeared to be more robust indicators of residential location compared to PUMA residential density.



# 9. Conclusion: Equity and Policy Implications of Super-Commuting

The analysis shows that, while super-commutes are big, the number of super-commuters is not. Indeed, they are a small percentage of all workers in both the Los Angeles region and in California as a whole. That said, super-commuters comprise a relatively substantial share of workers in a handful suburban and exurban neighborhoods in the greater Los Angeles region.

With respect to equity, our top-line finding is that super-commuting is *positively* related to income. In other words, lower-income workers are *less* likely than higher-income workers to super-commute. Why? Super-commuting is resource intensive – requiring significant time and money. Lower-wage jobs, which tend to be more spatially dispersed than higher-wage work, typically neither require nor justify very long commutes to reach them. In addition to income, rates of super-commuting are, all else equal, higher among men, Black workers, and those who commute to work by public transit and lower among older workers. Finally, while a few higher-income super-commuters likely travel long distances to work on commuter rail services such as Metrolink, the vast majority drive. Low-income super-commuters, however, are more often high-duration super-commuters who commute 90+ minutes on comparatively slow public transit. Indeed, more than a quarter of low-income super-commuters commute by bus, compared to only five percent of higher-income super-commuters.

Among all income groups, super-commuter households have slightly higher H+T expenditure burdens than non-super-commuter households. Transit use and remote work somewhat mitigate this association, particularly among lower-income households. However, while the presence of super-commuters in the household *is* a statistically-significant predictor of the H+T burden, its contribution to this burden is comparatively small relative to other factors, such as levels of vehicle ownership, household size, and the presence of older adults in the household. In sum, concerns about the growth and negative effects of super-commuting may be warranted on multiple grounds, but equity is, at best, a second-order consideration.

With respect to commuters more broadly, lower-income households, on average, have higher H+T expenditure burdens than middle- and higher-income households. Among households in the bottom two income quintiles, the H+T expenditure burden exceeds commonly touted affordability guidelines (at 45%). So it is fair to say that the H+T burden among lower-income California households is an important equity issue, regardless of whether they endure very long commutes. Of course, policy efforts to increase incomes or reduce either housing or transportation expenditures would lower household H+T burdens.

Our models of super-commuting households suggest four realms of policy interventions. First, automobiles provide travelers with tremendous accessibility to opportunities, particularly in suburban and non-metropolitan areas designed around private vehicle travel where most households live (Shen, 1998). However, lower-income households often struggle to afford the costs of automobile ownership (Brown, 2017; Klein, 2024), which can put them at significant disadvantage accessing opportunities in auto-oriented environments. California already has a number of programs to subsidize the purchase of and access to clean fuel vehicles by lower-income households, as well as to offset the costs of auto insurance and maintenance (California Air Resources Board, nd; California Department of Consumer Affairs, Bureau of Automotive Affairs, 2025; California Department of Insurance, 2022; Community



Housing Development Corporation (CHDC, nd); these programs could be expanded to, among other things, ease the burdens of long commutes.

Second, our models also find that, perhaps counter-intuitively, super-commuting households that own homes have *lower* H+T burdens, all else equal, regardless of income. Homeownership is a particularly influential determinant of lower H+T burdens among middle-income households, likely related to such households either renting in high-cost central areas (and not super-commuting) or owning in outlying neighborhoods where housing prices are lowest. That said, homeownership is out of reach for most lower-income households in California (Bentz, 2025; Mejia et al., 2024; Shoag et al., 2023). Accordingly, the expansion of programs to help low-income, first-time home buyers could help reduce their H+T burdens.

Third, housing growth in California across all price levels has lagged employment growth for many years. This mismatch has contributed significantly to a housing affordability crisis, which has motivated increasing numbers of residents and employers to move to other states; it has also increased supercommuting for households moving to the fringes of metropolitan areas in search of home ownership. Over the past decade the California Legislature has passed and the Governor has signed a number of bills to streamline housing production broadly, and near transit stops and stations in particular (Fulton et al., 2023). Increasing such efforts could meaningfully enhance the housing supply in urban areas and weaken at least one motivation for super-commuting.

Fourth, households that use public transit also tend to have lower H+T burdens. This is not surprising considering how low the out-of-pocket costs of transit use are relative to owning and driving cars and trucks. Given this, savvy investments in improved public transit service in (typically more central) areas where transit provides good access to jobs within a reasonable travel time could serve multiple purposes (particularly if paired with concerted efforts to increase the production of multi-unit housing in already built-up urban areas). Such service improvements could reduce travel times among current transit users and, consequently, the number of low-income duration super-commuters and could, in addition, attract additional travelers and trips to public transit. Assuming these investments successfully increase transit use, they also would reduce H+T burdens more broadly.

However, reduced transportation and/or housing expenditures may not be desirable outcomes on their own, if they compromise other quality-of-life outcomes in the process. While households in the bottom income quintile tend to have very high H+T expenditure *burdens*, they typically spend less than half of what households in the top income quintile spend in absolute terms on housing and transportation—which is perhaps too little. These expenditure data suggest that many low-income households may actually have unmet or under-met housing or transportation access needs—a question that is outside the scope of this analysis. Thus, it is important to bear in mind that simply spending less on housing (that is inconveniently located, too small, or sub-standard) or transportation (that is unsafe, unreliable, or too slow) is not, on its own, a good thing. The challenge instead is to ease housing and transportation

<sup>&</sup>lt;sup>12</sup> In 2022, low-income households—those with incomes below \$25,000—without vehicles spent only five percent of their after-tax income on transportation, compared to 38 percent among low-income households with at least one vehicle (Bureau of Transportation Statistics, U.S. Department of Transportation, 2023).



expenditure burdens without compromising household members' access to decent housing in safe neighborhoods with quality transportation access to needed destinations.

