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Models and Strategies to Address Housing and Transportation Challenges

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Models and Strategies to Address Housing and Transportation Challenges

DISSERTATION

Submitted in partial satisfaction of the requirements
For the degree of

DOCTOR OF PHILOSOPHY

In Civil and Environmental Engineering

By

Elaine N. Gilbert

Dissertation Committee:
Professor Michael F. Hyland, Chair
Professor Michael McNally
Professor Elisa Borowski

2026

DEDICATION

"*If you want to change the world, find someone to help you paddle*."

-Admiral William H. McRaven

To my sons, Kellan and Kaden, who grew up alongside me as I pursued my education and built my career, and who reminded me, in more ways than they will ever know, why it was worth finishing.

To my family and friends who encouraged me, believed in me, and carried me forward when the road felt impossibly long.

To those I lost along the way: my mom, my grandparents, and my sister Brittany. I wish you could have been here to see me finish.

And to anyone who has ever wondered whether they have what it takes to reach for something more: be brave enough to choose your own path, and reach anyway.

This is for all of you.

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Acronym List

Acronym	Definition
ACS	American Community Survey
AIC	Akaike Information Criterion
AM	Morning Peak Period
API	Application Programming Interface
BIC	Bayesian Information Criterion
BLS	Bureau of Labor Statistics
CAASPP	California Assessment of Student Performance and Progress
CAST	California Science Test
CHTS	California Household Travel Survey
CNS	Census NAICS Supersector
GIS	Geographic Information System
GTFS	General Transit Feed Specification
HUD	U.S. Department of Housing and Urban Development
LEHD	Longitudinal Employer-Household Dynamics
LODES	LEHD Origin-Destination Employment Statistics
LUTI	Land Use-Transportation Interaction
MNL	Multinomial Logit
MPO	Metropolitan Planning Organization
NAICS	North American Industry Classification System
NHTS	National Household Travel Survey
NIBRS	National Incident-Based Reporting System
NREL	National Renewable Energy Laboratory
OD	Origin–Destination
SOC	Standard Occupational Classification
TAZ	Traffic Analysis Zone
TIGER	Topologically Integrated Geographic Encoding and Referencing
TSDC	Transportation Secure Data Center
VOT	Value of Time
WAC	Workplace Area Characteristics
WSZ	Worker Stress Zones
WTP	Willingness to Pay
ZCTA	ZIP Code Tabulation Area
ZHVI	Zillow Home Value Index
ZIP	Zone Improvement Plan

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I would first like to express my sincere gratitude to my dissertation committee, Professors Michael Hyland, Michael McNally, and Elisa Borowski. Their technical guidance, thoughtful feedback, mentorship, and support were invaluable throughout this research and challenged me to become a better researcher, engineer, and scholar. I am especially grateful to my committee chair and advisor, Professor Hyland, for his guidance throughout this process and for the time and care he invested in helping me bring this dissertation to completion. I am also grateful to Professor R. (Jay) Jayakrishnan, whose teaching and example made a lasting impression on me, and to my classmates and peers for their friendship and for helping me navigate the many challenges of graduate school.

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My doctoral education was made possible in part through financial support provided by the Dwight David Eisenhower Transportation Fellowship Program (DDETFP), U.S. Department of Transportation Federal Highway Administration, Grant No. 693JJ32545015; the California Transportation Foundation Lipman Family Sustainable Transportation Graduate Fellowship; and the Pacific Southwest Region University Transportation Center (PSR UTC) Graduate Student Fellowship. Additional educational support was provided through the Post-9/11 GI Bill and teaching assistant opportunities at the University of California, Irvine.

On a more personal level, I owe immeasurable gratitude to my sons, Kellan and Kaden. They grew up alongside me as I pursued my education and built my career, from my undergraduate years in civil engineering through graduate school, professional licensure, and ultimately this doctorate. They have witnessed the long nights, competing responsibilities, setbacks, successes, and persistence behind every degree and professional milestone. More than anything, they gave those accomplishments meaning. I hope that watching this journey has shown them that there is no single timeline for becoming who you want to be, and that a difficult path is not the same thing as an impossible one.

I am grateful to my Aunt Christian, whose influence first led me toward civil engineering and, in doing so, helped set in motion a path that would profoundly shape my life. I am also deeply thankful to my Aunt Ellen and Uncle Dave for their mentorship, wisdom, and encouragement throughout the years, and to the members of my family who have celebrated and supported me along the way.

And to Brett, thank you for arriving at precisely the chapter in which I needed to remember that finishing something enormous is not only an ending. Your encouragement, perspective, and presence

helped me look beyond the dissertation and toward everything that might come after it. Most importantly, you reminded me that after years spent relentlessly pursuing the next obligation, achievement, or destination, there is also value in simply enjoying where I am and looking forward to where life might lead next.

Finally, this degree represents far more than the research contained in the pages that follow. My educational journey unfolded alongside raising my children, building an engineering career, earning my professional licensure, serving in the United States Air Force Reserve, and navigating the many unexpected turns that life placed along the way. There were many moments when completing a Ph.D. seemed impractical, inconvenient, or simply too far away. I finished because of persistence, certainly, but also because of the people who offered guidance, encouragement, friendship, opportunity, patience, and perspective when I needed them.

To everyone who helped me keep moving forward: thank you. I did not get here alone.

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Abstract of the Dissertation

Models and Strategies to Address Housing and Transportation Challenges

by

Elaine N. Gilbert

Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2026

Associate Professor Michael F. Hyland, Chair

Southern California's rapid urbanization and persistent housing constraints have intensified the spatial mismatch between residential locations and employment centers, contributing to long-distance commuting, congestion, and reduced quality of life for many workers. Employment opportunities remain concentrated in high-cost coastal and central job hubs, while housing affordability pressures continue to displace households toward inland and peripheral regions. These dynamics have produced some of the longest and most burdensome commute patterns in the United States, with significant implications for accessibility, equity, environmental sustainability, and workforce stability. This dissertation examines the extent of the jobs–housing imbalance in Southern California and evaluates how targeted housing and land-use interventions may influence commuting burdens and regional employment accessibility.

This research is organized into three empirical studies that collectively develop an integrated analytical framework combining descriptive accessibility analysis, behavioral joint residence-work location choice modeling, and policy-based commuting simulation. Together, the studies integrate concepts from urban economics, land-use planning, and transportation modeling to examine how housing-market constraints, employment geography, and mobility between residences and work locations jointly shape commuting behavior and regional spatial structure.

Study 1, presented in Chapter 2, provides a comprehensive empirical assessment of commuting burdens and job accessibility across Southern California. Using worker-level data from the California Household Travel Survey, congestion-adjusted travel times derived from the Google Maps Distance Matrix API, and ZIP-level housing and employment indicators, the study documents substantial spatial and demographic variation in commute duration and accessibility. Threshold-based measures identify populations experiencing long-duration and long-distance commuting, including “supercommuting,” and demonstrate how housing affordability, occupation, income, household structure, and educational attainment interact with residential location to shape commuting outcomes.

Study 2, presented in Chapter 3, develops a Joint Residence-and-Work Location Choice Model to examine how households simultaneously choose where to live and work. The model captures trade-offs among commuting costs, housing affordability, employment accessibility, occupational matching, and neighborhood characteristics using a multinomial logit framework grounded in random utility theory. By jointly modeling residential and employment decisions, the study estimates behavioral sensitivities and substitution patterns between the attributes of home locations, work locations, and travel between home and work locations. The resulting behavioral parameters form the analytical foundation for the policy simulations developed in Study 3.

Study 3, presented in Chapter 4, applies the estimated residence-and-work location choice model to evaluate two housing-policy interventions: (1) employer-sponsored housing subsidies for professional and essential workers and (2) office-to-residential conversion strategies near employment centers. Choice probabilities are updated under counterfactual policy scenarios and translated into revised commuting patterns using a behavioral simulation framework. The analysis evaluates how policy interventions influence commute durations, accessibility, residential location patterns across worker groups, congestion exposure, and regional equity outcomes under varying housing-market conditions.

The results demonstrate that commuting behavior in Southern California is shaped by transportation conditions and interaction of housing affordability, employment concentration, occupational structure, and employment accessibility constraints. Housing subsidies alone produce relatively limited regional relocation effects, while housing expansion strategies generate substantially larger residential redistribution responses. The greatest commute-related improvements emerge from an integrated policy approach that combines increased housing availability with targeted workforce allocation mechanisms near major employment centers.

Overall, this dissertation contributes an integrated behavioral and policy-evaluation framework for analyzing jobs–housing imbalance within large metropolitan regions. The findings provide empirical evidence and modeling tools that can inform housing, land-use, and transportation planning strategies aimed at reducing long-distance commuting, and improving employment accessibility for the regional workforce.

Chapter 1: Introduction

1.1 Background and Motivation

Southern California faces a persistent jobs–housing imbalance characterized by a geographic and economic disconnect between employment concentration and housing availability. High-wage employment centers, including Downtown Los Angeles, the Irvine Business District, and coastal and central San Diego, continue to generate strong labor demand, while relatively affordable housing is concentrated in inland and peripheral counties such as Riverside, San Bernardino, and Imperial. This spatial mismatch compels many workers to undertake long-distance commutes, contributing to congestion, high vehicle miles traveled (VMT), environmental externalities, and low measures of household well-being (Mitra & Saphores, 2019; Wang et al., 2025).

Because this dissertation evaluates commuting burden using travel time rather than physical distance, the term "long-duration commuting" is used throughout to refer to prolonged one-way commute times. For descriptive purposes, this dissertation defines a long-duration commute as a one-way commute of 45 minutes or more. The 45-minute threshold is used as an operational measure of substantial commute burden. It captures commute durations well above the typical regional travel times while retaining sufficient observations for ZIP-level spatial analysis. More restrictive 60- and 75-minute thresholds are also reported, with 75 minutes used to represent the most extreme commuting category. Where the broader literature uses the term "long-distance commuting," the terminology is retained when referring to prior studies.

The roots of the jobs-housing imbalance lie in decades of postwar suburbanization, restrictive land-use regulations, and uneven urban development patterns that have constrained housing production in high-opportunity job centers. A substantial body of research demonstrates that regulatory constraints, such as zoning restrictions, height limits, and land-use controls, reduce housing supply elasticity, increase prices, and intensify spatial mismatch between jobs and housing (Baum-Snow & Duranton, 2025; Conway, 2021; Martin, 1997). As a result, many workers, particularly those in community service type occupations and middle-income occupations, are unable to reside near employment centers and instead commute from more affordable but distant locations.

These dynamics are especially pronounced in Southern California's major employment hubs shown in Figure 1. In this dissertation, an employment hub/center refers broadly to a geographically concentrated area of employment activity and is not limited to conventional commercial business districts. Employment centers may include office and financial districts, industrial and logistics clusters, university campuses, medical centers, and other institutional locations characterized by substantial employment concentration. In Irvine, development constraints such as statutory housing caps and administrative barriers to entitlement expansion limit residential supply despite sustained job growth. In San Diego, coastal height restrictions and environmental regulations constrain high-density housing near job centers, while in Los Angeles, zoning complexity and redevelopment limitations continue to restrict residential intensification in key employment districts. Collectively, these land-use regimes reinforce spatial separation between housing and employment, contributing to longer commutes and uneven access to housing near major employment centers across the region.

Recent economic and policy shifts have further intensified the jobs-housing imbalance pressures. Although elevated commercial vacancy rates, particularly following the COVID-19 pandemic and the expansion of remote and hybrid work, have created opportunities for adaptive reuse, housing supply in job-rich areas has not increased proportionately (Southern California Association of Governments, 2024). Instead, housing prices have continued to outpace household incomes, further reducing housing affordability and highlighting the need for policy interventions such as office-to-residential conversions, employer-sponsored housing, and targeted workforce-oriented housing programs.

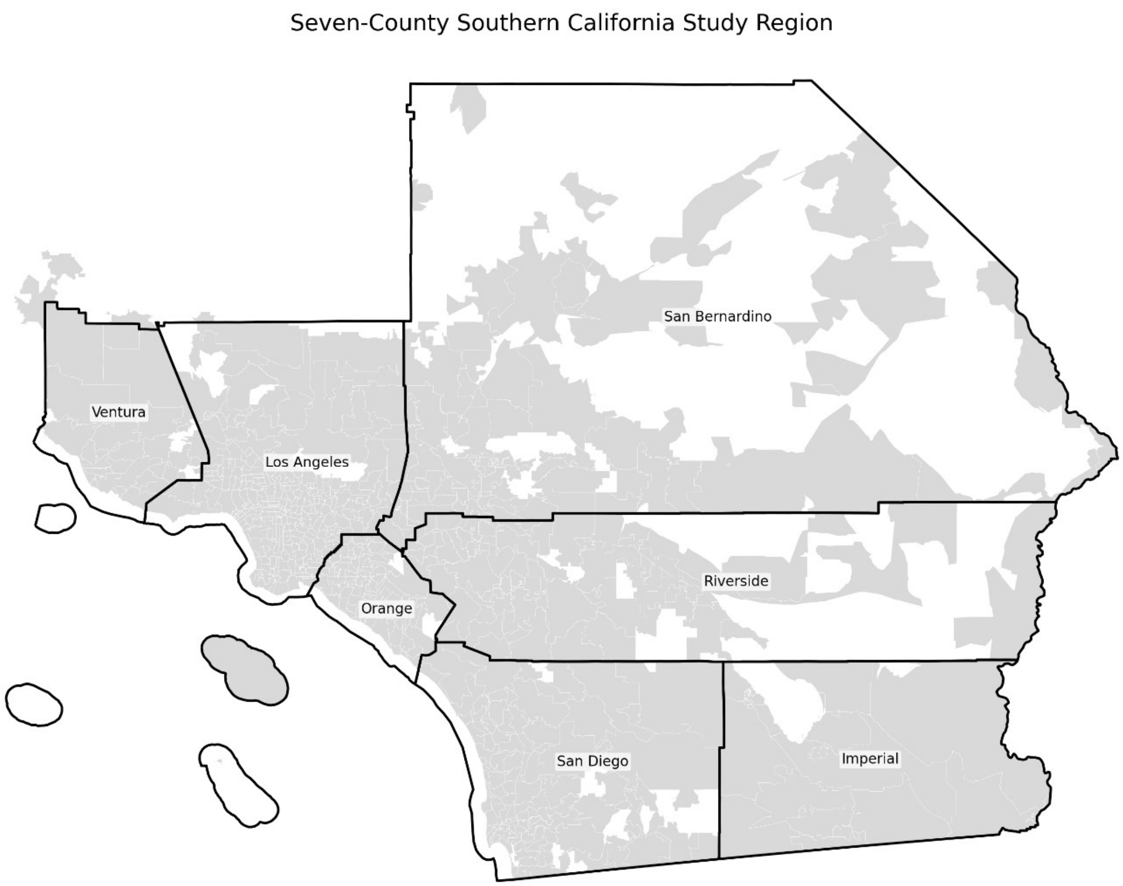

Figure 1 - Seven-County Southern California Study Region

1.1.1 Structural Land-Use Constraints in Major Jobs Centers

Understanding why workers do not live closer to their jobs requires explicit consideration of land-use and zoning constraints that structurally limit housing supply in Southern California's major employment centers. Research consistently shows that restrictive zoning reduces housing supply elasticity, increases prices, and exacerbates spatial mismatch between jobs and housing (Baum-Snow & Duranton, 2025; Conway, 2021). These constraints are particularly relevant in the region's core job hubs, where employment and housing demand are concentrated and regulatory barriers can limit residential expansion.

Irvine Business District (Orange County)

The Irvine Business Complex (IBC) is one of Orange County's largest and fastest-growing employment clusters, encompassing technology, aerospace, healthcare, and professional services. Despite sustained job growth, residential development within the IBC is constrained by a statutory cap of 15,000 dwelling units, established through the City of Irvine's Planning Area 36 guidelines and codified in the General Plan and zoning ordinance (City of Irvine, Planning Area 36). Once this ceiling is reached, additional residential entitlements require a General Plan amendment, which is an administratively complex and politically sensitive process. This numerical cap functions as a binding constraint on housing supply near a major employment center, increasing competition for existing units and pushing many workers into longer commutes along the I-5, SR-55, and SR-133 corridors.

Coastal and Central San Diego

San Diego's major employment areas face similarly binding constraints, most notably the Coastal Height Limit Overlay Zone, which restricts building heights west of Interstate 5 to 30 feet (Proposition D, 1972), as well as airport-related height limitations near San Diego International Airport. These regulations effectively preclude mid- and high-rise residential development in many amenity-rich, job-accessible neighborhoods. Additional protections for Prime Industrial Lands in Kearny Mesa, Sorrento Mesa, and Otay Mesa further restrict residential construction near key employment clusters, reinforcing outward residential displacement into East County and along the I-15 corridor.

Downtown Los Angeles (DTLA)

Although Downtown Los Angeles has experienced substantial residential growth following the 1999 Adaptive Reuse Ordinance, regulatory constraints remain uneven across districts. Hybrid Industrial zones, Qualified Opportunity Zone conditions, and Community Plan Implementation Overlays (CPIOs) continue to limit residential conversion or restrict height and floor-area ratios in several job-intensive areas. While the DTLA 2040 Plan seeks to expand residential capacity, these layered regulatory regimes contribute to persistent disparities between housing supply and employment concentration.

Collectively, these policies illustrate that Southern California's jobs–housing imbalance is not solely a market outcome, but a structurally reinforced condition shaped by local land-use regimes. Because many mid-wage and essential occupations do not provide sufficient incomes to compete for housing in high-opportunity employment centers, these workers are more likely to reside in lower-cost peripheral communities and undertake longer commutes, contributing to regional congestion.

1.1.2 Occupational Group Definitions

Table 1 summarizes the occupational definitions used to distinguish professional, essential, and other workers in the empirical analysis.

Worker Bin	Description	Representative Occupations
Professional Workers	Workers in knowledge-intensive and specialized occupations requiring advanced technical, analytical, or professional skills	engineers, software developers, finance professionals, researchers, architects, lawyers, scientists
Essential Workers	Workers in occupations that support critical public services, infrastructure, healthcare, education, transportation, and other essential functions	healthcare staff, teachers, first responders, transportation operators, utilities workers, public services
Other Workers	Workers in occupations not classified as professional or essential under the occupational grouping used in this study	retail, hospitality, construction, manufacturing, logistics, administrative support

Table 1 - Occupational Group Definitions Used in the Empirical Analysis

Figure 2 through Figure 4 show that all three occupational groups are geographically dispersed across the seven-county study region rather than being confined to a small number of residential areas. Professional workers have the largest sample and broadest residential ZIP representation, while essential and other workers are also distributed throughout the region. These maps provide important context for the analyses that follow by illustrating differences in commute burden and Worker Stress Zones within a broadly shared regional geography rather than entirely separate residential markets.