Finally, this analysis raised a number of data and methodological challenges. To effectively analyze the relationship between super-commuting and household expenditures requires data on household travel behavior linked to information on housing and transportation expenditures; such data are currently unavailable at scale. These data need to include reliable information on total household travel. For worker households, this may vary from day-to-day based on whether workers travel to their jobs or work from home.

Moreover, the household H+T burden is the outcome of a complicated and interrelated set of decisions that unfold over time. These decisions are shaped by household characteristics (e.g. income, race, household composition), the built environment (e.g. location of jobs, housing, and other destinations), and the institutional environment (e.g. the availability of transportation services, education and job training, etc.). The sorts of cross-sectional data we used here are useful for examining associations between various factors; but single-point-in-time data can reveal neither the temporal order of household location decisions, nor shed much light on cause-effect relationships. Both of these are necessary to fully understand the relationship between super-commuting and the housing and transportation burdens they entail.



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## **Appendices**

### Appendix 1. Data Sources

Data Source	Variable(s) of Interest	Other Variables
American Automobile Association (2017). Your Driving Costs: How much are you really paying to drive?	Auto ownership and operating costs	[none]
Center for Neighborhood Technology (2022 update). H+T Affordability Index.	<ul> <li>Homeownership cost</li> <li>Monthly gross rent</li> <li>Monthly housing cost</li> <li>Annual transportation cost</li> <li>H, T, and H+T cost burden</li> </ul>	[none]
Federal Highway Administration. <u>California Add-on of the 2017</u> <u>National Household Travel</u> <u>Survey</u> , U.S. Department of  Transportation	<ul> <li>Commute duration</li> <li>Commute distance</li> <li>Mode</li> <li>Vehicle miles of travel/transportation expenditures</li> </ul>	Income, race/ethnicity, age, children, household size, homeownership status, # of vehicles, work from home, residential location
StreetLight, Inc. (2019)	Trip duration (90+ minutes) by time of day and direction	[none]
U.S. Census Bureau (2005-2022), 1-Year American Community Survey (ACS), <u>Public Use</u> <u>Microdata Sample</u> (PUMS) (Ruggles et al., 2024)	<ul> <li>Super-commuter number and rates (90+ minutes)</li> <li>Commute duration</li> </ul>	Age, sex, race/ethnicity, nativity, household income, educational attainment, mode
U.S. Census Bureau, 2015-2019 5- Year American Community Survey (ACS), <u>Public Use</u> <u>Microdata Sample</u> (PUMS) (Ruggles et al., 2024)	<ul> <li>Super-commuter number and rates (90+ minutes)</li> <li>Super-commuter characteristics relative to non-super-commuters</li> <li>Household housing expenditures</li> </ul>	Income, race/ethnicity, age, children, household size, homeownership status, mode, # of vehicles, work from home, residential location
U.S. Census Bureau (2019)  Longitudinal Employer- Household Dynamics (LEDH) Origin-Destination Employment Statistics (LODES)	<ul> <li>Super-commuter numbers and rates (50+ miles)</li> <li>Cross-county super-commuters</li> <li>Super-commuter hot spots</li> <li>Super-commuter characteristics</li> </ul>	All workers, workers by wage category



Appendix 2. Strengths and Weaknesses of Data Sources

Data Sources	Strengths	Weaknesses
American Automobile Association (2017). Your Driving Costs: How much are you really paying to drive?	<ul> <li>Estimation of comprehensive costs of driving including ownership and operating costs for different types of vehicles</li> </ul>	<ul> <li>Estimation based on national average of various cost components and uniform assumptions regarding insurance coverage, financing plan, and annual miles driven</li> </ul>
Center for Neighborhood Technology (2022 update). H+T Affordability Index.	<ul> <li>Estimation of average neighborhood housing and transportation costs and cost burdens</li> </ul>	Inability to vary estimates by resident characteristics such as income or commute distance/duration
StreetLight, Inc. (2019)	> Large and customizable data	<ul> <li>No reliable data on trip purpose and mode</li> <li>No reliable data on characteristics of travelers</li> <li>Inability to compare pre- and post-pandemic data</li> </ul>
U.S. Census Bureau (2005-2022), 1-Year American Community Survey (ACS), Public Use Microdata Sample (PUMS) (Ruggles et al., 2024) U.S. Census Bureau, 2015-2019 5-Year American Community Survey (ACS), Public Use Microdata Sample (PUMS) (Ruggles et al., 2024)	<ul> <li>Yearly data</li> <li>Includes post-pandemic data (2021, 2022, 2023)</li> <li>Includes data on housing expenditures</li> <li>Extensive individual and household characteristics, including commute mode and remote work.</li> </ul>	<ul> <li>Limited geographies</li> <li>Small sample sizes in outlying counties</li> <li>Reliability issues with 2020 data</li> <li>Limited data on travel</li> <li>No information on transportation expenditures</li> </ul>
U.S. Census Bureau (2019)  Longitudinal Employer- Household Dynamics (LEDH) Origin-Destination Employment Statistics (LODES)	<ul> <li>Home and work locations of all workers (in the unemployment insurance program)</li> <li>Some worker characteristics (age, earnings)</li> </ul>	<ul> <li>Limited worker characteristics</li> <li>No indication of whether or how often workers travel to their workplace</li> <li>Must run each of the O-D pairs through the network to estimate network-based travel distance</li> <li>Pre-pandemic data</li> </ul>



Appendix 3. Super-Commuting Rates (90+ minutes) by Individual and Household Characteristics and County

Characteristics	Counties in the Greater Los Angeles Region									
	Imperial* Los Angele		Orange	Riverside	San Bernardino	Ventura*	LA Region			
Total	3.9%	4.0%	3.0%	7.8%	6.4%	3.3%	4.5%			
Sex										
Women		3.7%	2.5%	5.5%	4.3%		3.7%			
Men		4.4%	3.4%	9.6%	8.2%		5.2%			
Race										
NH White		3.6%	3.0%	8.2%	6.1%		4.3%			
NH Black		5.1%	6.1%	9.0%	7.1%		5.8%			
NH Asian		3.9%	3.7%	8.2%	5.9%		4.2%			
Hispanic		4.2%	2.5%	7.2%	6.6%		4.5%			
Education										
< HS		4.7%	2.6%	6.8%	6.1%		4.6%			
HS		3.9%	3.0%	7.6%	6.8%		4.7%			
Some College		4.0%	2.5%	7.8%	6.4%		4.5%			
College		4.0%	3.6%	9.0%	6.4%		4.5%			
Advanced degrees		3.6%	3.6%	8.2%	6.2%		4.2%			
Age										
16-19		2.9%	1.1%	2.1%	3.4%		2.4%			
20-29		3.5%	2.3%	5.8%	4.6%		3.7%			
30-39		3.9%	3.3%	8.3%	7.1%		4.6%			
40-49		4.3%	3.4%	8.9%	7.0%		5.0%			
50-59		4.4%	3.1%	8.5%	7.6%		4.9%			
60-69		4.6%	3.5%	9.6%	7.4%		5.1%			
70+		3.7%	3.6%	7.5%	6.2%		4.3%			
Income										
< \$30,000		4.5%	2.3%	5.2%	5.1%		4.3%			
\$30,001-\$50,000		4.1%	2.6%	6.0%	5.4%		4.2%			
\$50,001-\$80,000		4.0%	3.1%	6.3%	6.3%		4.3%			
\$80,001-\$100,000		4.0%	2.3%	8.0%	6.4%		4.4%			
\$100,001- \$130,000		4.0%	2.9%	8.4%	6.9%		4.6%			



\$130,000+	4.0%	3.4%	9.8%	7.2%		4.8%
Poverty						
Above poverty	4.0%	3.0%	8.0%	6.5%		4.5%
Below poverty	4.6%	2.7%	5.2%	5.4%		4.4%
Mode						
Drive alone	3.1%	2.5%	6.8%	5.6%		3.7%
Carpool	4.9%	2.8%	12.6%	9.8%		6.1%
Transit	16.1%	21.7%	26.9%	32.9%		17.7%
Other	2.2%	4.8%	6.6%	4.2%		3.1%
Departs						
Rush Hour (6:30-9:30)	3.3%	2.4%	4.6%	3.7%		3.3%
Non Rush Hour	4.9%	3.9%	10.5%	8.7%	6	

<sup>\*</sup>Sample sizes are too small for reliable analysis.

Source: Ruggles et al., (2022). 2015-2019 American Community Survey, Public Use Microdata Sample.



Appendix 4. Composition of Super-Commuters (90+ minutes) for Counties in the Greater Los Angeles Region

Region Super-Commuters									
Characteristics	, , , , , ,	1 .	· · · · · · · · · · · · · · · · · · ·	1		I	Los		
	Imperial*	Los Angeles	Orange	Riverside	San Bernardino	Ventura*	Los Angeles Region		
Sample (#)									
Weighted	2,195	183,942	44,268	74,474	55,001	12,689	372,569		
Unweighted	76	9,583	2,093	3,369	2,298	643	18,062		
Sex									
Men		58.9%	62.3%	68.8%	70.3%		0.6%		
Women		41.1%	37.7%	31.2%	29.7%		0.4%		
Race									
NH White		23.8%	40.9%	36.1%	27.6%		29.8%		
NH Black		9.0%	3.4%	6.8%	8.0%		7.5%		
NH Asian		14.9%	24.8%	7.6%	7.2%		13.2%		
Other		2.8%	2.3%	3.2%	2.7%		2.8%		
Hispanic		49.5%	28.6%	46.3%	54.4%		46.8%		
Education									
< HS		18.6%	10.9%	11.9%	13.1%		15.2%		
HS		20.0%	17.2%	28.5%	28.3%		22.5%		
Some College		28.9%	25.0%	34.9%	36.0%		30.8%		
College		22.3%	30.6%	16.5%	15.0%		21.1%		
Advanced degrees		10.2%	16.3%	8.3%	7.6%		10.3%		
Age [age]									
16-19		1.6%	1.0%	0.8%	1.6%		1.4%		
20-39		20.0%	16.6%	17.0%	18.1%		18.7%		
30-39		22.9%	23.6%	24.6%	25.7%		23.6%		
40-49		23.1%	24.1%	25.3%	22.4%		23.5%		
50-59		20.6%	20.9%	20.9%	21.7%		21.0%		
60-69		10.2%	11.5%	9.8%	9.2%		10.2%		
70+		1.6%	2.4%	1.6%	1.2%		1.7%		
Income							_		
< \$30,000		10.0%	4.4%	5.2%	7.1%		7.7%		
\$30,001- \$50,000		13.0%	7.4%	9.5%	10.8%		11.2%		