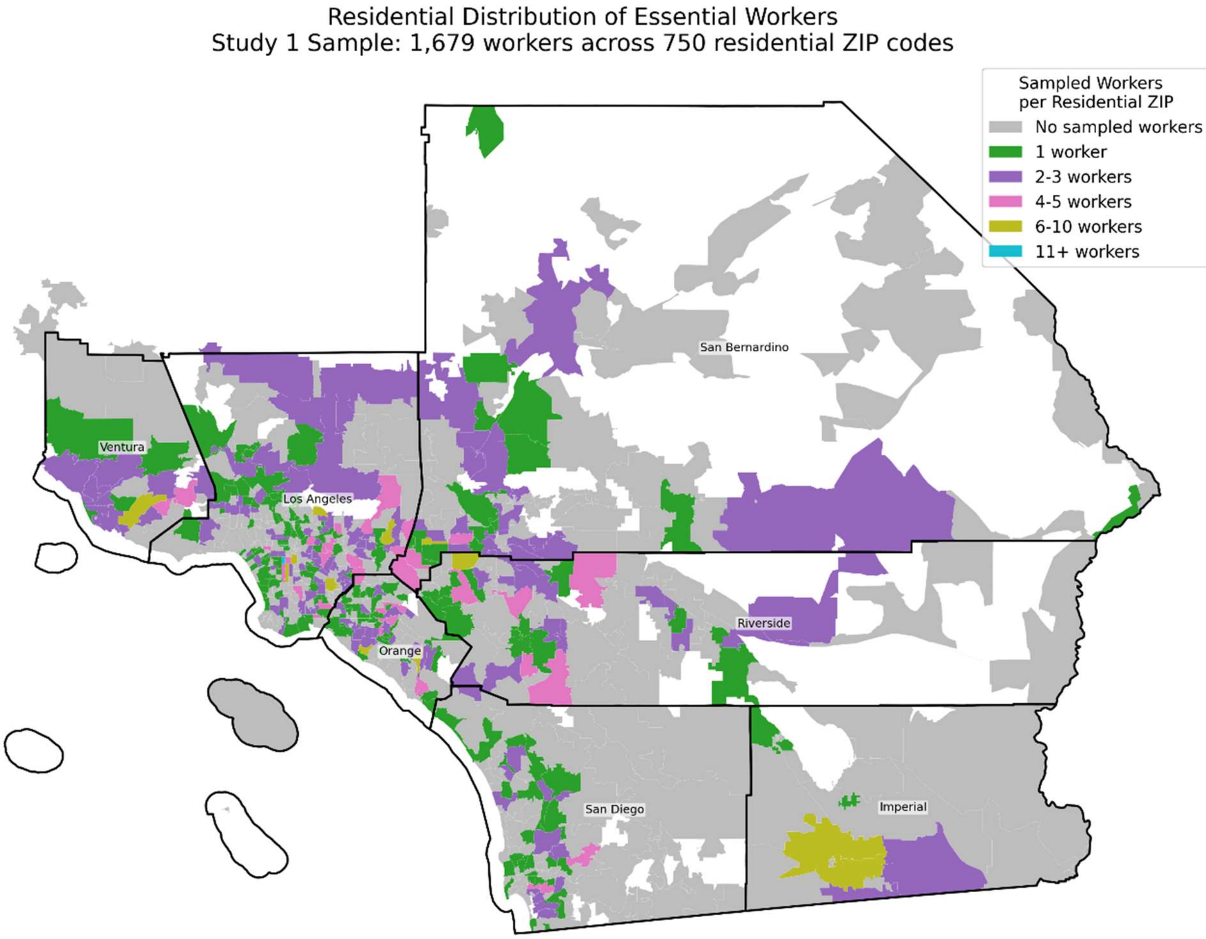

Figure 2 - Residential Distribution of Essential Workers in the 2016 California Household Travel Survey

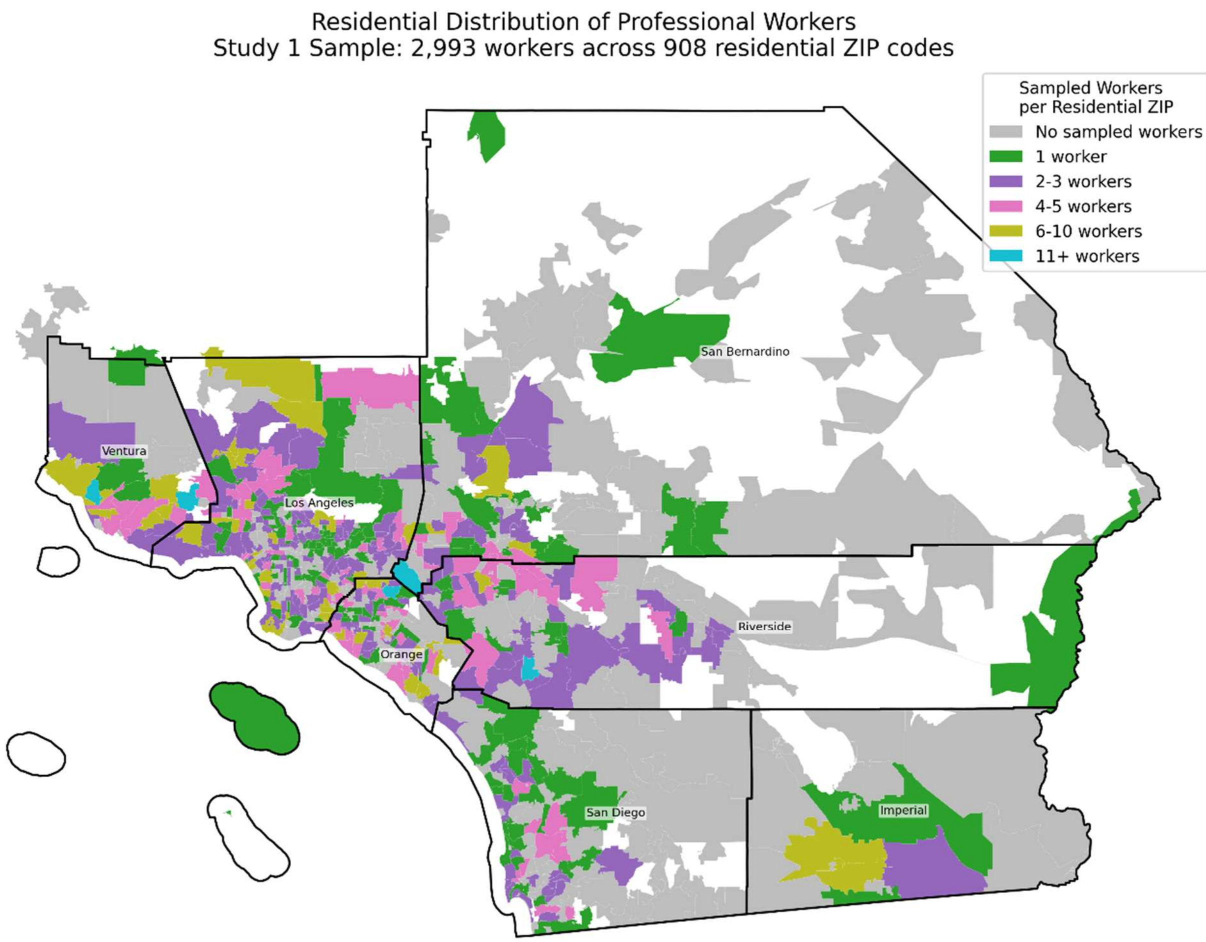

Figure 3 - Residential Distribution of Professional Workers in the 2016 California Household Travel Survey

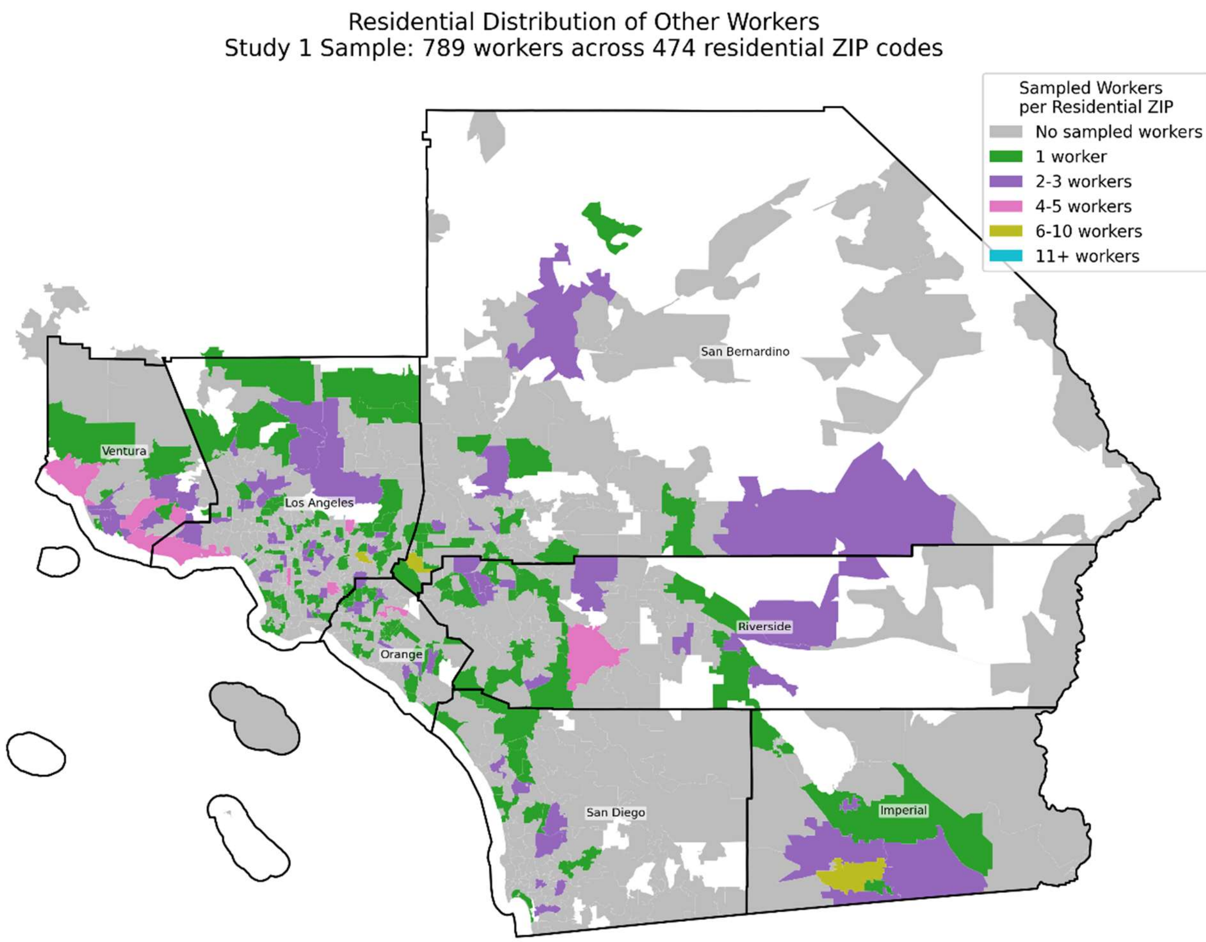

Figure 4 - Residential Distribution of Workers Other than Professional or Essential in the 2016 California Household Travel Survey

1.1.3 Worker Stress Zones

To better capture the distributional impacts of these dynamics, this dissertation introduces the concept of Worker Stress Zones (WSZs), or geographic areas where essential and professional workers face compounded housing and commuting constraints. A ZIP code area is classified as a WSZ when multiple stress conditions are present, including high housing cost burdens, long commute times, and limited access to nearby employment opportunities. Examples of this might be the City of Fallbrook in the northern portion of San Diego County. This city has relatively high housing costs, limited opportunities for professional-type careers, and long commute times during peak-hour traffic due to congestion on the I-15 freeway. The concept of WSZs builds on established measures of housing affordability and commute burden (Blumenberg et al., 2025; Giménez-Nadal et al., 2025), while extending them into a unified spatial framework. WSZs provide a tool for identifying ZIP code areas where workers simultaneously experience housing affordability burdens, long commuting times, and limited access to nearby employment opportunities.

The purpose of the WSZ framework is to categorize ZIP codes according to the number of concurrent structural stress conditions observed:

- Housing stress: estimated annual housing cost exceeds 50 percent of estimated annual housing income for the applicable worker group;
- Commute stress: at least 15 percent of resident workers report a one-way commute of 45 minutes or longer; and
- Employment accessibility stress: gravity-based employment accessibility for the relevant occupational group falls below the regional 25th percentile of valid accessibility values.

Although the WSZ label is newly introduced in this dissertation, its conceptual foundations align with long-established standards, including the Department of Housing and Urban Development's (HUD's) housing cost burden thresholds, U.S. Census definitions of extreme commuting, and regional planning analyses conducted by SCAG and SANDAG. WSZs provide a unifying lens for understanding how structural housing constraints and transportation burdens disproportionately affect the workers who sustain critical public services and drive regional economic productivity.

1.1.3 Modeling Framework for Understanding Policy Impacts

Addressing the jobs–housing imbalance requires an integrated framework that connects observed commuting patterns, joint residential-workplace location choice, and policy interventions. This dissertation adopts a multiscale analytical approach combining:

- descriptive analysis of commuting patterns and job accessibility

- behavioral modeling of joint residential and workplace location choices
- policy simulation of housing and land-use interventions

At the core of this framework is a joint residence–workplace location choice model grounded in discrete choice theory (Train, 2009; Greene, 2008). The model represents how workers evaluate combinations of housing costs, commuting burdens, housing availability, workplace earnings, and job accessibility when selecting among residence-workplace alternatives.

Together, these components provide a coherent framework for evaluating how housing supply, affordability, employment accessibility, and commuting conditions interact to shape location choices and regional spatial inequality.

1.2 Research Questions

Understanding the complexity of the jobs–housing imbalance in Southern California requires an integrated examination of commuting patterns, household decision-making, land-use constraints, and the potential for policy intervention. While individual studies often analyze these components separately, the present dissertation brings them together within a unified empirical framework. To guide this multi-scalar analysis, linking individual-level commuting outcomes, ZIP-code-level housing and accessibility conditions, and regional commuting patterns, the research is organized around a set of overarching questions.

Across its three empirical studies, this dissertation is guided by the following research questions:

1. How do spatial patterns of job accessibility and long-duration commuting vary across Southern California, and which populations experience the greatest commuting burdens?
2. How do workers select among residential-workplace location alternatives when balancing housing costs, commute time, job accessibility, and residential and workplace characteristics?
3. What are the impacts of targeted housing policies, such as employer-sponsored housing and housing subsidies, on commuting patterns, accessibility, and jobs–housing balance?

4. How do the modeled effects of these interventions vary across occupational groups and policy scenarios?

Together, these questions provide a conceptual foundation for the three empirical studies that follow. Study 1 documents existing accessibility and commuting burdens across the region and examines how these patterns vary across occupational groups; Study 2 investigates the behavioral processes underlying worker residence–workplace choices; and Study 3 evaluates the potential for targeted housing and housing-supply policies to reshape these patterns. Collectively, the studies examine the drivers and consequences of jobs–housing mismatch and the conditions under which housing interventions may improve employment accessibility, commuting outcomes, and worker welfare across Southern California.

1.3 Research Contributions

This dissertation conceptualizes commuting burdens as the product of interactions among housing-market constraints, employment geography, accessibility, and household residential-workplace decision-making. This dissertation makes the following contributions.

Analytical Contributions

Integrated Multi-Scale Analytical Framework

This dissertation develops a multi-scalar analytical framework that integrates individual-level commuting behavior, ZIP-code-level housing and accessibility measures, and regional commuting patterns within a single analytical structure. This framework links descriptive spatial analyses, behavioral choice modeling, and policy simulation to evaluate the causes and consequences of the jobs-housing imbalance.

Worker Stress Zones

This dissertation introduces and operationalizes Worker Stress Zones (WSZs), a composite spatial framework identifying ZIP-code areas where workers simultaneously experience housing affordability burdens, long commute durations, and limited occupation-specific employment accessibility.

Empirical Contributions

Using data for 5,461 workers and 3,744 households across the seven-county Southern California study area, this dissertation documents substantial geographic variation in commuting burden. The regional mean one-way commute is 29.33 minutes, while 19.6 percent of workers commute at least 45 minutes, 9.3 percent commute at least 60 minutes, and 4.4 percent commute at least 75 minutes. Riverside County records the highest mean home-based commute time at 35.95 minutes, and 29.0 percent of its sampled workers commute at least 45 minutes. The Worker Stress Zone analysis identifies 97 essential worker and 105 professional worker ZIP codes experiencing at least two of the three evaluated stress conditions. Nineteen essential worker ZIP codes and 18 professional worker ZIP codes meet all three conditions.

The joint residence and work location model provides additional evidence regarding the behavioral mechanisms underlying these patterns. Model estimates indicate that workers place value on shorter commute times, lower housing-cost burdens, greater housing availability, higher workplace earnings, and occupational compatibility when evaluating residential–workplace alternatives. The policy simulations translate these estimated utility changes into annual housing-cost equivalents to provide a more interpretable measure of their magnitude. Under Policy 1, the primary subsidy scenarios produce mean annual housing-cost-equivalent gains ranging from approximately $314 to $6,700 per worker, depending on the subsidy level and commute-eligibility radius. The upper-bound sensitivity scenarios produce larger equivalent gains, reaching approximately $31,854 per worker annually under the 90% subsidy and 30-minute commute-radius scenario. Policy 2 produces more modest gains, ranging from approximately $40 to $510 per worker annually as housing capacity increases from 5% to 90%. Under the combined Policy 1 and Policy 2 scenarios, mean annual housing-cost-equivalent gains range from approximately $126 to $2,139 per worker. These results indicate that the modeled welfare effects are substantially larger for targeted housing subsidies than for housing-capacity expansion alone, while the combined scenarios provide intermediate gains.

Policy Contributions

This dissertation evaluates employer-sponsored housing subsidies and office-to-residential housing capacity expansion using a probability-based simulation framework. Under the broadest primary subsidy scenario, a 20 percent subsidy and 30-minute eligibility threshold applies to 880 workers and 2,774 eligible residence and workplace alternatives across 14 residential ZIP codes. The expected probability of selecting a qualifying alternative increases from approximately 1.895 percent to 1.951 percent, and approximately 52.7 percent of workers experience an increase in their total probability of selecting a targeted alternative. However, expected mean commute time decreases by only approximately 0.006 minutes, demonstrating that localized residential choice responses do not necessarily produce proportionally large changes in regional commuting outcomes. The corresponding mean housing-cost-equivalent welfare gain is approximately $558 per worker per month, providing a more interpretable measure of the modeled benefit than the change in expected commute time alone.

The housing capacity scenarios provide a complementary supply-based test. A 20 percent increase in housing capacity across 16 targeted ZIP codes adds approximately 54,081 housing units and produces an implied housing price reduction of approximately 3.40 percent under the literature-informed price response assumption. This scenario produces a mean housing-cost-equivalent welfare gain of approximately $12 per worker per month, compared with approximately $558 per worker per month under the broadest primary housing-subsidy scenario. Together, these results indicate substantially larger modeled welfare gains from the targeted subsidy intervention than from the housing-capacity expansion alone, while also demonstrating that changes in residential choice opportunities can generate welfare improvements even when regional commute-time effects remain modest.

1.4 Dissertation Roadmap

This dissertation is organized into three empirical studies that build sequentially:

- **Study 1 (Chapter 2)** provides a comprehensive descriptive analysis of commuting patterns, accessibility, and spatial mismatch across Southern California, identifying the populations and geographies most likely to experience long-duration commuting.
- **Study 2 (Chapter 3)** develops and estimates a joint residence–work location choice model, capturing how households balance housing costs, commute time, job accessibility, and occupational alignment.
- **Study 3 (Chapter 4)** applies the estimated behavioral model in Chapter 3 to simulate housing policy scenarios, and evaluate their impacts on residential location choices, commuting patterns, and regional accessibility.

Together, these studies form an integrated empirical and behavioral modeling framework that moves from diagnosing existing commuting burdens, to estimating the mechanisms underlying residential sorting behavior, to evaluating policy interventions capable of improving regional accessibility and reducing long-duration commuting. This progression provides both theoretical insight and practical guidance for addressing the jobs–housing imbalance in Southern California and similar metropolitan regions. See **Figure 5** below for the project workflow diagram.