\$50,001-	20.2%	17.2%	16.5%	21.4%	19.0%
\$80,000					
\$80,001-	11.4%	8.5%	12.7%	13.1%	11.5%
\$100,000					
\$100,001-	14.1%	14.2%	17.1%	16.9%	15.2%
\$130,000					
\$130,000+	31.3%	48.3%	39.0%	30.8%	35.4%
Poverty Status					
Above poverty	7.2%	4.2%	3.7%	5.7%	5.8%
Below poverty	92.8%	95.8%	96.3%	94.3%	94.2%
Mode					
Solo auto	60.6%	69.8%	73.3%	73.3%	66.7%
Carpool	11.9%	9.3%	20.0%	17.4%	14.1%
Transit	24.6%	15.0%	4.3%	7.5%	16.2%
Other	2.8%	5.9%	2.4%	1.8%	3.0%

<sup>\*</sup>Sample sizes are too small for reliable analysis.

Source: Ruggles et al. (2022). 2015-2019 American Community Survey, Public Use Microdata Sample.



#### Appendix 5. Detailed Methodology for Cluster Analysis

This dataset contains detailed demographic variables and socioeconomic indicators, as well as transportation characteristics like commute duration and mode of travel. The sample reflects 428,966 individuals, providing a basis for analyzing super-commuting patterns and their relationship to various sociodemographic factors in the greater Los Angeles region. All data processing and analysis used the open-source data analysis package in R for accurate weighting of the data, and the factoextra package was used to create visualizations of the data. The study defines super-commuting using the TRANTIME variable, the length of a respondent's commute duration in minutes.

We first had to transform the data to standardize the variables for subsequent cluster analysis. Continuous variables—including age, number of children under five, wage, and years of education—remained in their original form for the most accurate and representative analysis. In contrast, we transformed several categorical variables into binary variables to simplify interpretation and modeling. The table below summarizes these transformations.

#### Data Transformations for Cluster Analysis

Variable	Transformation
Sex	0=Male; 1=Female
Race	0=Non-Hispanic White; 1=Other Races
Ethnicity	0=Non-Hispanic; 1= Hispanic
Commute Mode	0=Drive; 1=Public Transit
Homeownership Status	0=Renters; 1=Homeowners

To account for the different scales of the continuous and binary variables, we transformed all of the variables into z-scores. This ensured that each variable contributed equally to the analysis by rescaling them to a common metric. Due to computational limitations regarding memory constraints, we drew a reproducible random sample of 5,000 super-commuters, which preserved the variability of the dataset while allowing for a more efficient clustering process. To determine the optimal number of clusters we used the elbow and silhouette methods, followed by the k-means algorithm to determine the characteristics of each cluster.



Appendix 6. Top Five Job Centers from Super-Commuting Hotspots

Appendix 6. Top Five Job Centers from Super-Commuting Hotspots  Mean commute Number of super- Share of super-									
Hot Spots and Job Center Names	distance	commuters	commuters						
Hotspot #1: Perris - Elsinore - Temecula	G.100000		30111111313						
Costa Mesa/Irvine/Santa Ana	61	3,938	7.1%						
Mission Valley/Five Points/Hillcrest +	01	3,333	71270						
Downtown San Diego	67	2,424	4.4%						
Sorento Valley/UC San Diego	60	2,165	3.9%						
Kearny Mesa Industrial Complex	60	1,889	3.4%						
Downtown Los Angeles (DTLA)	77	1,830	3.3%						
Hotspot #2: Moreno Valley									
Wilshire Corridor	74	394	6.5%						
Downtown Los Angeles (DTLA)	65	289	4.8%						
Costa Mesa/Irvine/Santa Ana	52	241	4.0%						
Santa Fe Springs	54	144	2.4%						
Mission Valley/Five Points/Hillcrest +									
Downtown San Diego	90	132	2.2%						
Hotspot #3: Jurupa Valley									
Wilshire Corridor	60	368	7.9%						
Downtown Los Angeles (DTLA)	52	326	7.0%						
Los Angeles International Airport (LAX)	64	206	4.4%						
Sorento Valley/UC San Diego	95	121	2.6%						
Kearny Mesa Industrial Complex	96	91	2.0%						
Hotspot #4: Oxnard									
Wilshire Corridor	57	437	9.1%						
Downtown Los Angeles (DTLA)	62	247	5.1%						
Costa Mesa/Irvine/Santa Ana	98	184	3.8%						
Los Angeles International Airport (LAX)	65	167	3.5%						
Disneyland/Platinum Triangle	91	150	3.1%						
Hotspot #5: Fontana - Rialto									
Wilshire Corridor	60	1,573	9.3%						
Downtown Los Angeles (DTLA)	53	1,157	6.9%						
Costa Mesa/Irvine/Santa Ana	52	719	4.3%						
Los Angeles International Airport (LAX)	67	520	3.1%						
Commerce/Vernon/East LA Railyards	53	344	2.0%						
Hotspot #6: Victor Valley									
Costa Mesa/Irvine/Santa Ana	82	1,376	4.7%						
Downtown Los Angeles (DTLA)	83	1,180	4.0%						
Wilshire Corridor	91	1,027	3.5%						
Disneyland/Platinum Triangle	77	827	2.8%						
Commerce/Vernon/East LA Railyards	82	441	1.5%						
Hotspot #7: Lancaster - Palmdale									
Downtown Los Angeles (DTLA)	68	6,578	11.2%						