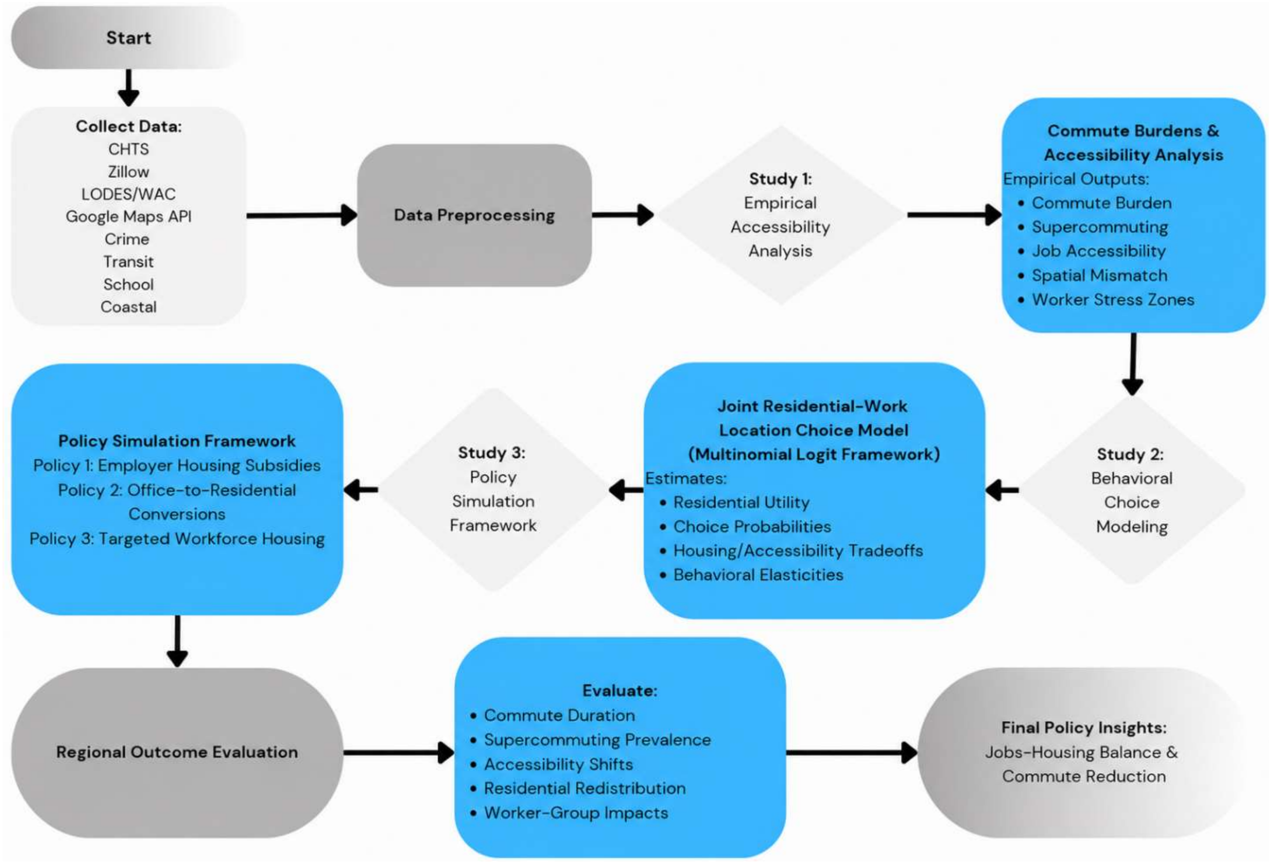

Figure 5 - Dissertation Workflow

Chapter 2 - Study 1: Commute Burdens and Patterns in Southern California

2.1 Overview

Southern California's long-standing jobs–housing imbalance has produced one of the most extreme commuting landscapes in the United States. Major-employment centers, including Downtown Los Angeles, the Irvine Business Complex, and central San Diego, are surrounded by increasingly constrained and expensive housing markets. As housing affordability pressures intensify near these job centers, many workers are displaced toward peripheral regions such as the Inland Empire and northern portions of Ventura County, resulting in rising rates of long-duration (encompasses one-way commute durations of 45 minutes or more) and supercommuting (specifically one-way commute durations of 75 minutes or more). These extended commutes impose substantial economic, environmental, and quality-of-life burdens while increasing congestion, vehicle miles traveled (VMT), infrastructure stress, and regional emissions.

The purpose of Study 1 is to quantify the spatial distribution and socioeconomic structure of commute burdens across the seven-county Southern California region. Using a descriptive analytical framework that integrates household travel survey data, ZIP-code-level housing and employment indicators, and peak-period travel times derived from the Google Maps API, the study evaluates how commuting burdens vary across demographic, occupational, and geographic groups. Particular attention is given to professional and essential workers whose employment is often concentrated in job centers with high housing costs.

Beyond documenting commuting patterns, Study 1 establishes the empirical foundation for the behavioral modeling and policy simulations developed in subsequent chapters. The analysis examines the spatial distribution of housing affordability, employment accessibility, commuting burdens, and employment geography to identify geographic patterns associated with long-distance commuting. These findings motivate the later residential location choice models by identifying the structural conditions associated with long-duration commuting and constrained residential accessibility.

Study 1 introduces the concept of Worker Stress Zones (WSZs), defined as geographic areas where workers face overlapping burdens related to housing affordability, commute duration, and employment accessibility for essential and professional workers. WSZs provide a spatial framework for identifying ZIP codes where housing-market constraints and transportation burdens intersect most acutely for workers supporting critical public services as well as those experienced by highly-skilled workers who drive regional economic productivity. Although introduced descriptively in this chapter, the concept provides an organizing structure that informs the policy simulations evaluated in future studies.

2.1.1 Research Questions

Study 1 addresses five core research questions:

1. How does job accessibility vary spatially across ZIP codes in Southern California, and where are areas of relatively high and low job accessibility concentrated?
2. How do commuting burdens vary across demographic, occupational, and household groups, including differences in commute duration and the prevalence of commutes exceeding 45, 60, and 75 minutes?
3. Which worker characteristics and residential contexts are most frequently associated with long-duration commuting?
4. How can Worker Stress Zones be operationalized to identify ZIP-code areas where housing affordability burdens, long-duration commuting, and limited employment accessibility coincide?

2.1.2 Structure of the Study

To address these research questions, Study 1 proceeds through four primary analytical components:

1. **Data Assembly and Integration**

Multiple datasets; including California Household Travel Survey (2016), Zillow housing data, LEHD/LODES employment data, crime indices, school quality ratings, coastal indicators, transit accessibility metrics, and Google Maps travel times, are cleaned, standardized, and integrated into a unified worker-level analytical dataset.

2. **Spatial Characterization of Accessibility and Commute Burdens**

   Descriptive statistics, ZIP-code analyses, accessibility measures, and spatial mapping are used to characterize regional variation in job accessibility, commute durations, and Worker Stress Zones across Southern California.

3. **Demographic and Occupational Assessment of Commuting Burdens**

   Commuting outcomes are evaluated across demographic, occupational, household, and income groups to identify populations most likely to experience long-duration commuting and housing accessibility constraints.

4. **Worker Stress Zone Identification**

   Housing affordability, commute duration, and employment accessibility measures are integrated to operationalize Worker Stress Zones (WSZs), identifying ZIP-code areas where workers experience overlapping structural burdens.

2.2 Literature Review

Understanding long-distance commuting patterns in Southern California requires situating the region within a broader body of scholarship on residential location choice, jobs–housing imbalance, accessibility, and housing market constraints. Across these literatures, a consistent finding emerges: commuting outcomes reflect trade-offs made within constrained spatial and economic systems shaped by housing affordability, land-use regulation, transportation infrastructure, the distribution of employment opportunities, and individual preferences. This review synthesizes key theoretical, empirical, and policy-oriented insights to frame the analysis in this chapter.

2.2.1 Residential Location Choice and Multi-Attribute Trade-offs

Residential location choice is widely understood as a multi-attribute decision-making process in which households balance competing factors, including housing costs, accessibility to employment, neighborhood characteristics, and household-specific constraints. Empirical and modeling-based studies consistently demonstrate that commute-related variables play a central role in this process, with households internalizing travel time and distance alongside housing price and neighborhood amenities (Kane et al., 2020; Prashker et al., 2008).

Recent advances in empirical and data-driven methods further show that relationships between the built environment and commuting behavior are complex and often nonlinear. Machine learning and spatial modeling approaches reveal threshold effects and heterogeneous responses across income groups, occupations, and household structures (Zhang et al., 2026; Wang et al., 2025). These findings suggest that households do not respond uniformly to changes in accessibility or housing cost; instead, location decisions reflect varied sensitivities and constraints.

These insights provide the conceptual foundation for interpreting commuting burdens in this study as the outcome of multi-attribute trade-offs under structural constraints, rather than purely voluntary choices.

2.2.2 Jobs-Housing Imbalance and Spatial Mismatch

Jobs–housing imbalance provides a structural framework for understanding the spatial separation of employment and residential opportunities and its implications for commuting behavior. In metropolitan regions where employment is concentrated in a limited number of high-access locations while housing remains constrained or dispersed, workers are required to travel longer distances to access employment opportunities.

Empirical research demonstrates that the spatial relationship between jobs and housing plays a central role in shaping commuting patterns. Boustan et al. (2009) provide causal evidence that changes in job location influence residential location decisions, reinforcing the interdependence between labor and housing markets. Martin (1997) similarly shows that decentralized employment combined with constrained housing supply can produce persistent spatial mismatch, particularly for lower- and middle-income households.

In high-cost metropolitan regions, housing affordability further intensifies jobs–housing imbalance by displacing workers away from employment centers. Baum-Snow and Duranton (2025) highlight how limited housing supply elasticity in high-demand areas leads to rising housing prices and outward residential displacement, contributing to longer commutes. Empirical evidence from Southern California reinforces this pattern, with housing cost pressures significantly increasing commute distances and durations (Mitra & Saphores, 2019; Islam & Saphores, 2022).

Importantly, recent work emphasizes that spatial mismatch is not solely a function of geographic distance, but also of accessibility and transportation system performance. Congestion and travel-time variability can amplify effective separation between jobs and housing, making accessibility-based measures more meaningful than simple proximity (Wang et al., 2024).

This perspective informs the analytical approach used in this study, which operationalizes jobs–housing imbalance through congestion-adjusted travel times and accessibility thresholds.

2.2.3 Employment Accessibility and Commute Burdens

Employment accessibility, defined as the ability of households to reach employment opportunities within reasonable travel times, remains a foundational concept in transportation planning and urban economics. Contemporary research emphasizes that accessibility is not solely a function of geographic distance, but reflects congestion, transportation network structure, and the spatial distribution of employment relative to residential locations (Wang, Kwan, & Xiu, 2024). In highly congested metropolitan regions, travel time variability and peak-period delays can substantially alter effective accessibility, producing disparities that are not captured by static distance-based measures.

The theoretical foundations of accessibility measurement are commonly traced to Hansen (1959), who conceptualized accessibility as the cumulative set of opportunities reachable from a given origin, weighted by a generalized impedance function representing travel cost. Hansen's framework established accessibility as a function of both the quantity of opportunities available and the friction imposed by spatial separation. Since then, transportation researchers have widely operationalized Hansen-style accessibility using gravity-based formulations in which opportunities decay as travel time increases.

Consistent with this literature, this study employs a gravity-style accessibility measure in which employment opportunities are weighted using a negative exponential travel time decay function. This approach captures the continuous reduction in effective job accessibility associated with increasing commute times while avoiding arbitrary threshold cutoffs. Accessibility measures are constructed using congestion-adjusted peak-period travel times between residential and employment ZIP codes within the seven-county Southern California study region.

A growing empirical literature demonstrates that accessibility is strongly associated with commuting outcomes, labor market participation, and residential sorting patterns. Recent studies using advanced econometric and machine learning approaches find that accessibility effects are nonlinear and interact with built environment characteristics, often amplifying long-distance commuting in regions with spatially concentrated employment and dispersed housing patterns (Zhang et al., 2026; Wang et al., 2025).

Together, this literature highlights that accessibility is best understood as a dynamic, system-level outcome shaped by transportation conditions, land use structure, and regional economic geography. These insights directly inform the accessibility measures developed in this study, which integrate congestion-adjusted travel times, gravity-based accessibility metrics, and threshold-based commute burden indicators to capture both continuous variation and extreme commuting outcomes.

2.2.4 Supercommuting and the Rise of Long-Distance Travel

Long-distance and long-duration commuting represent related but distinct dimensions of commuting burden. Long-distance commuting refers to substantial geographic separation between home and workplace, whereas long-duration commuting is defined by the amount of time spent traveling between them. Supercommuting is used in the literature to describe particularly extreme commuting patterns and may be defined using distance, duration, or a combination of the two. In this dissertation, supercommuting is operationalized as a one-way commute duration of 75 minutes or more, providing a consistent time-based measure that can be applied across the seven-county study region. Recent empirical research shows that long-duration commuting is increasingly concentrated in regions where employment opportunities are spatially clustered and housing affordability near job centers is constrained (Mitra & Saphores, 2019; Islam & Saphores, 2022).

Additional research shows that long-distance commuting is shaped by complex interactions between the built environment and transportation systems. Nonlinear relationships between density, accessibility, and travel behavior can produce disproportionate increases in commute distances under certain conditions (Zhang et al., 2026). Similarly, decentralized development strategies may increase long-distance commuting when housing and employment growth are not spatially coordinated (Wang et al., 2025).

This body of literature suggests that supercommuting is an emergent outcome of constrained spatial systems. Consistent with these insights, this study operationalizes commuting burden using both continuous measures of travel time and threshold-based indicators, defining supercommuting as a one-way commute exceeding 75 minutes.

2.2.5 Housing Supply Constraints, Zoning, and Travel Behavior

Housing supply constraints and land-use regulation play a central role in shaping commuting behavior and spatial accessibility. In high-demand metropolitan regions, zoning restrictions, development limitations, and regulatory processes can significantly limit the availability of housing near employment centers, effectively constraining residential location choices and increasing commute distances.

Empirical and theoretical research consistently identifies housing market constraints as a primary driver of commuting outcomes. Baum-Snow and Duranton (2025) show that limited housing supply elasticity in high-demand regions leads to rising prices and outward displacement of households, contributing to longer commutes and greater spatial inequality. Similarly, Mitra and Saphores (2019) and Islam and Saphores (2022) provide direct evidence that rising housing costs in job-rich areas increase commuting distances, particularly for workers with fewer residential options.

Zoning policy further reinforces these dynamics by shaping both residential location choices and travel behavior. Conway (2021) demonstrates that zoning regulations act as binding constraints on access to high-opportunity neighborhoods, while zoning reforms that increase housing supply in these areas can reduce commute distances and improve accessibility outcomes.

In addition to regulatory constraints, the feasibility of increasing housing supply is influenced by building characteristics, financial considerations, and implementation challenges. Research on office-to-residential conversions shows that while such strategies can expand housing supply in urban cores, they are subject to significant feasibility constraints related to building design, cost structures, and regulatory approval processes (Geraedts et al., 2017; Peiser et al., 2024).

Taken together, this literature indicates that commuting patterns are deeply embedded in the structure of housing markets and land-use regulation. In regions where housing availability near employment centers is constrained, households face a fundamental tradeoff between affordability and accessibility, resulting in longer commutes and greater spatial inequality.

2.2.6 Equity, Essential Workers, and Housing Burdens

A growing body of research highlights the unequal distribution of commuting burdens across demographic and occupational groups. Low- and moderate-income workers, as well as essential workers in sectors such as healthcare, education, and public safety, often face disproportionate housing affordability constraints and limited residential mobility, increasing their exposure to long commute times.

These disparities reflect broader structural inequalities in housing and labor markets, where access to high-opportunity locations is unevenly distributed. As a result, commuting burdens are not experienced uniformly, but vary systematically across income groups, occupations, and geographic areas. This perspective provides the empirical foundation for examining heterogeneous commuting outcomes across population groups in this study.

2.2.7 Policy Context: Land Use, Adaptive Reuse, and Regional Planning

Recent policy discussions in Southern California increasingly focus on the integration of land use and transportation planning to reduce vehicle miles traveled and improve accessibility. Strategies such as transit-oriented development, zoning reform, and office-to-residential conversion aim to expand housing supply near employment centers and reduce commuting burdens.

Policy-oriented research highlights both the potential and limitations of these approaches. While increasing housing supply in high-accessibility areas can improve jobs–housing balance and reduce commute distances, implementation is often constrained by regulatory, financial, and design challenges (Geraedts et al., 2017; Peiser et al., 2024). At the same time, regional planning frameworks emphasize the importance of coordinated land use and transportation policies in addressing spatial mismatch and improving accessibility outcomes.

This policy backdrop provides a critical context for the present analysis, which aims to identify where commuting burdens are most severe and which spatial patterns may be most responsive to targeted interventions.

Across these literatures, a consistent conclusion emerges: long-distance commuting in Southern California is not driven by a single factor, but by the interaction of housing market constraints, employment concentration, accessibility conditions, and household-level trade-offs. Together, these forces produce spatial patterns of residential displacement and extended commuting that disproportionately affect certain populations and regions. This framework provides the foundation for the empirical analysis that follows.

2.3 Data and Variables

This study integrates multiple data sources to construct a comprehensive dataset describing workers, their residential and workplace locations, and the accessibility and travel-time conditions shaping commute burdens in Southern California. The primary data source is the CHTS data ("Transportation Secure Data Center", 2016), which provides person-level and trip-level observations for households across the region. These individual records are merged with ZIP-code-level housing, employment, accessibility, and travel-time indicators to quantify commute duration and disparities in access to major job centers. Commute burden is operationalized in two complementary ways: continuous travel time in minutes, and threshold-based measures aligned with the Worker Stress Zone (WSZ) framework showing commutes of 45 minutes or more.

2.3.1 Descriptive Statistics

Worker-Level Data

Worker characteristics come from the merged CHTS person and trip files. For each employed respondent, the following information is extracted:

- Home ZIP code and workplace ZIP code, enabling linkage to ZIP-level travel-time matrices and job accessibility metrics.
- Socio-demographic characteristics, including age, gender, household structure, and household income.
- Employment-related characteristics, including detailed occupation, industry, and worker type (professional, essential, or other categories) for the final 5,461 unique Study 1 workers.
- Housing characteristics, such as housing structure type and tenure (owner vs. renter).

These variables provide the foundation for analyzing who experiences the longest and most burdensome commutes, and for evaluating heterogeneity across demographic and occupational subgroups.

Travel-Time Variables

To measure peak-period automobile travel times, Google Maps Distance Matrix API data were generated for the unique home-work ZIP-code pairs represented in the Study 1 worker sample. Morning and evening travel-time matrices were matched to these observed origin-destination pairs. Valid peak-period commute times were obtained for 5,414 of the 5,461 Study 1 workers. Two measures were constructed:

- AM peak auto travel time (representing travel-to-work conditions), and
- PM peak auto travel time (representing travel-from-work conditions).

Peak-period Google Maps travel times for observed ZIP-to-ZIP origin-destination pairs are used as the travel-impedance component of the gravity-based accessibility measure. This bidirectional measure represents generalized peak-period commuting impedance and was used to calculate continuous commute duration, upper-tail commute statistics, and 45-, 60-, and 75-minute burden indicators. These modeled times capture peak-period congestion conditions and provide the basis for the continuous and threshold-based commute burden measures used throughout Study 1.

Employment Accessibility Variables

ZIP-level employment accessibility variables were constructed by combining regional employment data from the LEHD LODES Workplace Area Characteristics (WAC) dataset with congestion-adjust peak-period travel times derived from Google Maps. Accessibility measures quantify the availability of employment opportunities reachable from each residential ZIP code while weighing opportunities by peak-period travel-time impedance between residential and employment locations.

Accessibility measures were computed separately for:

- Overall regional employment accessibility, representing access to all jobs; and
- Worker-group-specific employment accessibility, representing access to employment opportunities relevant to professional and essential workers.

These accessibility metrics were derived from:

- LEHD LODES WAC data, providing total jobs and industry-specific employment counts by workplace ZIP,
- Observed home–work ZIP-code pairs from the 2016 California Household Travel Survey (CHTS), used to define the origin–destination pairs represented in the worker sample and link them to corresponding Google Maps peak-period travel times,
- Peak-period Google Maps travel times, used as the travel-impedance measure between observed residential and workplace ZIP-code pairs in the gravity-based accessibility calculation.

The computation of accessibility measures using the Hansen gravity-based formulation is described in Section 2.4.

Data and Variables Summary

The merged dataset provides a comprehensive worker-level representation of commuting behavior across Southern California by integrating individual sociodemographic and employment characteristics with ZIP code level housing, employment, accessibility, and peak-period travel-time measures. The integrated dataset supports the descriptive characterization of commuting burdens, subgroup comparisons across demographic and occupational populations, accessibility analyses, and the identification of Worker Stress Zones presented throughout this chapter.

2.4 Methods

2.4.1 Construction of ZIP-to-ZIP Travel-Time Matrices

Weekday morning and evening peak-period travel times were generated for each observed home-work ZIP-code pair using the Google Maps Distance Matrix API. Traffic-adjusted morning home-to-work and evening work-to-home travel times were averaged and converted to minutes to represent generalized peak-period commute duration. Valid commute-time estimates were obtained for 5,414 of the 5,461 Study 1 workers. The individual AM and PM measures were retained for diagnostic evaluation of directional congestion patterns.

2.4.2 Operationalizing Commute Burdens

Commuting burden was operationalized using complementary continuous and threshold-based measures. The continuous measure captures the magnitude of an individual worker's commuting burden, while the threshold-based indicators summarize the prevalence of increasingly long commute durations across demographic and occupational groups. Together, these measures characterize both the severity and distribution of commuting burdens throughout Southern California.

Continuous Commute Burdens

Continuous commute burden was measured as the average weekday peak-period commute duration for each worker. To limit the influence of implausible or extreme modeled travel-time values on the descriptive analysis, commute duration was bounded between 1 and 180 minutes.

Continuous commute duration is retained throughout the descriptive analyses and summarized using:

- Mean commute duration,
- Median commute duration, and
- 90th percentile commute duration (P90)

These statistics characterize the severity of commuting burdens within demographic, occupational, household, and geographic subgroups.

Threshold-Based Indicators of High Commute Burden

To characterize the prevalence of burdensome commuting, binary indicators were constructed identifying workers whose average commute duration was at least 45, 60, and 75 minutes. These thresholds serve as analytical benchmarks that permit comparisons across progressively higher levels of commuting burden.

Specifically:

- **45 minutes** represents a commonly used lower bound for high commute burden in regional planning analyses and prior empirical work.
- **60 minutes** reflects the upper bound of typical commute tolerance frequently used in studies of long-duration commuting.
- **75 minutes** represents extreme commuting (“supercommuting”) and corresponds to the upper tail of the regional commute-time distribution.

2.4.3 Gravity-Based Job Accessibility Framework

Accessibility calculations were performed at the ZIP-code level using employment estimates from the LEHD Longitudinal Employer-Household Dynamics (LODES) Workplace Area Characteristics (WAC) data and peak-period automobile travel times obtained from Google Maps. Travel times were available for a set of observed ZIP-to-ZIP origin-destination pairs represented in the study data rather than for every possible origin-destination combination within the seven-county region. Morning and evening peak-period travel times were averaged to represent generalized peak-period travel impedance for each available ZIP pair.

Accordingly, the resulting measure is interpreted as sample-conditioned gravity-based employment accessibility. For each residential ZIP code, employment opportunities at observed destination ZIP codes are weighted by their peak-period travel-time impedance. The measure therefore reflects the relative accessibility of employment destinations represented in the available origin-destination data rather than comprehensive accessibility to every employment location in Southern California.

A gravity-based accessibility formulation was selected because it simultaneously accounts for both the quantity of employment opportunities and the travel-time impedance required to reach them, providing a continuous measure of regional employment accessibility. Following Hansen (1959), accessibility is conceptualized as the sum of opportunities reachable from a given origin, weighted by an impedance function reflecting travel cost. For workers residing in ZIP code i, accessibility to the set of employment destinations represented by valid origin-destination observations is defined as:

$$A_i = \sum_{j \epsilon R_i} W_j \cdot e^{-\beta c_{ij}}$$

Equation 1 - Cumulative Employment Accessibility Formulation (Hansen, 1959).

Where:

- A_i represents regional gravity-style job accessibility for home ZIP i,
- W_j denotes the number of employment opportunities in destination ZIP code j,
- c_{ij} is the peak-period travel time between the centroids of ZIP codes i and j,
- $\beta = 0.05$ controls the exponential travel-time decay, and
- R_i represents the set of destination employment ZIP codes j within the seven-county Southern California study region in which there are observed commute trips starting in ZIP i.

Under this formulation, employment opportunities represented by shorter observed travel times contribute more strongly to accessibility than otherwise comparable employment opportunities associated with longer travel times. Because the destination set is limited to observed origin-destination pairs with valid employment data, the measure is intended for relative spatial comparison within the available sample rather than as a complete measure of access to all regional employment opportunities. Residential ZIP codes without sufficient valid origin-destination travel-time and destination-employment observations are not assigned an accessibility value and therefore appear as missing areas in the mapped results.

2.4.4 Worker Stress Zone Framework

The Worker Stress Zone (WSZ) framework, introduced conceptually in Chapter 1, is applied separately to essential, professional, and other workers to identify locations where multiple structural constraints coincide. Unlike the individual commute burden measures described above WSZs identify ZIP codes where multiple structural constraints occur simultaneously. Specifically, WSZs are ZIP codes exhibiting at least two of three adverse conditions: 1) commute burdens exceeding 15% or more of resident workers having one-way commute times greater than or equal to 45 minutes, 2) employment group accessibility below the regional 25th percentile of valid positive accessibility values for the corresponding worker group, and 3) housing cost burdens exceeding 50 percent of estimated household income. ZIP codes satisfying all three conditions are classified as Severe Worker Stress Zones.

Because the three Worker Stress Zone conditions are derived from separate data sources, complete WSZ classification requires overlapping information for all three dimensions. The commute-stress indicator is derived from ACS 2024 five-year Travel Time to Work estimates; housing stress combines worker-group income information from the California Household Travel Survey with ZIP-level Zillow housing prices; and employment-accessibility stress uses LODES/WAC employment estimates and the gravity-based accessibility measure described in Section 2.4.3. Consequently, not every residential

ZIP represented in the worker sample has complete information for all three WSZ components. ZIP codes lacking one or more required measures are retained in the geographic framework but are shown as having insufficient or missing data rather than being assigned a complete WSZ score.

Stress Dimension	Data	Condition
Housing Stress	Zillow housing prices + CHTS income categories	Estimated average annual housing costs greater than 50% of average worker's annual income
Commute Stress	ACS 5-yr Travel Time to Work	ZIP code of 15% or more of resident workers having 1-way commute times of 45 minutes or more
Employment Accessibility Stress	LODES / WAC	ZIP-level gravity-style employment accessibility below the regional 25th percentile

Table 2 - Three-Threshold Measurable Conditions Used to Determine WSZ Classification

Housing Stress

A standardized affordability screen is used to determine the stress of housing costs for workers in the seven-county region of Southern California. For worker group g, where g is essential worker, professional, or other workforce, the housing stress is calculated using the following equation:

$$HousingStress_{z,g} = 1 \text{ if } \frac{AnnualHousingCos_{z}}{AnnualEarni_{z,g}} > 0.50$$

Equation 2 - WSZ Housing Stress Indicator Equation

The $AnnualHousingCost_z$ represents the estimated annual mortgage payment (excluding property taxes, HOA, homeowners' insurance, and maintenance costs) and were determined using the following strategy:

$$AnnualHousingCost_z = 12 \cdot MonthlyHousingCost_z$$

Monthly housing costs can be estimated using the Zillow median housing price data and current annual percentage rates from FreddieMac.com assuming a fixed 30-year mortgage. The equation used to estimate the monthly housing cost is as follows:

$$M_z = P_z \frac{r(1+r)^n}{(1+r)^n - 1}$$

Where:

- M_z is the equation for monthly housing costs;
- Principal, $P_z = HomePrice_z \times (1 - DownPayment)$;
- Interest rate, $r = \frac{0.065}{12}$ (Freddie Mac, 2026);
- Anticipated number of months of the loan, $n = 360$;
- Annual Earnings can be determined using the CHTS data.

Down Payment is assumed to be 20% of the listed home price while home price can be determined from the ZIP code level Zillow data.

Then:

$$AnnualHousingCost_z = 12M_z$$

Equation 3 - WSZ Annual Housing Cost Formula

Commute Stress

Commute stress was measured using American Community Survey (ACS) 2024 5-year estimates (Table B08303: Travel Time to Work) aggregate to the ZIP Code Tabulation Area (ZCTA) level. Rather than using average commute duration, the indicator captures the proportion of resident workers experiencing long commutes, consistent with regional transportation planning practice emphasizing commute burden prevalence rather than central tendency.

For each ZIP code, the percentage of resident workers with one-way commute times of 45 minutes or longer was calculated as:

$$P_i = \frac{N_{45-5\ ,i} + N_{60-8\ ,i} + N_{90+,i}}{N_i}$$

Where:

- N_i is the total number of resident workers

- $N_{45-59,i}$, $N_{60-8\ \ ,i}$, and $N_{90\ \ ,i}$ represent workers commuting 45-59, 60-89, and 90 or more minutes, respectively

A ZIP code is classified as experiencing commute stress when at least 15 percent of resident workers report one-way commute durations of 45 minutes or longer. This threshold identifies locations in which long commuting is sufficiently prevalent to represent a meaningful spatial burden while avoiding classification based on isolated long-commute observations.

$$CommuteStress_z = 1 \text{ if } P_i \geq 0.15$$

Equation 4 - WSZ Commute Stress Indicator Equation

Employment Accessibility Stress

The Employment Accessibility Stress is determined using a gravity-based cumulative employment accessibility measure derived from Hansen's (1959) accessibility formulation, described in detail in Section 2.4.3 Gravity-Based Job Accessibility Framework. The accessibility metric combines the quantity of employment opportunities reachable from a residential ZIP code with the travel-time impedance required to reach those opportunities.

Accessibility measures were computed separately for each group, g:

- Professional employment opportunities;
- Essential employment opportunities; and
- Other employment opportunities.

Professional and essential employment categories were derived using LEHD LODES WAC industry-sector classification aggregated from Census NAICS Supersector (CNS) employment groups. ZIP codes with valid positive gravity-accessibility values below the regional 25th percentile of the valid accessibility distribution for the corresponding worker group were classified as experiencing employment accessibility stress. Exact zero accessibility values arising from incomplete travel-time/accessibility coverage were treated as unavailable rather than as observed zero accessibility and were excluded from calculation of the regional percentile threshold. Therefore, the Employment Accessibility Stress for each group, g, is defined as:

$$AccessStress_{z,g} = 1 \text{ if } A_{z,g} < Q_{25}(A_g)$$

Where,

- g represents the employment group (essential, professional, or other)
- z represents the ZIP code being analyzed

Equation 5 - WSZ Employment Accessibility Stress Indicator

Treatment of Study-Area Boundaries

To maintain consistency between the accessibility calculations and the mapped results, accessibility is computed using destination employment opportunities located within the seven-county Southern California study region. Residential ZIP codes for which required travel-time or employment observations were unavailable after data processing are displayed as missing.

Restricting destination opportunities to the study region ensures that the accessibility metric reflects the regional labor market examined throughout this dissertation and maintains consistency between the accessibility analysis and subsequent Worker Stress Zone classifications. Consequently, the accessibility surfaces should be interpreted as measures of regional employment accessibility within Southern California, rather than accessibility to all employment opportunities beyond the study-area boundary.

Combined WSZ Score

The combined WSZ Score for Essential and Professional workers is as follows:

$$WSZScore_{z,g} = HousingStress_{z,g} + CommuteStress_{z,g} + AccessStress_{z,g}$$

Then the classification categories are as follows:

$$WSZCategory_{z,g} = \begin{cases} None = 0 \\ Low = 1 \\ WSZ = 2 \\ Severe\ WSZ = 3 \end{cases}$$

Equation 6 - WSZ Level of Severity Formula

The resulting score is interpreted as a cumulative indicator of overlapping structural burdens. A score of zero indicates that none of the three conditions is observed, while a score of one indicates exposure to a single dimension of stress. ZIP codes with a score of two are classified as Worker Stress Zones because workers face at least two concurrent constraints. ZIP codes with a score of three are classified as three-condition, or severe, Worker Stress Zones because housing affordability stress, long-commute prevalence, and low employment accessibility occur simultaneously.

The framework is applied independently to essential, professional, and other workers. The commute-stress condition is based on the same residential commute distribution for all worker groups, while the housing-stress and employment-accessibility conditions are calculated using worker-group-specific income and employment-opportunity measures. Consequently, the same ZIP code may receive different WSZ classifications across occupational groups.

The WSZ classification is intended as an exploratory spatial diagnostic of overlapping structural pressures. It identifies ZIP codes in which measurable housing, commuting, and employment-accessibility burdens coincide. Because worker-group sample sizes vary across residential ZIP codes, worker counts are reported alongside the classification as an indicator of local sample support. The framework therefore provides a consistent basis for comparing regional patterns of stress and their geographic distribution across occupational groups.

2.4.5 WAC Industry Classification Framework

To determine what employment opportunities are geographically accessible from each residential ZIP code the LODES WAC employment data is used. This provides the data necessary to distinguish essential and professional employment opportunities available within the region in order to determine if the two groups experience different spatial constraints in residential and workplace location decisions. This classification is intended to distinguish labor-market structures that may generate different commuting. Essential occupations generally require workers to be physically present to provide services within the communities they serve, making remote work infeasible and potentially increasing vulnerability to local housing affordability constraints. In contrast, professional occupations are generally more concentrated within major metropolitan employment centers, where specialized employment opportunities may encourage workers to accept longer commutes in exchange for career opportunities and higher wages. Separating these employment groups allows accessibility and Worker Stress Zone analyses to examine how different labor-market structures may contribute to commuting burdens.

Table 3 below shows industry sectors that were derived from the LEHD LODES Workplace Area Characteristics (WAC) dataset Census NAICS Supersector (CNS) codes.

WAC Industry Classification		
Worker Group	**WAC CNS Sectors Included**	**Industry Description**
Professional	CNS09, CNS10, CNS11, CNS12	Information; Finance & Insurance; Real Estate; Professional, Scientific, and Technical Services
Essential	CNS03, CNS04, CNS05, CNS08, CNS15, CNS16, CNS19	Utilities; Construction; Manufacturing; Transportation/Warehousing; Education; Healthcare/Social Assistance; Public Administration
Other	Remaining CNS sectors	Remaining industries not classified as professional or essential

Table 3 - WAC Industry Sector Classification for Accessibility Analysis

2.4.6 CHTS Worker Classification Framework

To examine observed committing outcomes, worker records from the CHTS (2016) were used. Because the commute burden analysis evaluates individual workers rather than employment opportunities, survey respondents were classified into three mutually exclusive categories using the occupation variables available in the CHTS based on their Standard Occupational Classification (SOC) codes. These classifications were developed to align conceptually with the LEHD LODES WAC employment classifications used in the accessibility analysis while recognizing differences in the underlying datasets.

Professional workers include occupations associated with management, business, science, technology, legal services, and other knowledge-intensive sectors that are more likely to cluster within major metropolitan employment centers. Essential workers include occupations associated with healthcare support, transportation, utilities, construction, maintenance, protective services, production, and other in-person operational activities requiring limited telework flexibility. The remaining occupations are classified as *Other* workers. See Table 4 below for details on the classification structure.

CHTS Worker Classification		
Worker Group	**SOC Major Groups Included**	**Description**
Professional	11, 13, 15, 17, 19, 21, 23, 25, 27, 29	Management, business, STEM, legal, education, arts, healthcare professional occupations
Essential	31, 33, 35, 37, 39, 43, 47, 49, 51, 53	Healthcare support, protective service, food service, maintenance, office support, construction, transportation, production occupations
Other	Remaining occupation groups	Occupations not classified as professional or essential

Table 4 - CHTS Worker Classification Categories Using CHTS Occupation Codes (2016)

2.5 Results

2.5.1 Worker Stress Zones

Figure 6 through Figure 8 below illustrate the spatial distribution of Worker Stress Zones (WSZs) for essential, professional, and other workers across the seven-county Southern California study region. The figures below are color coded in the following manner: light gray for ZIP codes with 0 conditions met, dark gray for ZIP codes with missing/no WSZ data, white is used for areas with no ZIP polygon information (likely water bodies, large public lands, military/open-space areas, or mountains/desert regions).

Essential Worker Stress Zones

Figure 6 shows that Essential Worker Stress Zones are concentrated throughout portions of Los Angeles County, northern Orange County, western Riverside County, southwestern San Bernardino County, and portions of San Diego County. Additional clusters appear within Ventura County and Imperial County, although these are more spatially isolated.

Several contiguous corridors exhibit Severe Worker Stress Zones (three-condition stress), particularly within the Los Angeles metropolitan area, the western regions of San Bernardino and Riverside counties, and portions of central San Diego County. These areas simultaneously exhibit relatively high housing costs, elevated shares of long-duration commuters, and comparatively limited access to employment opportunities.

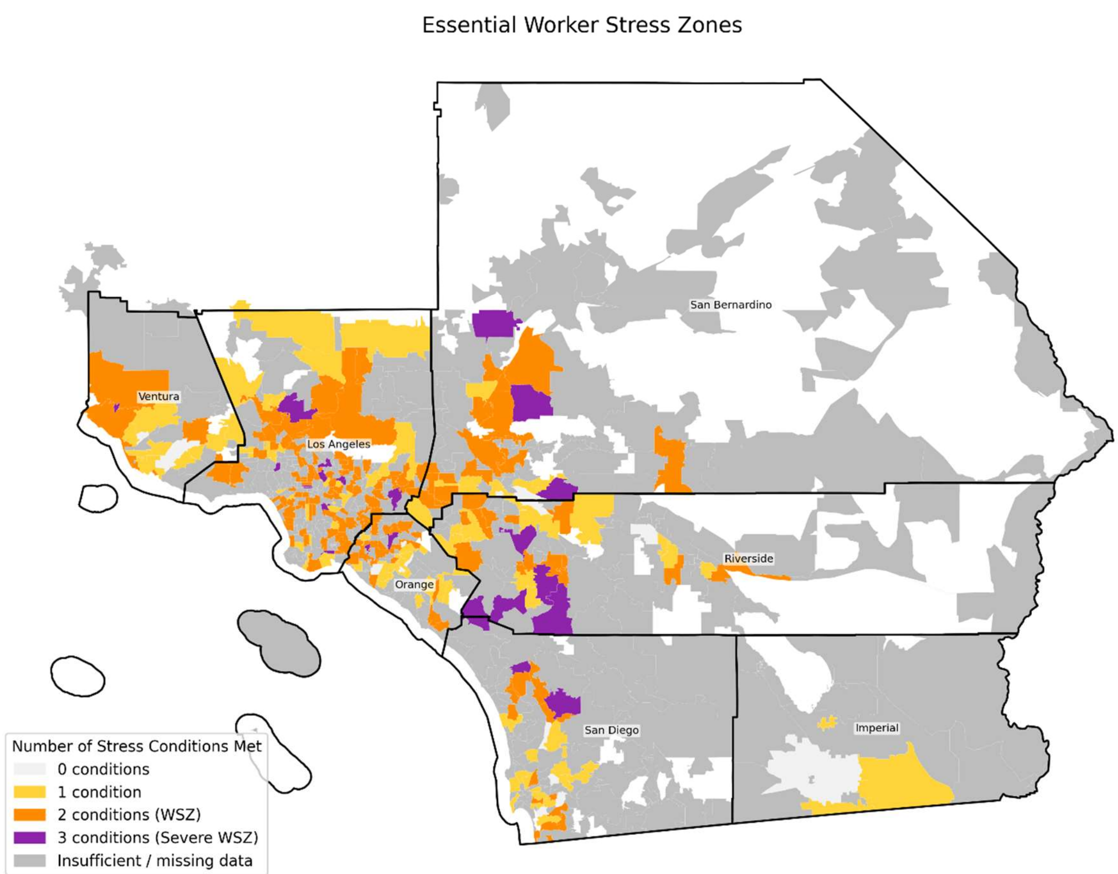

Figure 6 - Spatial Distribution for Essential Worker Stress Zones Across Study Region

Professional Worker Stress Zones

Figure 7 presents the corresponding Worker Stress Zone classification for professional workers. While the overall geographic pattern is similar to that observed for essential workers, notable differences emerge in the spatial distribution of employment accessibility. Professional Worker Stress Zones appear to affect parts of San Diego County more especially near the northern and southern county boundaries, as well as the middle areas of both San Bernardino and Riverside counties where housing costs remain high despite relatively higher commute burdens to professional employment rich areas.

Several ZIP codes transition between Worker Stress Zone classifications for the two worker groups, reflecting differences in the spatial distribution of employment opportunities available to essential and professional occupations.

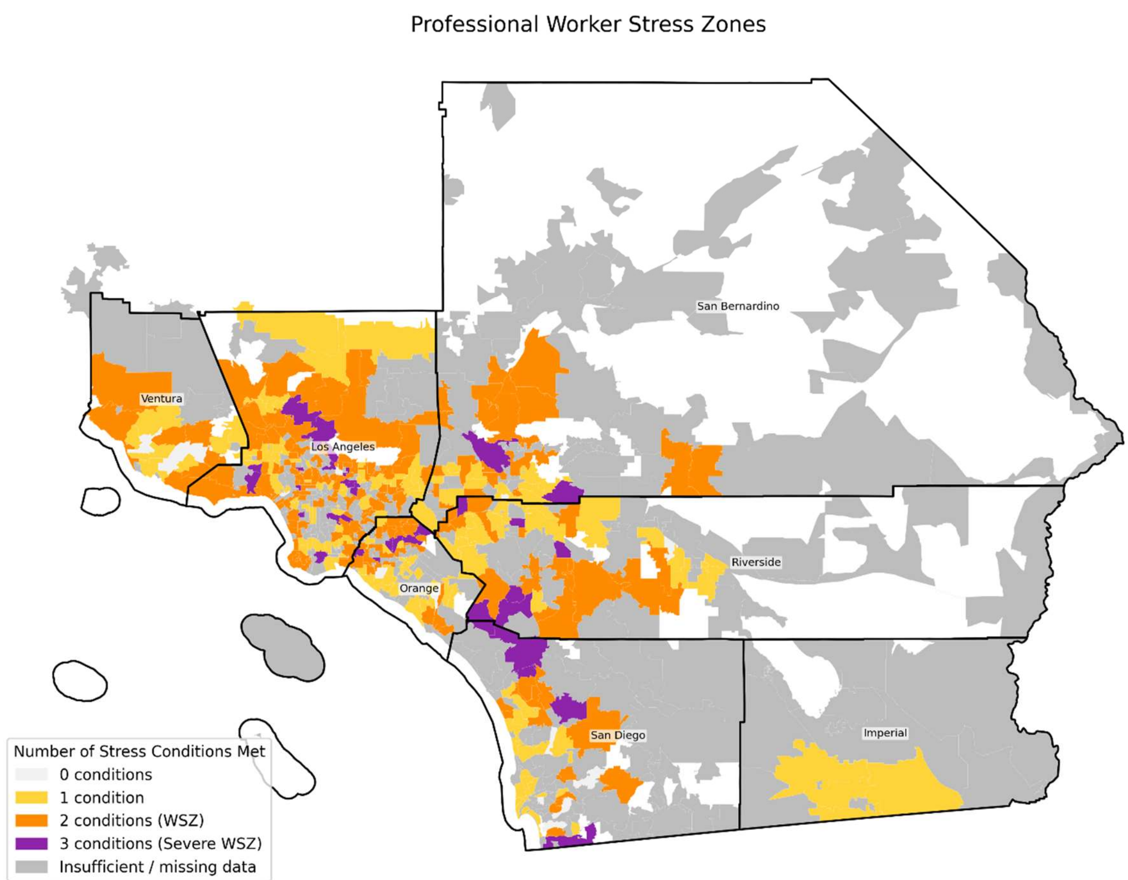

Figure 7 - Spatial Distribution for Professional Worker Stress Zones Across Study Region

Stress Zones for Workers Other Than Professional or Essential

Figure 8 presents the Worker Stress Zone classification for workers whose occupations are not included in the professional or essential-worker categories used in this study. This group includes occupations such as retail, hospitality, construction, manufacturing, logistics, and administrative support. The purpose of this additional analysis is to provide a broader comparison group and to evaluate whether the spatial pattern of overlapping housing, commuting, and employment-accessibility burdens observed for essential and professional workers is unique to those occupational groups or reflects more general regional conditions.