Wilshire Corridor	64	4,911	8.4%	
Los Angeles International Airport (LAX)	74	2,491	4.3%	
Warner Center	61	1,108	1.9%	
Culver City - Mar Vista	68	904	1.5%	



# Appendix 7. Estimated Commute Duration from Super-Commuter Hotspots to Top-5 Employment Centers\*

Hotspot #1: Perris - Elsinore - Temecula

Cluster Name		# of super-	Share of super- commuters	Hour / Peak Direction	PM Peak Hour / Peak Direction (min.)	Hour / Off Direction	PM Peak Hour / Off Direction (min.)	Off Peak / Off Direction (min.)
Costa Mesa/Irvine/Santa Ana	61	3,938	7.10%	98	111	85	88	87
Mission Valley/Five Points/Hillcrest + Downtown San Diego	67	2,424	4.40%					
Sorento Valley/UC San Diego	60	2,165	3.90%					
Kearny Mesa Industrial Complex	60	1,889	3.40%					
Downtown Los Angeles (DTLA)	77	1,830	3.30%	132	140	104	113	111

#### Hotspot #2: Moreno Valley

	Mean commute distance (miles)	# of super-	Share of super- commuters	Hour / Peak Direction	PM Peak Hour / Peak Direction (min.)	ŀ	Hour / Off Direction	PM Peak Hour / Off Direction (min.)	Off Peak / Off Direction (min.)
Wilshire Corridor	74	394	6.50%	135	146		105	118	114
Downtown Los Angeles (DTLA)	65	289	4.80%	115	132		95	95	95
Costa Mesa/Irvine/Santa Ana	52	241	4.00%	99	115		76	84	85
Santa Fe Springs	54	144	2.40%	ND	ND		ND	ND	ND
Mission Valley/Five Points/Hillcrest + Downtown San Diego	90	132	2.20%						

#### Hotspot #3: Jurupa Valley

		# of super-	Share of super- commuters	Hour / Peak	PM Peak Hour / Peak Direction (min.)	AM Po Hour Direc (min.)	Off	PM Peak Hour / Off Direction (min.)	Off Peak / Off Direction (min.)
Wilshire Corridor		368	7.90%	127	137		90	99	99
Downtown Los Angeles (DTLA)	52	326	7.00%	105	110		79	82	84
LAX	64	206	4.40%	130	134		100	103	103
Sorento Valley/UC San Diego	95	121	2.60%						
Kearny Mesa Industrial Complex	96	91	2.00%						

#### Hotspot #4: Oxnard

	Mean commute distance	# of super-	Share of super-	Hour / Peak	PM Peak Hour / Peak Direction	Hour / Off	PM Peak Hour / Off Direction	Off Peak / Off Direction
Cluster Name	(miles)	commuters	commuters	(min.)	(min.)	(min.)	(min.)	(min.)
Wilshire Corridor	57	437	9.10%	102	109	96	105	90
Downtown Los Angeles (DTLA)	62	247	5.10%	119	130	115	138	102
Costa Mesa/Irvine/Santa Ana	98	184	3.80%	ND	ND	'ND	ND	ND
LAX	65	167	3.50%	110	122	122	124	103
Disneyland/Platinum Triangle	91	150	3.10%	ND	ND	'ND	ND	ND



#### Hotspot #5: Fontana - Rialto

		# of super- commuters	Share of super- commuters	Hour / Peak	PM Peak Hour / Peak Direction (min.)	AM Peak Hour / Off Direction (min.)	PM Peak Hour / Off Direction (min.)	Off Peak / Off Direction (min.)
Wilshire Corridor	60	1,573	9.30%	126	139	95	99	100
Downtown Los Angeles (DTLA)	53	1,157	6.90%	106	120	79	84	86
Costa Mesa/Irvine/Santa Ana	52	719	4.30%	95	111	79	86	85
LAX	67	520	3.10%	132	147	101	108	102
Commerce/Vernon/East LA Railyards	53	344	2.00%	106	118	85	91	83

#### Hotspot #6: Victor Valley

		# of super- commuters	Share of super- commuters	Hour / Peak	PM Peak Hour / Peak Direction (min.)	H	lour / Off Direction	PM Peak Hour / Off Direction (min.)	Off Peak / Off Direction (min.)
Costa Mesa/Irvine/Santa Ana	82	1,376	4.70%	119	140		107	112	110
Downtown Los Angeles (DTLA)	83	1,180	4.00%	131	143		105	113	113
Wilshire Corridor	91	1,027	3.50%	142	152		119	124	124
Disneyland/Platinum Triangle	77	827	2.80%	125	139		102	110	106
Commerce/Vernon/East LA Railyards	82	441	1.50%	129	138		118	114	115

#### Hotspot 7: Lancaster - Palmdale

	Mean commute distance		Share of super-	Hour / Peak	PM Peak Hour / Peak Direction	Hour / Off	PM Peak Hour / Off Direction	Off Peak / Off Direction
Cluster Name	(miles)	commuters	commuters	(min.)	(min.)	(min.)	(min.)	(min.)
Downtown Los Angeles (DTLA)	68	6,578	11.20%	114	122	96	103	100
Wilshire Corridor	64	4,911	8.40%	114	125	88	90	95
LAX	74	2,491	4.30%	128	141	111	117	104
Warner Center	61	1,108	1.90%	100	117	90	87	90
Culver City - Mar Vista	68	904	1.50%	124	135	87	97	97

\*Note: The hotspot tables are shaded according to roadway travel duration values, with the 90-minute super-commute duration threshold in yellow. Shorter durations are increasingly green, and longer durations are increasingly red.