The Other-worker map exhibits many of the same broad regional patterns observed for essential and professional workers, including concentrations of stress in portions of Los Angeles, Ventura, Riverside, and northern San Diego County. However, the location and severity of individual Worker Stress Zones differ across groups because housing burden and employment accessibility are calculated using worker-group-specific income and employment-opportunity measures. This comparison therefore indicates substantial geographic overlap in structural stress while also demonstrating meaningful occupational variation in where those burdens coincide.

Other Worker Stress Zones

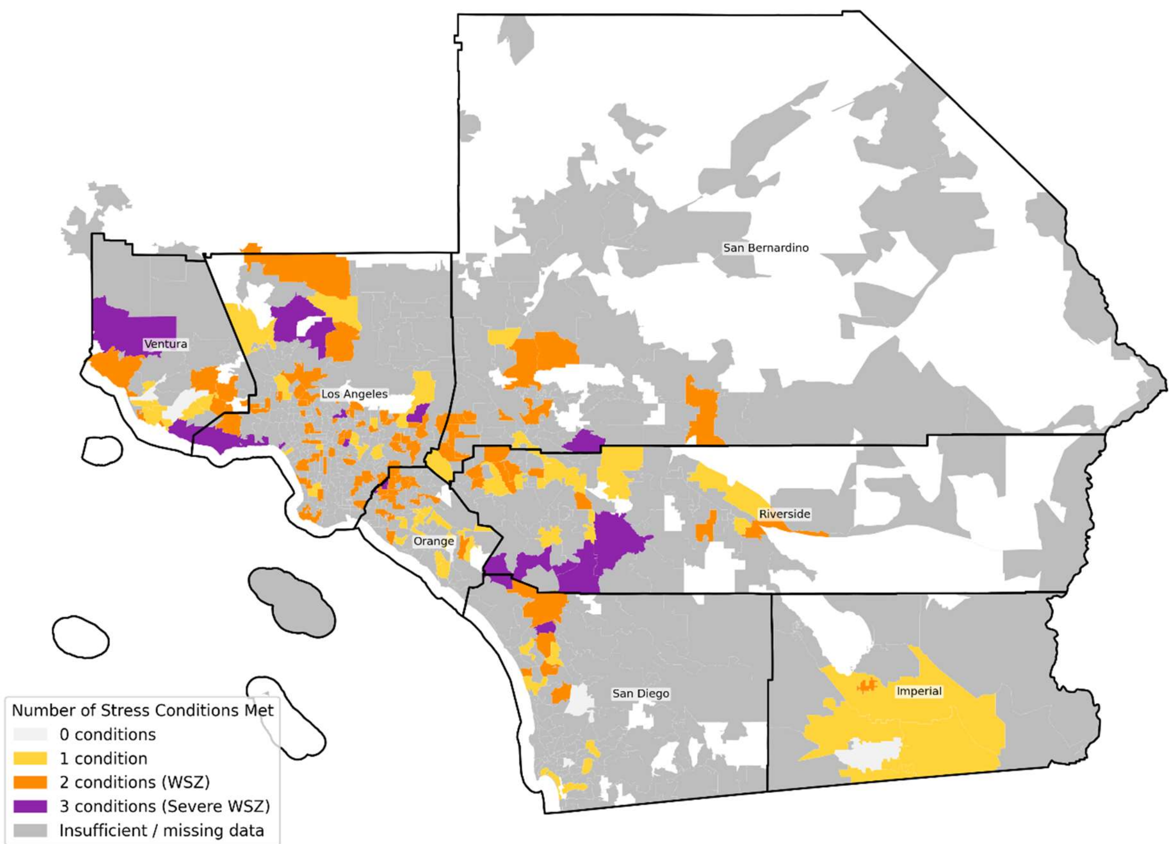

Figure 8 - Spatial Distribution for Workers not Classified as Essential or Professional

Comparison

Figure 6 through Figure 8 demonstrate that the spatial distributions of Worker Stress Zones overlap substantially across occupational groups but are not identical. This similarity is expected in part because all three groups are exposed to the same regional housing market, and the commute-stress measure is based on the same ZIP-level ACS commuting conditions. Differences across groups arise from worker-group-specific housing burdens and employment-accessibility measures.

Because the WSZ framework integrates three independently derived measures, complete classification requires overlapping information for all three dimensions. Of the residential ZIP codes represented by essential, professional, and other workers, 287, 367, and 175 ZIP codes, respectively, contained complete information for commute stress, housing stress, and employment accessibility.

Diagnostic checks confirmed that these counts are reproduced by the intersection of the required input datasets. ZIP codes lacking one or more required measures remain represented geographically but are classified as having insufficient or missing data rather than being assigned a complete WSZ score.

Worker Stress Zone Analysis Matrix							
Worker Group	**Study 1 Workers**	**Residential ZIPs Represented**	**ZIPs with Complete WSZ Data**	**Median Sampled Workers per Complete WSZ ZIP**	**Range of Sampled Workers per Complete WSZ ZIP**	**WSZ ZIPs (2+)**	**Severe WSZ ZIPs**
Essential	1,679	750	287	2	1–11	185	22
Professional	2,993	908	367	2	1–14	209	33
Other	789	474	175	1	1–6	114	15

Table 5 - WSZ Analysis Matrix

Table 5 provides additional context for interpreting the maps by reporting the number of Study 1 workers in each occupational group, residential ZIP coverage, ZIP codes with complete data for all three WSZ dimensions, and the resulting number of Worker Stress Zones. Professional workers have the largest Study 1 sample and broadest residential ZIP coverage, followed by essential and other workers. Among ZIP codes with complete WSZ data, 209 professional-worker ZIP codes, 185 essential-worker ZIP codes, and 114 other-worker ZIP codes meet at least two stress conditions. Of these, 33, 22, and 15 ZIP codes, respectively, meet all three conditions and are classified as Severe Worker Stress Zones.

Because the WSZ framework combines ZIP-level ACS commuting conditions, worker-group-specific gravity-based employment accessibility, and worker-group-specific housing burden, the number of sampled workers represented within individual ZIP codes varies considerably. Worker counts are therefore reported as an indicator of local sample support rather than used as an exclusion criterion. Accordingly, the WSZ classifications describe combinations of conditions observed at the ZIP-code level and should not be interpreted as estimates of the share of individual workers personally experiencing all three conditions.

2.5.2 Regional Accessibility Patterns by Worker Type

Figure 9 through Figure 11 illustrate the resulting gravity-weighted accessibility surfaces for all employment opportunities, professional employment opportunities, and essential employment opportunities across the seven-county Southern California study region. Accessibility values represent the cumulative number of reachable jobs from each residential ZIP code after accounting for congestion-related travel-time impedance using the Hansen-style exponential decay formulation described in Section 2.5.1. The maps in this section are color coded in the following manner: colors (ranging from purple to yellow) represent areas with gravity-weighted job accessibility data, dark gray for ZIP codes with missing/no employment data, white is used for areas with no ZIP polygon information (likely water bodies, large public lands, military/open-space areas, or mountains/desert regions).

The spatial patterns reveal substantial regional disparities in employment accessibility across Southern California. In general, the highest accessibility levels are concentrated within the urbanized core of Los Angeles County and portions of Orange County, where employment density, transportation network connectivity, and geographic centrality combine to produce large numbers of reachable jobs within relatively short travel times. Accessibility gradually declines toward peripheral and geographically isolated areas, particularly in eastern Riverside County, Imperial County, and portions of San Bernardino County, where lower employment densities and longer interzonal travel times reduce the number of reachable opportunities.

All Employment Opportunities

Figure 9 presents gravity-weighted accessibility to all employment opportunities. Accessibility is highest in and around Southern California's major employment centers, particularly the Los Angeles metropolitan core, and gradually declines with increasing travel time from these concentrations. Residential ZIP codes near Downtown Los Angeles, the LA Westside, central Orange County, and portions of coastal Ventura and San Diego Counties exhibit substantially higher levels of accessible employment opportunities than peripheral inland locations.

The spatial gradient shown in Figure 9 reflects the combined influence of employment concentration and congestion-adjusted travel impedance. Although some inland areas contain localized employment centers, their overall accessibility remains lower because employment opportunities are less concentrated and generally require longer peak-period travel times to reach. These findings are consistent with prior research demonstrating that employment accessibility in highly urbanized metropolitan regions is strongly shaped by the interaction between spatial job concentration and transportation network performance (Geurs & van Wee, 2004).

In Figure 9, areas without mapped ZIP-code accessibility values include water bodies and other areas outside the represented ZCTA geography. Gray areas indicate ZIP-code areas for which an accessibility value was not available in the processed regional dataset. Unmapped areas should not be interpreted as having zero employment accessibility.

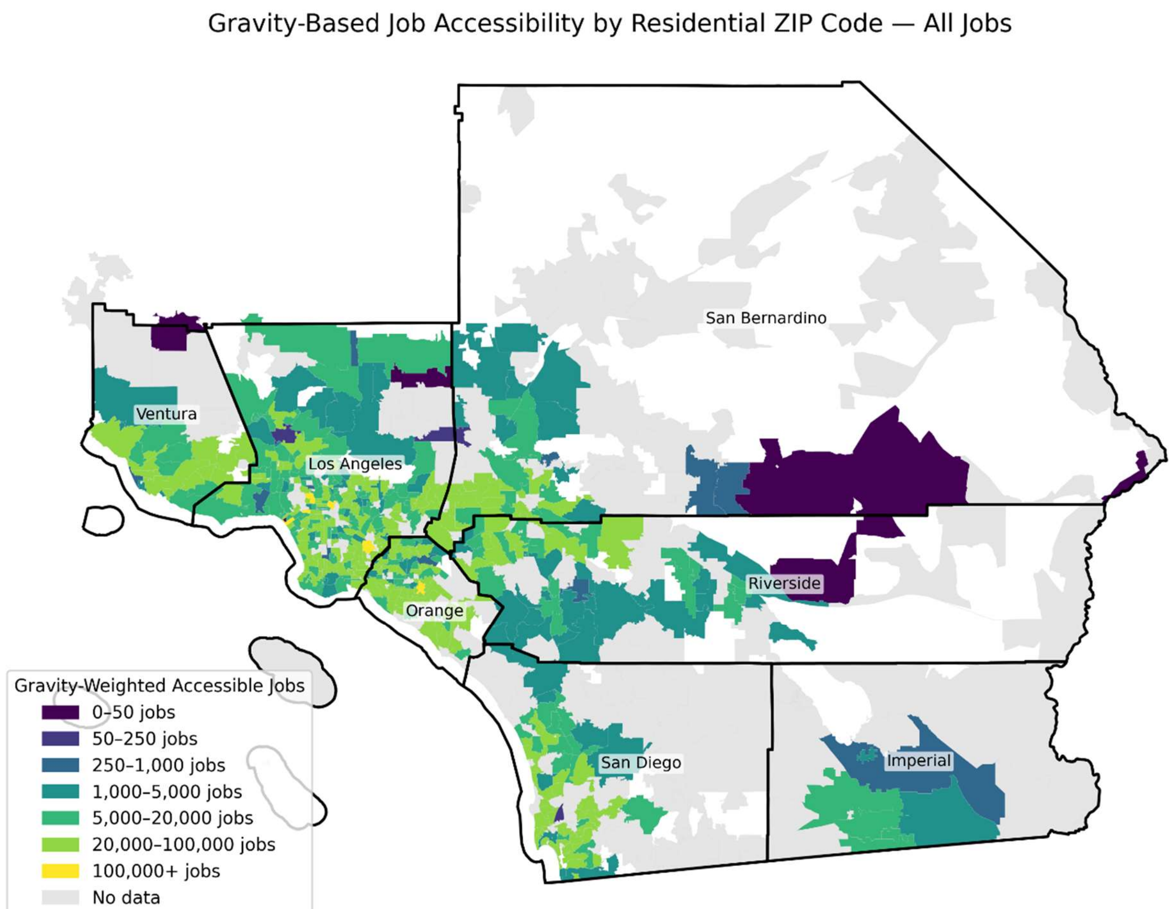

Figure 9 – Gravity-weighted accessibility to all employment opportunities by residential ZIP code

Professional Employment Accessibility

Figure 10 displays accessibility to professional employment opportunities derived from LEHD LODES industry classifications associated with finance, information, professional and scientific services, and related knowledge-intensive sectors. Compared with the overall employment surface, professional job accessibility is substantially more spatially concentrated.

High-accessibility clusters are strongly centered within the Los Angeles metropolitan core, coastal Orange County, portions of Ventura County, and select areas of San Diego County. This pattern reflects the spatial concentration of professional and knowledge-intensive industries within major urban business districts and high-income employment corridors. Peripheral inland areas exhibit markedly lower accessibility to professional employment opportunities, particularly across eastern Riverside and San Bernardino Counties as well as Imperial County.

The sharper spatial inequality observed in Figure 10 suggests that professional employment opportunities remain more geographically centralized than the regional labor market overall. Consequently, workers residing farther from major metropolitan employment centers may experience significantly reduced access to high-wage professional occupations despite remaining connected to broader labor markets for other job types.

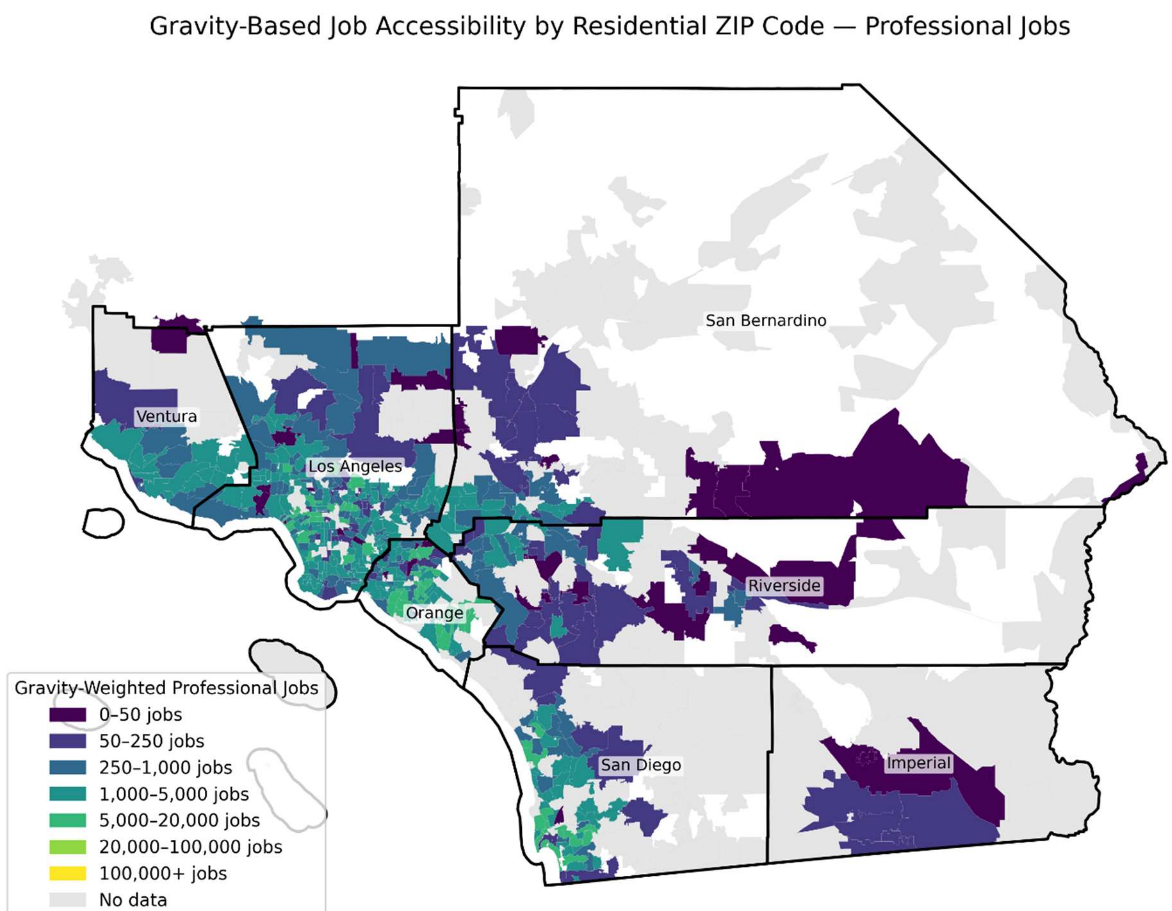

Figure 10 - Gravity-weighted accessibility to professional employment opportunities by residential ZIP code

Essential Employment Accessibility

Figure 11 presents accessibility to essential employment opportunities, including sectors such as healthcare, education, transportation and warehousing, utilities, construction, manufacturing, and public administration. Compared with professional employment accessibility, the essential employment surface is more spatially dispersed across the study region.

Higher levels of essential employment accessibility are observed not only within Los Angeles and Orange Counties, but also throughout portions of inland Southern California and San Diego County. This broader distribution reflects the geographically distributed nature of essential economic activities, many of which must remain spatially proximate to residential populations and regional infrastructure systems.

Although accessibility still declines toward more remote peripheral areas, the reduction is less severe than for professional employment opportunities. This finding suggests that essential-sector employment opportunities maintain a more decentralized spatial structure relative to professional occupations, potentially providing broader labor-market access for workers residing outside the metropolitan core.

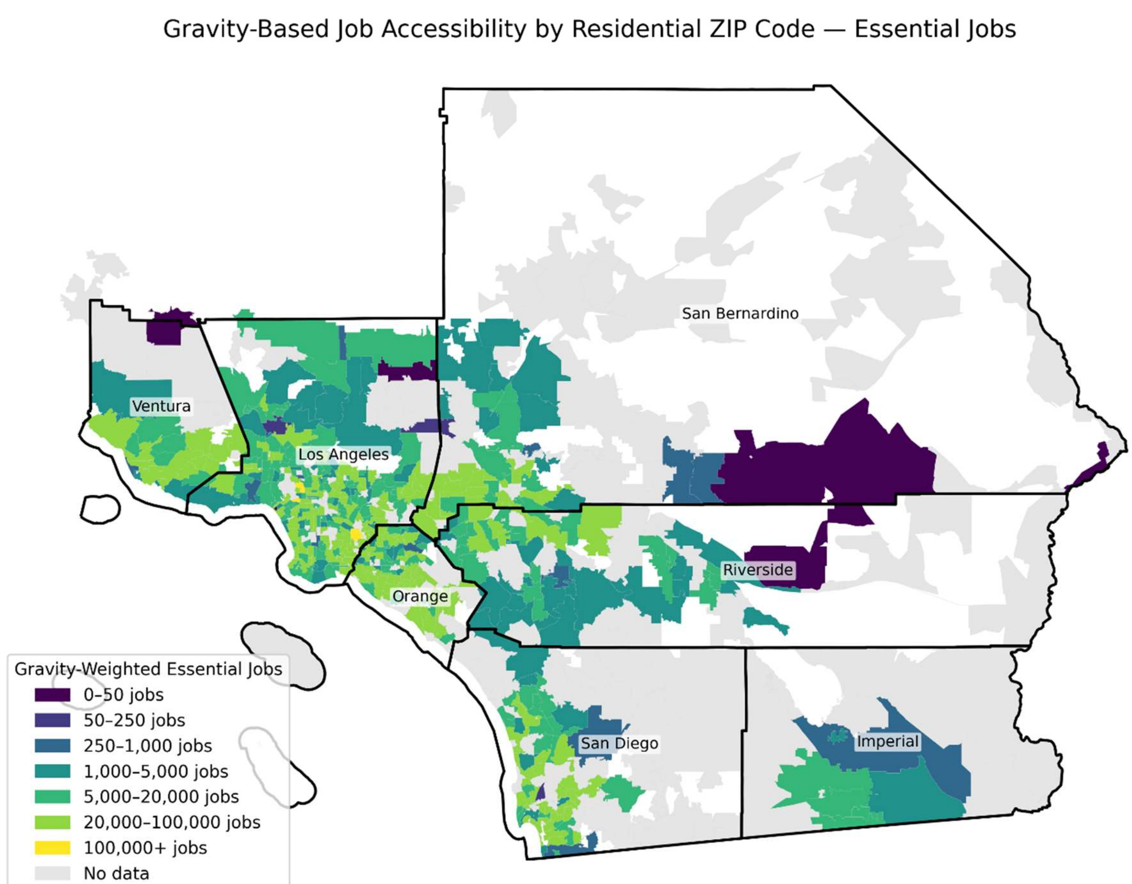

Figure 11 - Gravity-weighted accessibility to essential employment opportunities by residential ZIP code

Comparative Regional Patterns

Although the three accessibility maps share a similar regional structure, differences emerge in the spatial distribution of professional and essential employment opportunities. Professional employment accessibility is somewhat more concentrated around major metropolitan employment centers, whereas essential employment accessibly is distributed more broadly throughout suburban and inland communities. The accessibility surface representing all employment opportunities reflects the combined influence of these employment patterns Together, these maps establish the spatial context for the commute burden analyses presented in the following sections.

2.5.3 Commute Burden by Worker Type

Building on the regional accessibility patterns identified in the previous section, this subsection examines variation in commute durations across different categories of workers within the Southern California study region. The analysis focuses on whether particular worker groups experience systematically greater commuting burdens due to the spatial distribution of employment opportunities relative to residential locations.

Worker-level commute outcomes were derived using peak-period vehicular travel times between residential and employment ZIP codes. Commute duration is evaluated using multiple indicators, including mean commute duration, median commute duration, the 90th percentile commute duration, and the share of workers experiencing commutes exceeding 45, 60, and 75 minutes. These measures capture both average commuting conditions and the prevalence of extreme commuting outcomes across worker populations.

Overall Commute Burden Summary

Table 6 summarizes the final worker and household sample used in the analysis. After cleaning and deduplication procedures, the dataset contains 5,461 worker observations representing 3,744 households. Valid Google Maps peak-period commute times are available for 5,414 of these workers. Among workers with valid commute-time observations, the average peak-period commute duration is approximately 29 minutes, while the median commute duration is approximately 24 minutes. Nearly 20 percent experience commutes of at least 45 minutes, approximately 9 percent commute at least 60 minutes, and 4.4 percent experience commute durations of at least 75 minutes.

Overall Commute Burden Summary	
Measure	**Value**
Study 1 Workers	5,461
Workers with Valid Peak-Period Commute Time	5,414
Households	3,744
Average Workers per Household	1.46
Average Household Size	2.85
Mean Commute Time (min)	29.33
Median Commute Time (min)	24.12
Share ≥45 min (%)	19.6
Share ≥60 min (%)	9.3
Share ≥75 min (%)	4.4

Table 6 - Overall Commute Burden Summary - Derived from CHTS 2016 data

Figure 12 demonstrates that commute durations are strongly right-skewed, with most workers concentrated within shorter commute durations but with a substantial upper tail of long-distance commuters extending beyond 90 minutes. This pattern is consistent with previous research showing that California's housing costs and jobs-housing imbalance contribute to the persistence of long-distance commuting for a subset of workers (Mitra & Saphores, 2019).

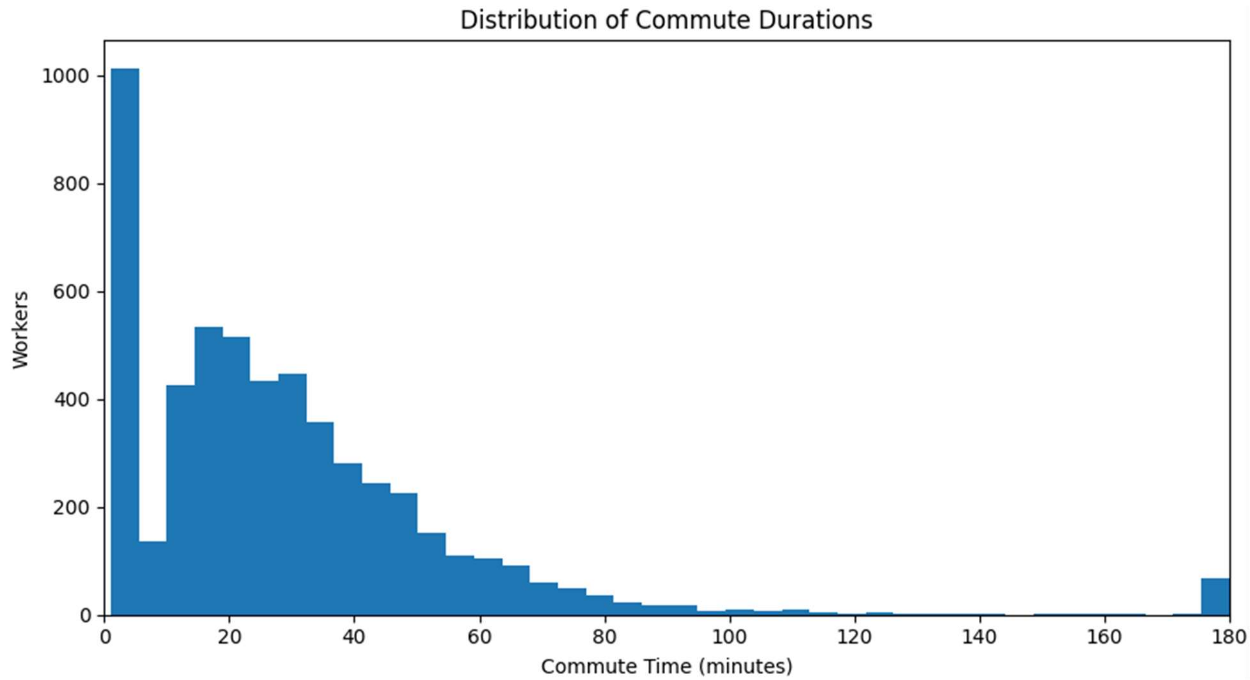

Figure 12 - Workers vs Commute Time Histogram

County-level Commute Burden Patterns

Table 7 and Figure 13 summarize commute burden variation by workers' residential county. Substantial geographic disparities emerge across the study region. Riverside and San Bernardino County residents experience the longest average commute durations and the highest rates of long-distance commuting. Workers residing in Riverside County exhibit an average commute duration of approximately 36 minutes, with nearly 29 percent experiencing commutes of at least 45 minutes and over 8 percent experiencing commutes exceeding 75 minutes.

In contrast, workers residing in coastal counties such as San Diego and Ventura generally experience shorter average commute durations and lower shares of extreme commuting. Imperial

County exhibits comparatively short average commute durations overall, although this finding likely reflects the region's distinct labor-market structure.

These findings reinforce the spatial accessibility patterns identified in Section 2.5.2, where inland residential areas exhibited lower accessibility to major employment concentrations relative to coastal metropolitan counties.

Commute Burden Summary by Home County							
Home County	**Sampled Workers**	**Mean Commute Time (min)**	**Median Commute Time (min)**	**P90 Commute**	**Share ≥45 min**	**Share ≥60 min**	**Share ≥75 min**
Riverside	279	35.95	28.86	72.86	29.0	17.9	8.2
San Bernardino	121	31.83	25.44	71.78	26.4	14.9	7.4
Los Angeles	1,200	31.8	28.38	57.96	23.5	9.1	3.5
Orange	302	27.21	23.55	53.02	15.9	7.3	1.7
Ventura	153	26.65	20.74	60.28	19.0	10.5	2.6
San Diego	186	25.57	22.4	59.55	6.5	2.7	2.2
Imperial	59	21.06	15.36	45.78	13.6	1.7	1.7

Table 7 - Commute Burden Summary by Worker Home County - Derived from CHTS 2016 data

Figure 13 highlights the substantial disparity between average commute durations and upper-tail commuting outcomes across counties. While mean commute times generally range from approximately 20 to 36 minutes, the 90th percentile commute durations are dramatically higher, exceeding 70 minutes in Riverside and San Bernardino Counties. This gap indicates that a significant subset of workers experience extremely long commute durations. The findings suggest that commute burden in Southern California is highly unevenly distributed, with inland counties exhibiting disproportionately severe long-distance commuting conditions relative to coastal employment centers.

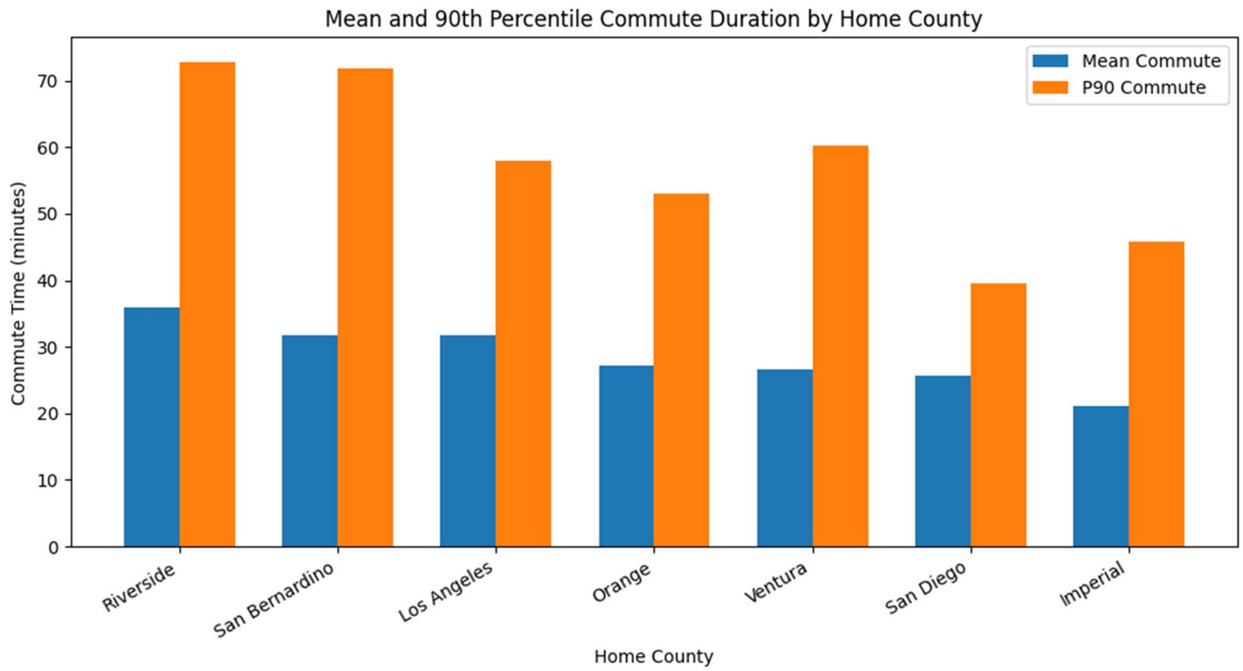

Figure 13 - Mean and 90th Percentile Commute Duration by Home County

Table 8 presents commute burden variation by workers' employment county showing geographic disparities emerge across the study region as Los Angeles and San Diego County employees experience the longest average commute among employment destinations. Workers employed in Los Angeles County exhibit an average commute duration of approximately 33 minutes, with nearly 12 percent experiencing commutes of at least 60 minutes and almost 4 percent experiencing commutes exceeding 75 minutes.

Commute Burden by Work County							
Work County	Sampled Workers	Mean Commute Time (min)	Median Commute Time (min)	P90	Share ≥45 min (%)	Share ≥60 min (%)	Share ≥75 min (%)
Los Angeles	1,225	32.95	28.89	62.68	26.2	11.5	3.8
San Diego	200	29.51	23.39	51.29	13	8.5	4.5
Riverside	251	29.06	26.39	54.12	17.5	7.6	3.6
Orange	313	27.67	24.51	49.61	15.3	6.1	3.5
San Bernardino	97	26.01	21.78	66.82	20.6	11.3	5.2
Ventura	127	21.01	18.8	47.91	11	4.7	1.6
Imperial	59	18.16	15.36	45.55	11.9	0	0

Table 8 - Commute Burden by Worker's Employment County – Derived from CHTS data

Commute Burden by Worker Group and County

Table 9 summarizes commute burden outcomes by home county and worker classification. Important differences emerge across worker groups and regions. In inland counties such as Riverside and San Bernardino, both professional and essential workers experience substantially elevated commute burdens relative to coastal counties. Essential workers residing in Riverside County exhibit average commute durations approaching 50 minutes, with nearly 39 percent experiencing commutes of at least 45 minutes.

Professional workers also experience elevated commute burdens, particularly in counties located farther from major employment centers. This finding suggests that although professional employment opportunities are highly concentrated within metropolitan job centers, many workers reside in peripheral suburban and exurban areas characterized by lower housing costs but longer commuting distances.

Commute Burden Summary by Home County and CHTS Derived Worker Groups							
Home County	**Worker Group**	**Sampled Workers**	**Mean Commute Time (min)**	**Median Commute Time (min)**	**Share ≥45 min**	**Share ≥60 min**	**Share ≥75 min**
Imperial	Essential	15	23.93	15.36	0.048	0.000	0.000
Imperial	Professional	14	23.66	17.31	0.095	0.000	0.000
Imperial	Other	10	53.24	41.51	0.294	0.059	0.059
Los Angeles	Essential	347	33.37	29.57	0.23	0.072	0.035
Los Angeles	Professional	641	35.12	31.26	0.235	0.104	0.035
Los Angeles	Other	175	33.85	28.39	0.219	0.080	0.037
Orange	Essential	89	26.71	19.47	0.118	0.059	0.020
Orange	Professional	151	33.04	28.36	0.164	0.082	0.016
Orange	Other	36	26.48	23.05	0.14	0.023	0.000
Riverside	Essential	92	49.57	41.57	0.389	0.265	0.150
Riverside	Professional	158	42.67	34.49	0.293	0.196	0.060
Riverside	Other	38	40.08	28.55	0.204	0.082	0.041
San Bernardino	Essential	33	48.92	38.47	0.304	0.196	0.130
San Bernardino	Professional	42	43.63	38.5	0.281	0.140	0.053
San Bernardino	Other	11	33.61	34.53	0.105	0.053	0.000
San Diego	Essential	58	26.17	23.8	0.045	0.015	0.015
San Diego	Professional	90	28.49	23.37	0.065	0.028	0.019
San Diego	Other	21	31.31	23.5	0.067	0.033	0.033
Ventura	Essential	33	32.66	25.73	0.195	0.073	0.000
Ventura	Professional	71	34.22	27.62	0.185	0.109	0.033
Ventura	Other	17	33.95	21.78	0.16	0.120	0.040

Table 9 - Commute Burden Summary by Home County and CHTS Derived Worker Group

Figure 14 presents the distribution of commute durations by worker classification. While all worker groups exhibit substantial variation, professional and essential workers generally display slightly higher median commute durations and broader upper-tail distributions relative to the *Other* worker category. These commute burden patterns align with the accessibility surfaces presented in Section 2.5.2, which demonstrated only small differences in spatial distributions of professional and essential employment opportunities across Southern California.

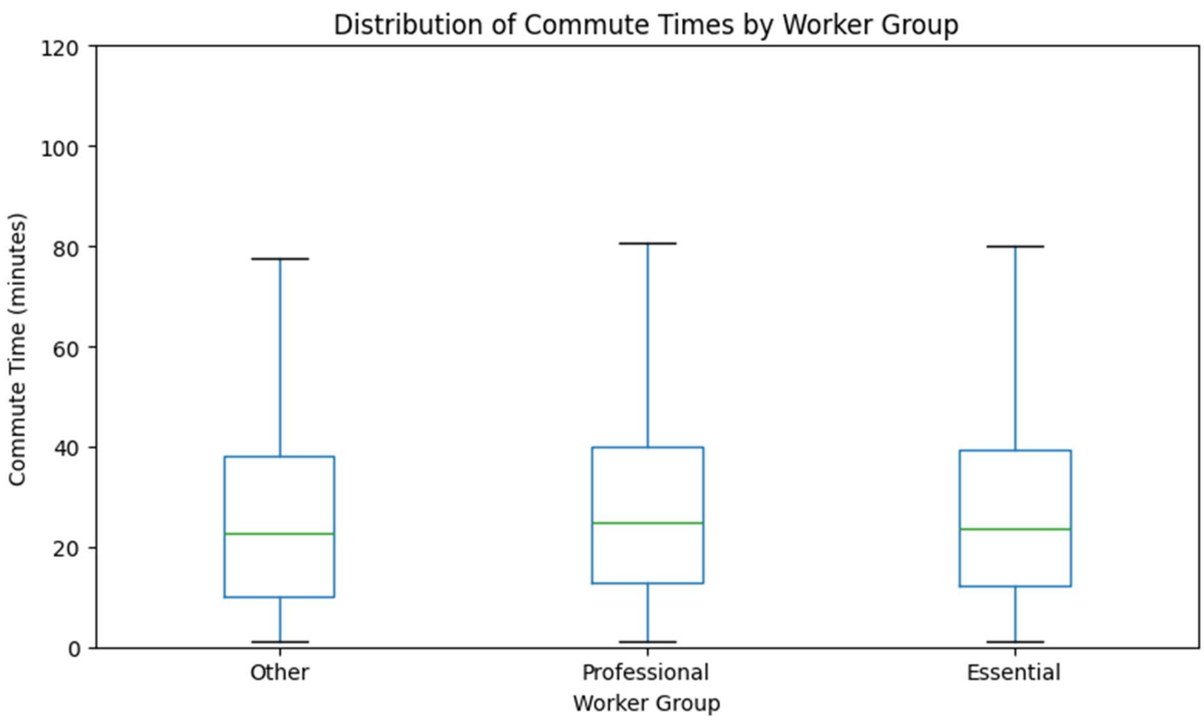

Figure 14 – Distribution of Commute Times by Worker Groups

2.5.4 Continuous and Threshold-based Commute Burden Analysis

Occupation

While the previous subsection examined commute burdens across broader worker classifications, important variation also exists at the occupational level. Different occupations are associated with distinct workplace geographies, wage structures, scheduling constraints, and levels of flexibility in residential location choice. As a result, commute burdens may vary substantially across occupational groups depending on the spatial distribution of employment opportunities relative to affordable housing.

Table 10 summarizes commute burden outcomes by occupation category using major Standard Occupational Classification (SOC) groupings available within the CHTS. Commute burden is evaluated using average commute duration, median commute duration, the 90th percentile commute duration, and the share of workers experiencing commute durations exceeding 45, 60, and 75 minutes.

The results demonstrate substantial occupational disparities in commuting outcomes across the Southern California region. Workers employed in construction and extraction occupations experience the highest overall commute burdens, with an average commute duration approaching 43 minutes and over one-third of workers experiencing commutes exceeding 45 minutes. These workers also exhibit the highest share of extreme commutes exceeding 75 minutes. Similar patterns are observed among farming, fishing, and forestry occupations, as well as life, physical, and social science occupations.

Several factors likely contribute to the elevated commute burdens observed among construction and extraction workers. Construction employment locations are frequently temporary, spatially dispersed, and project-dependent, often requiring workers to travel substantial distances between residential locations and changing job sites. Likewise, scientific and technical occupations may remain concentrated within major metropolitan employment hubs characterized by high housing costs, forcing many workers to reside farther from employment centers.

Occupations associated with architecture and engineering, computer and mathematical services, installation and maintenance, and protective services also demonstrate elevated commute burdens relative to the regional average. These occupations exhibit mean commute durations exceeding 30 minutes and relatively high shares of workers experiencing long-duration commutes.

By contrast, occupations associated with education and library services, personal care services, community and social services, food preparation, and building maintenance generally exhibit shorter commute durations and lower rates of extreme commuting. Many of these occupations are more geographically dispersed across local communities and therefore may provide workers with greater opportunities to reside closer to employment locations.