Appendix 8. Regression: Transportation Costs

Appendix 6. Regression. Transporta		Std.		Variables		Std.	
Variables	Coef.	Error		(cont'd)	Coef.	Error	
Intercept	7.345	0.111	***	105	0.611	0.139	
Race/ethnicity (excl. NH White)				6505	0.340	0.167	*
Hispanic	0.024	0.019		6506	0.412	0.216	+
Asian	0.006	0.021		6507	0.306	0.184	+
Black	-0.130	0.038	***	6508	0.237	0.209	
Other	0.022	0.026		6509	0.248	0.255	
Household composition				6510	0.208	0.171	
% household 65+	-0.176	0.021	***	6511	0.175	0.180	
Worker count	0.093	0.012	***	6512	0.333	0.224	
Child count	-0.079	0.018	***	6513	0.633	0.209	**
Household size	0.155	0.016	***	6514	0.309	0.209	
Household resources				6515	0.211	0.162	
Family Income				6701	0.212	0.115	+
\$10-15k	0.071	0.063		6702	0.181	0.111	
\$15-25k	0.024	0.053		6703	0.236	0.108	*
\$25-35k	0.139	0.051	**	6704	0.134	0.117	
\$35-50k	0.206	0.049	***	6705	0.306	0.116	**
\$50-75k	0.026	0.048	***	6706	0.386	0.120	**
\$75-100k	0.327	0.048	***	6707	0.113	0.105	
\$100-125k	0.393	0.048	***	6708	0.191	0.117	
\$125-150k	0.401	0.050	***	6709	0.103	0.115	
\$150-200k	0.408	0.050	***	6710	0.235	0.110	*
\$200k+	0.426	0.050	***	6711	0.276	0.122	*
Vehicle count	0.185	0.014	***	6712	0.221	0.109	*
Car per adult	0.072	0.024	**	7101	0.155	0.193	
Travel				7102	0.295	0.193	
Commute minutes	0.002	0.000	***	7103	0.163	0.216	
% commute by car	0.328	0.023	***	7104	0.755	0.256	**
Residential Location				7105	-0.551	0.169	
Block group density*	0.000	0.000		7106	0.485	0.255	+
PUMAs				7107	0.256	0.271	
102	0.774	0.137		7108	0.411	0.203	*
103	0.187	0.127		7109	0.188	0.232	
104	0.374	0.188					
Adj R <sup>2</sup>	0.338						
N	13,543						
*** < .001; ** < .01; * < .05; + < .10							

Data: 2017 National Household Travel Survey, California Add-On



Appendix 9. Expenditure Burdens by Household Characteristics and Type

	1+	Worker Househo	olds	Super-co	ommuter House	holds
	Т	Н	H+T	Т	Н	H+T
Homeownership Status						
Renter	13.8%	28.8%	44.1%	16.3%	25.9%	43.7%
Owner	10.3%	19.8%	31.6%	12.8%	18.7%	33.4%
Residential location						
Non-metropolitan	16.5%	20.5%	37.9%	19.4%	19.8%	40.7%
MetroCity	9.9%	25.0%	36.1%	12.9%	23.6%	37.9%
Metro-Noncity	13.3%	23.1%	37.6%	15.5%	20.8%	37.9%
Metro-Mixed	10.9%	22.7%	34.9%	12.5%	20.5%	34.6%
1+ transit commuter						
No transit commuters	11.8%	23.3%	36.3%	15.0%	20.9%	37.4%
1+ transit commuter households	8.2%	22.6%	32.3%	10.1%	21.9%	33.6%
Car ownership						
0-vehicle households	8.7%	30.7%	39.9%	10.7%	29.2%	40.0%
1+ vehicle households	11.7%	23.1%	35.9%	14.1%	20.9%	36.5%
Race/Ethnicity						
White	9.3%	21.5%	31.7%	11.1%	19.6%	31.9%
Hispanic	18.1%	26.6%	46.2%	21.1%	23.7%	46.6%
Asian	9.9%	22.4%	33.2%	11.2%	20.0%	32.4%
Black	10.5%	27.2%	38.3%	12.2%	24.8%	37.4%
Other	15.9%	17.6%	34.8%	17.3%	18.7%	38.9%

Note: H+T is the median housing and transportation expenditures combined; the figure is slightly different from the sum of the median housing and transportation expenditures.