Occupations concentrated within major metropolitan employment centers appear more likely to generate long-distance commuting patterns, particularly for workers residing in inland or lower-cost housing markets. The occupational disparities identified in Table 10 further reinforce the broader jobs–housing imbalance patterns observed throughout the study region. Workers employed in occupations requiring physical presence, specialized employment clusters, or regionally concentrated labor markets may face disproportionately high commute burdens relative to workers employed in more spatially distributed sectors. It is important to note that some occupational categories contain relatively smaller sample sizes and should therefore be interpreted cautiously; however, the overall spatial patterns remain broadly consistent across the regional labor market.

Commute Burden by Occupation						
Occupation	Sampled Workers	Mean Commute Time (min)	P90 Commute Time	Share ≥45 min (%)	Share ≥60 min (%)	Share ≥75 min (%)
Construction & extraction	155	42.89	79.88	33.5	18.1	12.3
Farming / fishing / forestry	58	38.22	63.46	29.3	15.5	8.6
Life / physical / social science	111	36.18	66.67	29.7	16.2	7.2
Architecture & engineering	225	34.84	65.92	24	13.3	5.8
Computer & math	241	34.53	67.08	28.2	14.9	6.2
Installation / maintenance	159	33.59	72.39	24.5	14.5	9.4
Protective services	107	31.81	61.34	29	11.2	3.7
Business & finance	373	31.72	60.38	22	10.2	3.8
Management	759	31.56	63.44	22.9	10.9	5.8
Arts / entertainment / media	130	31.11	60.58	21.5	11.5	3.1
Transportation & material moving	175	30.59	59.2	18.9	9.7	4
Production	125	29.24	54.87	20.8	7.2	2.4
Healthcare support	152	28.97	52.61	19.1	7.9	4.6
Healthcare practitioners & technical	273	28.41	58.24	17.6	8.8	3.7
Legal	78	28.18	49.9	15.4	5.1	2.6
Sales	403	26.86	52.04	16.1	7.2	4.2
Office & admin support	402	26.76	53.75	16.7	6.2	2.7
Military	25	26.71	56.64	12	12	4
Building & grounds maintenance	115	24.21	53.33	17.1	8.5	4.9

Food prep & serving	188	24.09	47.57	13	4.3	2.6
Community & social services	95	23.92	44.75	10.5	3.2	1.1
Personal care & service	90	23.23	51.83	14.4	6.7	2.2
Education & library	687	23.04	48.96	12.5	5.7	2.9

Table 10 - Commute Burden by Occupation - Derived from CHTS 2016 data

Figure 15 - Share of Workers with Commutes ≥ 45Minutes by Occupation

Income

Commute burdens vary systematically across household income groups, reflecting the interaction between housing affordability, residential sorting, and employment accessibility within Southern California's constrained regional housing market. Table 11 and Figure 16 summarize congested peak-period commute durations by household income category using worker-level observations from the CHTS.

Several important regional patterns emerge. Mean commute durations generally increase with household income, particularly among upper-middle and high-income households. Workers in households earning above $150,000 annually exhibit average commute durations exceeding 33 minutes, while households earning above $250,000 annually experience the highest observed average commute duration at approximately 35 minutes. In contrast, lower-income households generally exhibit shorter mean commute durations, particularly among households earning below $35,000 annually.

At first glance, this pattern may appear counterintuitive, as lower-income households are often assumed to experience the greatest transportation burden. However, these findings are consistent with Southern California's broader spatial structure and residential housing dynamics. Higher-income workers, particularly professionals employed in specialized industries such as finance, technology, management, engineering, healthcare, and legal services, are more likely to commute into major employment centers concentrated in coastal Los Angeles, Orange County, and central San Diego. These workers frequently reside in suburban or exurban communities where larger housing units, school quality, neighborhood amenities, and homeownership opportunities are more attainable, even at the cost of substantially longer commute distances.

Meanwhile, lower-income workers may prioritize residential proximity to employment centers, transit accessibility, or lower transportation costs due to financial constraints. Additionally, many lower-wage service-sector occupations are geographically dispersed throughout the region rather than concentrated exclusively within central business districts, reducing the need for extremely long-distance commuting.

Importantly, average commute durations alone mask substantial heterogeneity in commute burden exposure. Figure 16 demonstrates that upper-tail commute durations increase sharply across higher-income categories. The 90th percentile commute duration exceeds 65 minutes for several upper-income groups, indicating that a substantial share of high-income workers experience extreme commuting conditions despite relatively moderate average commute times. These findings suggest that higher-income workers may possess greater flexibility to tolerate longer commute durations in exchange for residential preferences, professional opportunities, or housing market advantages.

The results also reinforce the importance of distinguishing between mean commute outcomes and distributional measures of commute burden. While higher-income households exhibit longer average commute durations overall, lower- and middle-income workers may experience different forms of transportation stress associated with schedule rigidity, limited telecommuting flexibility, transit dependence, and congestion exposure. Consequently, subsequent analyses incorporate threshold-based commute burden indicators, including 45-, 60-, and 75-minute commute measures, to better capture the multidimensional nature of long-distance commuting across socioeconomic groups.

Commute Burden by Income						
Income Group	**Sampled Workers**	**Mean Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
$0–9,999	79	23.75	48.01	17.7	1.3	0
$10,000–24,999	313	23.15	47.78	12.5	4.8	3.2
$25,000–34,999	297	26.25	50.59	16.2	6.4	3.7
$35,000–49,999	478	26.8	53.22	15.5	7.1	3.8
$50,000–74,999	878	27.62	57.43	18.3	9.1	4.8
$75,000–99,999	882	29.71	60.44	20.4	10.2	4.9
$100,000–149,999	1118	30.39	59.65	21.3	9.9	4
$150,000–199,999	528	33.1	63.46	23.1	12.1	4.4
$200,000–249,999	230	33.88	66.1	26.1	12.6	6.1
$250,000+	214	35.37	67.47	26.6	12.6	7.9

Table 11 - Commute Burden by Income - Derived from CHTS 2016 data

Table 10 presents detailed commute burden statistics by household income category, while Figure 16 illustrates the regional commute duration gradient across income groups.

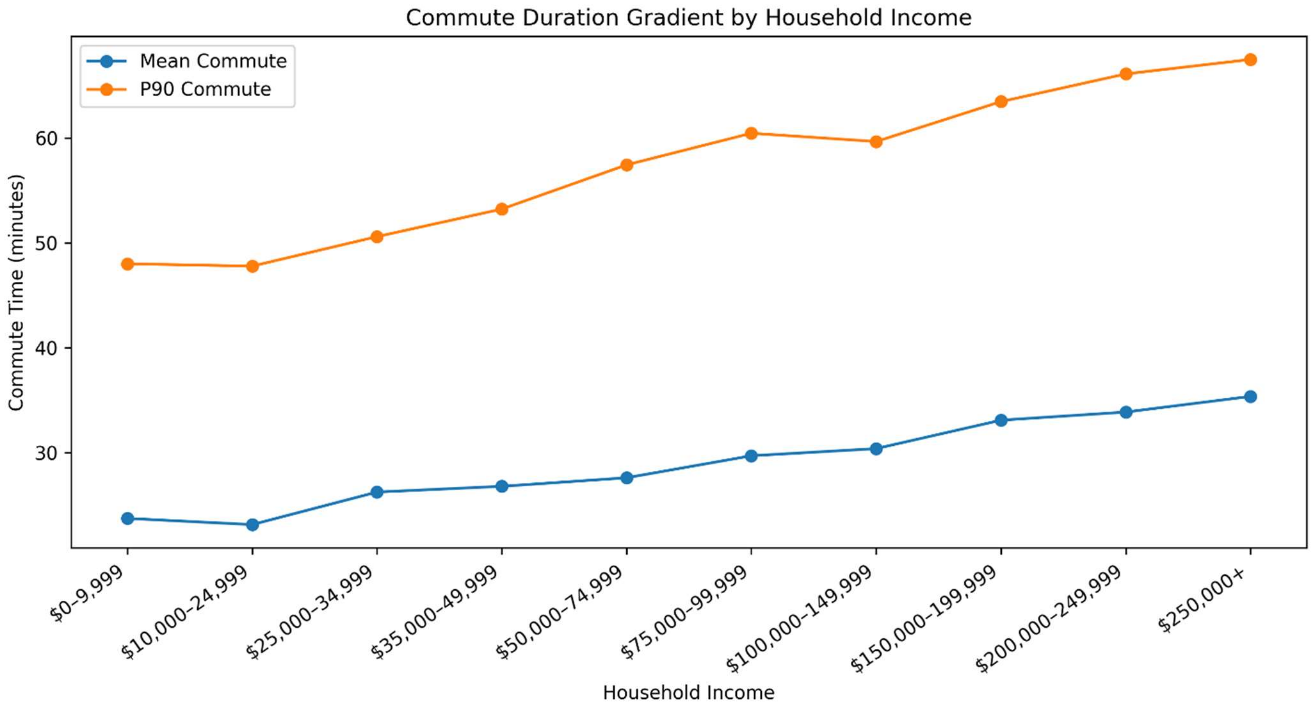

Figure 16 – Commute Duration Gradient by Household Income Group (CHTS).

Education

Table 12 and Figure 17 present commute burden outcomes by educational attainment. Overall, average commute durations are relatively similar across most education groups, generally ranging from approximately 27 to 30 minutes for workers with a high school diploma, some college, associate or technical degrees, bachelor's degrees, and graduate or professional degrees. Workers with a high school education or less exhibit the shortest average commute duration, at approximately 24 minutes, while workers with associate or technical degrees and graduate or professional degrees experience somewhat longer average commutes.

Although mean commute durations are broadly comparable across education groups, more meaningful differences emerge in the upper tail of the commute distribution. Workers with associate or technical degrees, bachelor's degrees, and graduate or professional degrees exhibit higher exposure to long-duration commuting, with roughly one-fifth of workers in these categories commuting 45 minutes or more. These groups also display elevated 90th percentile commute durations, indicating that a subset of higher-educated workers experience substantially longer commute burdens than suggested by mean values alone.

This pattern likely reflects occupational sorting into specialized labor markets. Workers with higher levels of education are more likely to be employed in professional, technical, managerial, healthcare, and specialized service occupations that are concentrated in major employment centers. As a result, these workers may tolerate longer commutes to access higher-wage or occupation-specific opportunities while residing in communities that better match housing preferences, affordability constraints, or household needs.

In contrast, workers with lower educational attainment may be more likely to work in locally distributed service, production, or retail occupations, which can reduce the need for long-distance commuting even when wages are lower. The lower commute burden among workers with a high school education or less therefore should not be interpreted as an absence of economic constraint, but rather as evidence that commute duration reflects both labor-market geography and residential sorting.

Commute Burden by Education						
Education Level	**Sampled Workers**	**Mean Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
< HS or less	288	23.85	47.72	12.2	4.5	3.5
HS diploma / GED	787	27.38	55.18	18	8	3.9
Some college, no degree	905	29.03	58.31	19	9	4.9
Associate / technical degree	612	30.46	61.75	21.6	11.9	4.2
Bachelor's degree	1500	30.11	59.26	20.8	9.7	4.7
Graduate / professional degree	1246	30.34	58.98	20.6	9.6	4.5

Table 12 - Commute Burden by Education - Derived from CHTS 2016 data

Figure 17 reinforces this interpretation by showing that the share of workers commuting 45 minutes or more is lowest among workers with a high school education or less and higher among workers with postsecondary credentials. These findings demonstrate that educational attainment shapes commute burden primarily through occupational specialization and access to regionally concentrated job markets, rather than through a simple linear relationship between education and average commute duration.

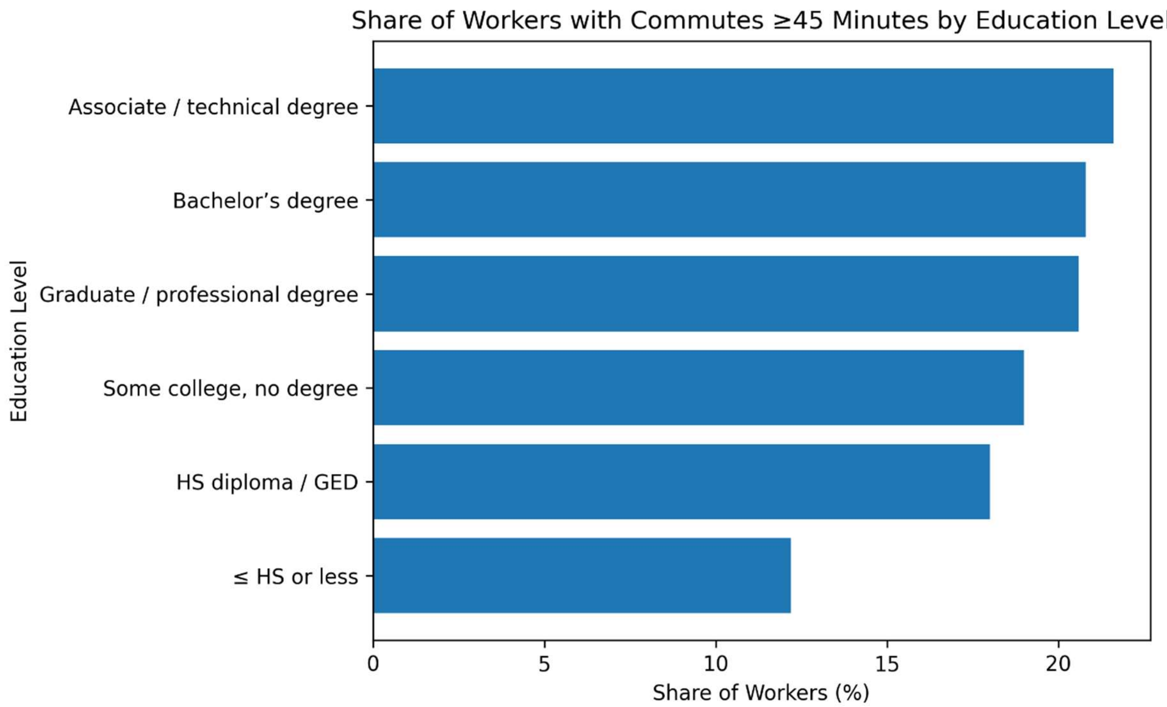

Figure 17 – Share of Workers with Commutes ≥ 45 Minutes by Education Level

Commute burdens also vary by educational attainment, although the relationship is not strictly linear. Workers with associate or technical degrees, bachelor's degrees, and graduate or professional degrees exhibit relatively elevated shares of long-duration commutes compared to workers with lower educational attainment. These patterns likely reflect occupational sorting into specialized employment clusters concentrated in coastal metropolitan centers, particularly in professional, technical, healthcare, and managerial industries. Meanwhile, workers with lower educational attainment may be more likely to reside closer to employment centers or participate in geographically dispersed labor markets with shorter commute requirements.

Housing Characteristics

Physical Housing Structure Type

Commute burdens vary across housing structure types, reflecting the spatial distribution of residential forms relative to employment centers, transportation infrastructure, and regional housing affordability constraints. Table 13 shows that workers residing in single-family detached housing experience the highest average commute duration among the major housing categories, with a mean commute of approximately 30 minutes and a 90th percentile commute of nearly 60 minutes. Approximately 21 percent of workers in single-family detached homes experience commutes of 45 minutes or longer, and 5 percent experience commutes of 75 minutes or longer.

Mobile-home residents also exhibit elevated long-commute exposure, with approximately 21 percent of workers exceeding the 45-minute threshold. Although their mean commute duration is lower than that of single-family detached residents, the relatively high share of long-duration commuters suggests that manufactured housing may be located in areas where regional job accessibility is limited or where workers must travel farther to reach employment opportunities.

Multifamily housing categories generally show lower commute burdens. Workers residing in large multifamily buildings have the lowest mean commute time among the major housing structure types, at approximately 26 minutes, and a lower share of commutes exceeding 45, 60, and 75 minutes. This pattern is consistent with the greater concentration of multifamily housing in urbanized areas, transit-served corridors, and locations closer to employment centers (Peiser, Decomposing Urban Sprawl, 2001).

These findings suggest that housing structure type functions as more than a household preference variable. It also reflects the geography of zoning, development feasibility, land costs, and residential location constraints. Low-density housing forms are more likely to be located in suburban or peripheral areas where land is relatively less expensive but employment accessibility may be lower. In contrast, multifamily housing is more likely to be permitted or financially feasible in locations with stronger access to jobs and transportation infrastructure. As a result, housing form serves as a spatial proxy for the broader land-use conditions that shape commute burden.

Commute Burden by Residence Type						
Residence Type	**Sampled Workers**	**Mean Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
SF detached	4303	29.88	59.87	20.6	10	5
SF attached / townhome	361	28.32	53.5	16.1	7.2	2.8
Other multifamily / dorm	220	27.14	54.39	17.3	7.7	1.4
Small multifamily (≤24 units)	177	27.28	53.2	14.1	7.3	5.6
Mobile home	89	26.95	58.2	21.3	7.9	2.2
Large multifamily (≥20 units)	256	25.92	50.99	16	5.5	2

Table 13 - Commute Burden by Residence Type - derived from CHTS 2016 data

Housing Tenure and Commuting Trade-offs

Housing tenure is also associated with commuting outcomes, although the differences are smaller than those observed across physical housing structure types. Table 14 shows that homeowners experience longer average and upper-tail commute durations than renters. Workers in owner-occupied households have a mean commute of approximately 30 minutes and a 90th percentile commute of approximately 61 minutes, compared with approximately 26 minutes and 51 minutes, respectively, among renters.

Commute Burden by Housing Tenure							
Housing Tenure	**Sampled Workers**	**Mean Commute Time (min)**	**Median Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
Owner (mortgage / own)	4351	30.11	24.92	60.64	20.8	10.2	4.9
Renter	1056	26.21	21.65	51.28	15.6	6	2.8

Table 14 - Commute Burden by Housing Tenure - Derived from CHTS 2016 data

Figure 18 illustrates this tenure-based commute gradient. Homeowners exhibit both higher average commute durations and higher 90th percentile commute durations, indicating that ownership is associated not only with longer typical commutes but also greater exposure to long-duration commuting. This pattern is consistent with suburban homeownership dynamics in Southern California, where households may trade longer commute distances for larger housing units, lower relative housing costs, school access, perceived neighborhood quality, or homeownership opportunities (Mitra & Saphores, 2019).

However, tenure should not be interpreted as the sole driver of commute burden. The stronger differences observed across housing structure types suggest that the physical form and spatial location of housing may play a more direct role in shaping commute outcomes than ownership status alone. Tenure captures lifecycle and financial considerations, while housing structure type more directly reflects the spatial constraints imposed by zoning, land availability, development density, and regional housing supply patterns.

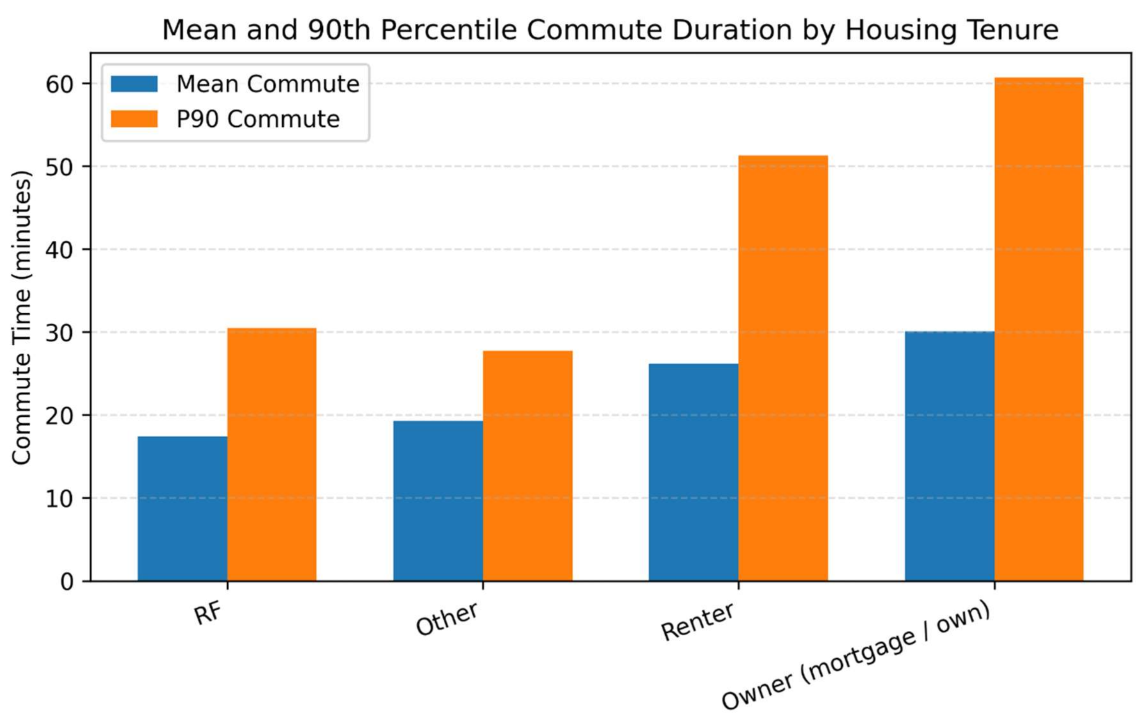

Figure 18 – Mean and 90th Percentile Commute Duration by Housing Tenure

Overall, the results indicate that housing characteristics are closely linked to commute burden in Southern California. Workers in lower-density and owner-occupied housing categories tend to experience longer commutes, while workers in multifamily housing generally experience shorter commute durations. These patterns reinforce the broader finding that commuting outcomes are shaped by the interaction between housing affordability, residential form, land-use regulation, and the spatial distribution of employment opportunities.