Appendix 10. Regression: Household and Transportation Expenditures (logged), California Households with 1+ Workers

	w/o inter	action terms			w/ interaction terms				
Variables	Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error		
(Intercept)	9.807	0.000	0.002	***	9.804	0.001	0.002	***	
Race/ethnicity (excl. NH White)									
Hispanic	-0.130	-0.116	0.001	***	-0.130	-0.116	0.001	***	
Asian	-0.010	-0.007	0.002	***	-0.010	-0.007	0.002	***	
Black	-0.112	-0.047	0.003	***	-0.112	-0.047	0.003	***	
Other	-0.247	-0.032	0.008	***	-0.246	-0.032	0.008	***	
Household composition									
% household 65+	-0.292	-0.150	0.002	***	-0.291	-0.149	0.002	***	
% child	-0.008	-0.004	0.003	**	-0.008	-0.004	0.003	*	
Household size	0.066	0.208	0.001	***	0.066	0.208	0.001	***	
Household resources									
Household income	0.000	0.342	0.000	***	0.000	0.341	0.000	***	
Homeowner	0.047	0.045	0.001	***	0.047	0.045	0.001	***	
# of vehicles	0.131	0.294	0.001	***	0.131	0.294	0.001	***	
Travel									
Super-commuter (SC) household	0.100	0.047	0.002	***	0.071	0.049	0.006	***	
Work-from-home household	0.014	0.008	0.002	***	0.014	0.008	0.002	***	
Transit household	-0.016	-0.008	0.002	***	-0.007	-0.005	0.002	**	
Residential location									
Non-metro	-0.211	-0.028	0.004	***	-0.218	-0.060	0.004	***	
Metro-noncity	-0.031	-0.014	0.002	***	-0.034	-0.028	0.002	***	
Metro-mixed	-0.014	-0.060	0.001	***	-0.016	-0.013	0.001	***	
Interaction terms									
SC*Work-from-home household					0.004	0.000	0.011		
SC*Transit household					-0.047	-0.006	0.006	***	
SC*Non-metro					0.143	0.010	0.018	***	
SC*Metro-noncity					0.054	0.012	0.006	***	



SC*Metro-mixed			0.035	0.008	0.006	***
N	499,541					
Adj. R <sup>2</sup>	0.432		0.433			
*** < .001; ** < .01; * < .05; + < .10						



Appendix 11. Regression: H+T Expenditures (logged) for Households with 1+ Workers by Income

Appendix 11. Regression. The Expe		ome House				Income H		ds	High-Income Households				
Variables	Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error		
(Intercept)	9.633	0.001	0.006	***	9.666	0.000	0.002	***	10.170	0.001	0.005	***	
Race/ethnicity (excl. NH White)													
Hispanic	-0.128	-0.146	0.004	***	-0.068	-0.072	0.002	***	-0.055	-0.039	0.004	***	
Asian	-0.015	-0.011	0.005	**	-0.004	-0.003	0.002	+	-0.007	-0.006	0.003	*	
Black	-0.125	-0.075	0.006	***	-0.074	-0.037	0.003	***	-0.084	-0.030	0.007	***	
Other	-0.254	-0.047	0.020	***	-0.196	-0.031	0.009	***	-0.225	-0.025	0.023	***	
Household composition													
% household 65+	-0.198	-0.114	0.007	***	-0.253	-0.153	0.002	***	-0.317	-0.178	0.005	***	
% child	-0.061	-0.036	0.009	***	0.024	0.012	0.004	***	0.158	0.075	0.007	***	
Household size	0.061	0.048	0.002	***	0.056	0.309	0.001	***	0.057	0.181	0.001	***	
Household resources													
Household income	0.000	0.218	0.000	***	0.000	0.212	0.000	***	0.000	0.189	0.000	***	
Homeowner	-0.059	-0.060	0.004	***	-0.024	-0.027	0.001	***	0.088	0.074	0.003	***	
# of vehicles	0.157	0.333	0.002	***	0.115	0.288	0.001	***	0.092	0.232	0.001	***	
Travel													
Super-commuter (SC) household	0.061	0.049	0.018	***	0.067	0.050	0.007	***	0.068	0.044	0.011	***	
Work-from-home household	-0.006	-0.001	0.006	ns	0.013	0.007	0.002	***	-0.001	0.000	0.003	ns	
Transit household	-0.056	-0.035	0.007	***	-0.034	-0.020	0.003	***	0.009	0.003	0.005	+	
Residential location													
Non-metro	-0.235	-0.094	0.010	***	-0.145	-0.048	0.004	***	-0.234	-0.050	0.012	***	
Metro-noncity	-0.042	-0.041	0.004	***	-0.021	-0.020	0.002	***	-0.044	-0.041	0.004	***	
Metro-mixed	-0.041	-0.043	0.004	***	-0.011	-0.011	0.002	***	-0.007	-0.007	0.003	*	
Interaction terms													
SC*Work-from-home household	0.090	0.010	0.072	ns	-0.012	-0.002	0.013	ns	0.016	0.003	0.016	ns	
SC*Transit household	-0.028	-0.003	0.019	ns	-0.031	-0.004	0.007	***	-0.042	-0.007	0.011	***	



SC*Non-metro	0.067	0.005	0.056	ns	0.123	0.010	0.019	***	0.139	0.008	0.041	***
SC*Metro-noncity	0.063	0.013	0.021	**	0.043	0.011	0.007	***	0.019	0.005	0.013	ns
SC*Metro-mixed	0.056	0.013	0.021	**	0.024	0.006	0.007	**	0.007	0.002	0.013	ns
N	58,727				319,360	)			121,454			
Adj. R <sup>2</sup>	0.231				0.371				0.248			
*** < .001; ** < .01; * < .05	; + < .10											

ns=not statistically significant



Appendix 12. Regression: Housing and Transportation Cost Burden – All Worker Households

	w/o inte	raction terms			w/ interac	tion terms		
	Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error	
(Intercept)	-1.028	0.000	0.003	***	-1.029	0.001	0.003	***
Race/ethnicity (excl. NH White)								
Hispanic	0.286	0.190	0.002	***	0.286	0.190	0.002	***
Asian	0.051	0.028	0.003	***	0.051	0.028	0.003	***
Black	0.142	0.045	0.004	***	0.142	0.045	0.004	***
Other	0.019	0.002	0.014	ns	0.019	0.002	0.014	ns
Household composition								
% household 65+	-0.153	-0.059	0.004	***	-0.153	-0.059	0.004	***
% child	0.162	0.053	0.006	***	0.162	0.053	0.006	***
Household size	0.021	0.051	0.001	***	0.021	0.051	0.001	***
Household resources								
Homeowner	-0.326	-0.235	0.002	***	-0.326	-0.235	0.002	***
# of vehicles	0.002	0.004	0.001	*	0.002	0.004	0.001	*
Travel								
Super-commuter (SC) household	0.030	0.011	0.004	***	0.047	0.008	0.009	***
Work-from-home household	-0.098	-0.041	0.003	***	-0.096	-0.042	0.003	***
Transit household	-0.182	-0.069	0.004	***	-0.188	-0.070	0.004	***
Residential location								
Non-metro	0.191	0.048	0.007	***	0.191	0.048	0.007	***
Metro-noncity	0.071	0.013	0.003	***	0.072	0.012	0.003	***
Metro-mixed	0.017	0.041	0.002	***	0.019	0.041	0.002	***
Interaction terms								
SC*Work-from-home household					0.038	0.004	0.017	*
SC*Transit household					0.033	0.003	0.010	***
SC*Non-metro					0.006	-0.002	0.029	ns
SC*Metro-noncity					-0.015	-0.007	0.011	ns



SC*Metro-mixed			-0.038	0.000	0.011	***
N	494,549					
Adj. R <sup>2</sup>	0.139		0.139			
*** < .001; ** < .01; * < .05; + < .10						

ns=not statistically significant



Appendix 13. Regression: Housing and Transportation Cost Burden – Income Groups

	Low-Inco	ome Hous	eholds		Middle-I	ncome Ho	useholds		High-Income Households			
	Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error		Coef.	Std. Coef.	Std. Error	
(Intercept)	-0.153	0.000	0.007	***	-1.154	0.000	0.003	***	-2.123	0.001	0.005	***
Race/ethnicity (excl. NH White)												
Hispanic	-0.101	-0.102	0.005	***	0.063	0.062	0.002	***	0.063	0.037	0.005	***
Asian	-0.002	-0.002	0.007	ns	0.016	0.012	0.002	***	0.019	0.014	0.004	***
Black	-0.090	-0.048	0.008	***	-0.011	-0.005	0.004	**	0.003	0.001	0.009	ns
Other	-0.220	-0.036	0.026	***	-0.121	-0.018	0.012	***	-0.171	-0.015	0.029	***
Household composition												
% household 65+	-0.244	-0.127	0.008	***	-0.179	-0.100	0.003	***	-0.354	-0.164	0.006	***
% child	0.029	0.015	0.012	*	0.125	0.058	0.005	***	0.002	0.001	0.009	ns
Household size	0.030	0.095	0.002	***	0.040	0.141	0.001	***	0.071	0.195	0.001	***
Household resources												
Homeowner	-0.104	-0.094	0.005	***	-0.136	-0.142	0.002	***	0.008	0.005	0.004	+
# of vehicles	0.113	0.209	0.003	***	0.068	0.158	0.001	***	0.084	0.175	0.002	***
Travel												
Super-commuter (SC) household	0.068	0.038	0.023	**	0.052	0.029	0.008	***	0.087	0.043	0.015	***
Work-from-home household	-0.002	-0.002	0.008	ns	-0.014	-0.009	0.003	***	-0.042	-0.025	0.004	***
Transit household	-0.049	-0.027	0.009	***	-0.086	-0.044	0.004	***	-0.036	-0.021	0.006	***
Residential location												
Non-metro	-0.183	-0.065	0.012	***	-0.029	-0.007	0.006	***	-0.123	-0.021	0.015	***
Metro-noncity	-0.031	-0.028	0.006	***	0.000	0.001	0.002	ns	0.036	0.030	0.005	***
Metro-mixed	-0.027	-0.025	0.005	***	-0.002	-0.002	0.002	ns	0.013	0.012	0.004	**
Interaction terms												
SC*Work-from-home household	-0.043	-0.004	0.095	ns	-0.035	-0.005	0.017	*	0.000	0.000	0.021	ns
SC*Transit household	0.009	0.001	0.024	ns	0.004	0.000	0.009	ns	-0.050	-0.007	0.014	***
SC*Non-metro	0.067	0.005	0.070	ns	0.096	0.007	0.025	***	0.130	0.006	0.052	*



SC*Metro-noncity	0.039	0.007	0.027	ns	0.014	0.003	0.009	ns	0.022	0.005	0.017	ns	
SC*Metro-mixed	0.040	0.008	0.026	ns	0.001	0.000	0.009	ns	0.000	0.000	0.016	ns	
N	53,752				319,343				121,454				
Adj. R <sup>2</sup>	0.101				0.132				0.156				

<sup>\*\*\* &</sup>lt; .001; \*\* < .01; \* < .05; + < .10

ns=not statistically significant