Gender

Commute burdens differ systematically by gender across the Southern California study region. Table 15 and Figure 19 summarize commute duration outcomes for male and female workers using worker-level observations from the CHTS. Overall, male workers exhibit substantially longer average commute durations and greater exposure to extreme commuting than female workers.

Male workers report a mean congested AM peak commute duration of approximately 32 minutes, compared with approximately 26 minutes for female workers. Differences become even more pronounced in the upper tail of the commute distribution. The 90th percentile commute duration for male workers exceeds 62 minutes, compared with approximately 53 minutes for female workers. Similarly, nearly 24 percent of male workers experience commute durations of 45 minutes or longer, compared with approximately 16 percent of female workers. Male workers are also substantially more likely to experience very long commutes exceeding 60 and 75 minutes.

Commute Burden by Gender						
Gender	**Sampled Workers**	**Mean Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
Male	2806	32.18	62.95	23.6	11.5	5.6
Female	2600	26.27	52.56	15.6	7	3.3

Table 15 - Commute Burden by Gender - Derived from CHTS 2016 data

Figure 19 illustrates these differences visually by comparing both mean commute durations and upper-tail commute outcomes across gender categories. While average commute differences are moderate, the gap widens considerably at the 90th percentile, indicating that male workers are disproportionately represented among the region's most extreme commuters.

These patterns likely reflect the interaction between occupational specialization, residential sorting, and household constraints. Male workers are more heavily represented in occupations associated with geographically dispersed or peripheral employment locations, including construction, transportation, logistics, installation and repair, and certain technical industries. Many of these occupations require travel to suburban, industrial, warehouse, infrastructure, or exurban employment centers where transit accessibility is limited and commute distances are often longer.

In contrast, female workers are more likely to be employed in healthcare, education, administrative support, and service-oriented occupations that may be more geographically distributed across residential communities or located closer to population centers. Household responsibilities and caregiving constraints may also influence residential and workplace location decisions, potentially reducing tolerance for extremely long commute durations among female workers.

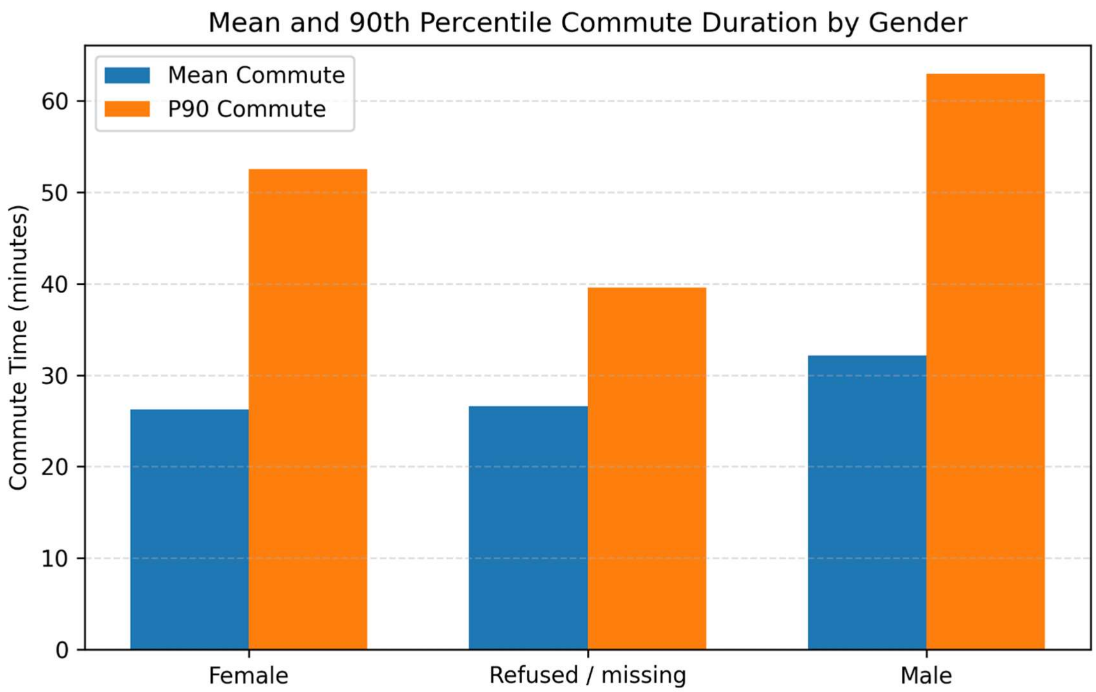

Figure 19 – Mean and 90th Percentile Commute Duration by Gender

Importantly, these results should not be interpreted as purely behavioral differences between men and women. Rather, they reflect broader structural labor-market and land-use dynamics that shape access to employment opportunities and residential location choices differently across demographic groups. The observed disparities underscore how occupation, housing affordability, transportation infrastructure, and household responsibilities jointly contribute to unequal exposure to commute burden across the region.

Additionally, the gender categories presented here reflect survey response classifications available within the CHTS and therefore do not capture the full spectrum of gender identity. Nonetheless, the findings provide important evidence that commute burden varies systematically across demographic groups and may contribute to broader inequities in time use, transportation stress, and access to regional opportunities.

Overall, the gender-based commute analysis reinforces the broader conclusion of Study 1: long-distance commuting in Southern California is not uniformly distributed across the population but instead reflects overlapping interactions among occupation, housing markets, regional accessibility, and household structure.

Household Composition

Commute burdens also vary according to household composition, although the magnitude of these differences is smaller than those observed across occupation, income, housing structure, or gender categories. Table 16 and Figure 20 summarize commute duration outcomes by household role, distinguishing between heads of household and non-heads of household using worker-level observations from the CHTS.

Overall, commute durations are remarkably similar across the two household role categories. Heads of household exhibit an average congested generalized peak-period commute duration of approximately 29 minutes, compared with approximately 30 minutes among non-heads of household. Median commute durations are also comparable, ranging between approximately 24 and 25 minutes across both groups. Likewise, the share of workers experiencing commute durations of 45 minutes or longer is nearly identical for heads of household and non-heads of household.

Commute Burden by Household Role						
Household Role	**Sampled Workers**	**Mean Commute Time (min)**	**P90 Commute Time**	**Share ≥45 min (%)**	**Share ≥60 min (%)**	**Share ≥75 min (%)**
Head of Household	2,606	29.15	58.63	19.8	9.5	4.1
Non-HOH	2,808	29.5	58.56	19.7	9.2	4.8

Table 16 - Commute Burden by Household Composition - Derived from CHTS 2016 data

Differences emerge only modestly in the upper tail of the commute distribution. Figure 20 shows that non-heads of household experience slightly higher 90th percentile commute durations and a marginally greater share of extremely long commutes exceeding 75 minutes. However, these differences remain relatively small compared with the disparities observed across occupational, housing, and income categories.

The limited differences observed across household role categories suggest that household composition alone is not a dominant determinant of commute burden within the Southern California region. Instead, commute outcomes appear to be shaped more strongly by broader structural factors, including occupational geography, housing affordability constraints, transportation accessibility, and the spatial distribution of employment opportunities.

At the same time, subtle differences between heads of household and non-heads of household may still reflect variations in residential decision-making, labor-market flexibility, and household responsibilities. Heads of household may prioritize residential stability, proximity to schools or household support networks, or predictable commute patterns when making housing decisions. Non-heads of household, particularly younger workers or secondary earners, may possess greater residential flexibility or may accept longer commute durations in exchange for employment opportunities, lower housing costs, or shared housing arrangements.

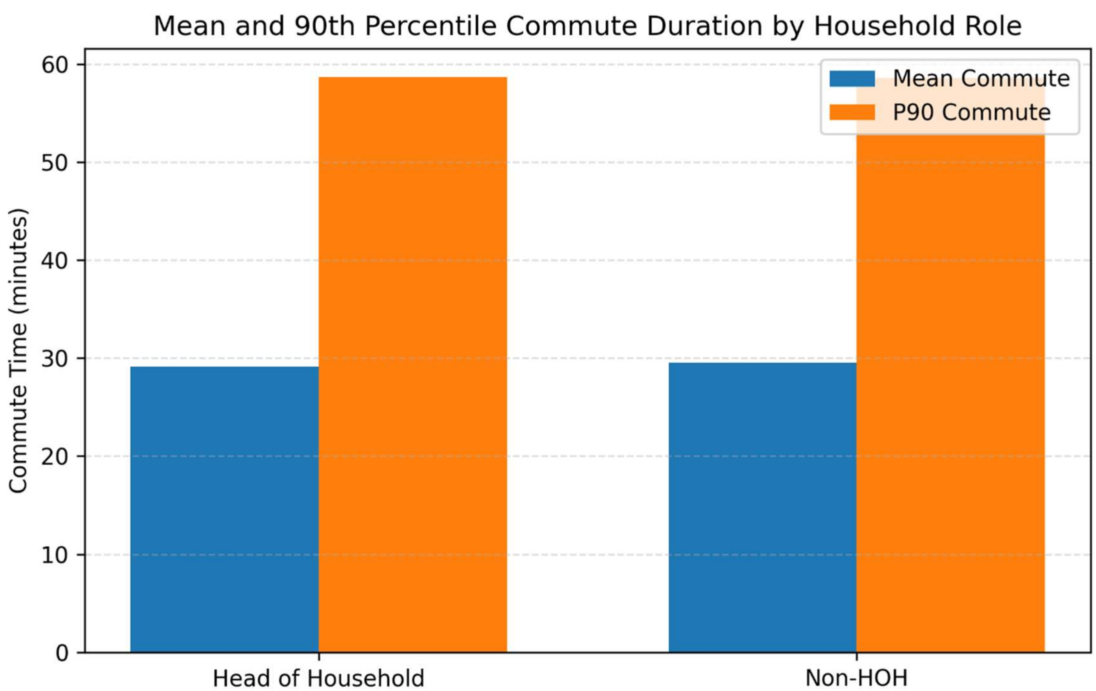

Figure 20 - Mean and 90th Percentile Commute Duration by Household Role

2.6 Discussion

The findings demonstrate that commute burdens vary systematically across worker groups, occupations, income levels, housing characteristics, and regional geographies. Among the 2,310 sampled workers residing within the seven-county Southern California study region, 353 workers (15.3 percent) had workplace ZIP codes outside the study region. These observations demonstrate that a nontrivial share of sampled residents commute to employment locations beyond the study boundary. Because destination employment and accessibility measures were constructed within the seven-county regional framework, analyses requiring in-region workplace attributes were restricted to workers whose residential and workplace ZIP codes were both represented within the study region. The resulting sample of 1,957 workers provides a consistent basis for analyses requiring both residential and workplace attributes within the regional framework.

Importantly, the analysis demonstrates that average commute durations alone obscure substantial inequality in exposure to extreme commuting conditions. Across nearly every demographic and occupational category, upper-tail commute burdens, measured through 90th percentile commute durations and threshold-based indicators of commutes at or above 45, 60, and 75 minutes, reveal sharper disparities than mean commute times alone. This distinction is particularly important in highly congested metropolitan regions where transportation stress, schedule unreliability, and cumulative time burdens may disproportionately affect certain workers despite only modest differences in average commute duration.

The observed patterns therefore motivate the behavioral and policy-focused analyses developed in Studies 2 and 3, which examine how residential location decisions and housing interventions may alter accessibility outcomes and regional commuting patterns.

2.6.1 Structural Constraints and Their Role in Commute Burdens

The spatial patterns documented throughout this chapter are consistent with structural land-use and housing-supply constraints within major Southern California employment centers. Areas such as Irvine, coastal San Diego, Downtown Los Angeles, West Los Angeles, and portions of Orange County exhibit high concentrations of employment opportunities alongside comparatively constrained housing availability. Prior research has identified zoning restrictions, density limitations, parking requirements, environmental constraints, industrial land preservation policies, and lengthy housing entitlement processes as mechanisms that can constrain residential supply near major employment hubs (Mitra & Saphores, 2019).

As a result, employment growth and housing growth have become increasingly spatially decoupled across the region. Jobs remain concentrated within a relatively small number of high-accessibility centers, while housing production has expanded more rapidly in suburban and exurban communities where land costs and regulatory barriers are comparatively lower. This spatial imbalance may require some workers, particularly those facing housing affordability constraints, to trade residential proximity for housing affordability and may thereby contribute to longer commuting patterns.

The accessibility maps developed in this chapter illustrate these dynamics clearly. Professional employment opportunities are heavily concentrated within coastal and central employment centers, whereas essential employment opportunities are more geographically dispersed but often remain disconnected from affordable housing supply. Workers located farther from major job centers consequently experience substantially lower gravity-weighted accessibility and greater exposure to long commute durations.

These findings suggest that commute burdens are fundamentally linked to regional land-use governance and housing-market structure. Transportation investments alone may therefore be insufficient to substantially reduce commute burdens unless accompanied by policies that address housing availability near employment concentrations. Likewise, housing policies that fail to consider regional employment accessibility may inadvertently reinforce long-distance commuting patterns.

More broadly, the findings demonstrate the need for integrated modeling approaches capable of capturing the interaction between residential location choice, employment geography, transportation conditions, and housing affordability. This motivates the behavioral modeling framework introduced in Study 2 and the policy simulation framework developed in Study 3.

2.6.2 Worker Stress Zones (WSZs)

The WSZ framework introduced in this dissertation integrates commute burden stress, housing affordability stress, and employment accessibility stress into a unified spatial indicator intended to identify regions where structural housing and transportation constraints disproportionately burden different worker groups. This framework therefore provides a transparent and policy-relevant mechanism for identifying communities where workers may face overlapping transportation and housing disadvantages. Rather than functioning solely as a descriptive metric, WSZs are intended to support future policy analysis, regional planning evaluation, and simulation-based intervention testing in Studies 2 and 3.

Importantly, the framework also highlights the multidimensional nature of commute burden. Long commute durations alone do not necessarily indicate transportation disadvantage unless considered alongside affordability, accessibility, occupational constraints, and labor-market structure. By integrating these dimensions, the WSZ framework offers a more comprehensive representation of transportation stress within constrained metropolitan housing markets.

2.6.3 Summary of Key Findings

This section highlights several of the study's key findings. First, long-distance commuting is not confined to low-income households. In many cases, the longest average commute durations are observed among higher-income workers and homeowners, reflecting trade-offs between commute distance, homeownership opportunities, housing quality, neighborhood amenities, and access to specialized employment markets.

Second, essential workers experience disproportionate exposure to extreme commute durations despite only modest differences in average commute times. This pattern reflects the spatial mismatch between affordable housing supply and geographically dispersed essential employment opportunities requiring physical workplace presence.

Third, occupational differences in commute burden are substantial. Workers in construction, transportation, logistics, science and engineering, and several technical occupations experience commute durations significantly above the regional average, highlighting the role of occupational geography in shaping accessibility outcomes.

Fourth, housing characteristics strongly influence commute burden. Workers residing in single-family detached housing and owner-occupied units consistently exhibit longer commute durations than workers in multifamily housing and rental units, reflecting suburban residential patterns and the regional geography of housing affordability.

Fifth, gender-based disparities persist across both average and upper-tail commute durations. Male workers experience longer average commutes and greater exposure to extreme commuting conditions, likely reflecting occupational segmentation and differences in labor-market geography.

Finally, the accessibility analysis demonstrates that job opportunities remain highly concentrated within a limited number of regional employment centers while many residential areas exhibit substantially lower accessibility to professional and high-opportunity employment. These accessibility disparities reinforce the importance of considering housing, transportation, and labor-market systems jointly rather than independently.

Together, these findings demonstrate that commute burden in Southern California is fundamentally shaped by the interaction between land-use regulation, housing affordability, regional accessibility, and employment concentration. The results therefore provide a strong empirical foundation for the behavioral residential location modeling developed in Study 2 and the policy simulation analyses conducted in Study 3.

2.7 Conclusion

This chapter presented a comprehensive empirical analysis of commute burden and regional job accessibility across Southern California using worker-level observations from the CHTS, ZIP-level employment estimates derived from LEHD LODES WAC data, and congestion-adjusted travel times obtained from Google Maps. The analysis demonstrated that commute burdens vary substantially across worker groups, occupations, income levels, housing characteristics, gender categories, and regional geographies.

The gravity-based accessibility analysis revealed substantial spatial inequality in access to employment opportunities throughout the region. Professional employment accessibility is highly concentrated within coastal and central employment hubs, while essential employment opportunities are more geographically dispersed yet frequently disconnected from affordable housing supply. Workers located farther from major employment centers consequently experience lower accessibility and greater exposure to long commute durations.

The results further showed that upper-tail commute burdens provide critical insight beyond mean commute durations alone. Threshold-based indicators and 90th percentile commute measures revealed pronounced disparities across occupations, income groups, and demographic categories that are not fully captured through average commute metrics. The chapter also introduced the WSZ framework as a spatially integrated approach for identifying communities experiencing overlapping housing, transportation, and job access pressures.

Overall, the findings from Study 1 establish a detailed descriptive foundation for the remainder of this dissertation. The observed spatial and demographic patterns motivate the behavioral residential location modeling developed in Study 2 and the policy simulation analyses implemented in Study 3. Together, these subsequent studies build upon the empirical evidence presented here to evaluate how housing and transportation policies may influence residential sorting, regional accessibility, and long-distance commuting outcomes in Southern California.

Chapter 3 - Study 2: Joint Residence-and-Work Location Choice Estimation

3.1 Overview

This study develops and estimates a joint residence and work location choice model for Southern California using discrete choice methods grounded in random utility theory. The model represents each worker's selection from a set of residence-workplace combinations and evaluates how housing costs, commuting time, housing capacity, workplace earnings, and occupational compatibility influence the relative attractiveness of those alternatives.

The term *joint* refers to the structure of the alternatives included in the model. Each alternative represents a pair of residential and workplace ZIP codes. The model therefore evaluates how residential and employment attributes, as well as commute attributes between the residence and employment locations, operate together within a single-worker-level location choice framework. The model framework does not represent coordinated decision making among multiple household members.

The analysis uses worker records from the California Household Travel Survey and is limited to workers with relevant residence and employment information within the seven-county Southern California study region. ZIP code level housing, employment, transportation, and accessibility variables are merged with the worker records to construct the residence and work location alternatives. These variables include housing price, housing capacity, commute time, workplace earnings, and occupational employment composition.

The model is estimated using a sampled choice set framework. For each worker, the observed residence-workplace combination is retained, and additional alternatives are sampled from empirically observed ZIP-to-ZIP combinations in the CHTS within the regional commuting network. This approach creates a behaviorally plausible choice set for each traveler for model estimation purposes while maintaining computational tractability. It also avoids presenting geographically unrealistic combinations that are not represented in the observed regional residence and work network.

Housing is represented in the estimated model through two observed attributes rather than through an explicit development or zoning constraint. Housing price reflects current market conditions while the housing capacity variable represents the number of existing housing units available within the ZIP code. The estimation model does not prevent workers from selecting alternatives after a fixed number of housing units has been reached, nor does it model construction, parcel availability, or zoning processes.

By estimating residence and workplace choices jointly, the study captures how structural housing conditions, employment geography, and transportation shape the set of residence-work combinations available and attractive to workers, particularly professional and essential workers facing high housing costs and substantial commuting burdens.

3.1.1 Research Questions

To investigate how housing costs, accessibility, and labor market factors jointly shape residence–work location decisions, this research addresses the following research questions:

1. How do housing costs, commuting time, employment accessibility, and residential characteristics influence workers' joint residence–work location choices in Southern California?
2. How do these location-choice trade-offs vary across workers with different income levels and occupational characteristics?
3. How sensitive are workers' joint residence–work location choices to changes in housing costs, commuting time, and employment accessibility?

These research questions are addressed through estimation and interpretation of model coefficients (e.g., housing cost, commute time, accessibility), as well as comparison of parameter magnitudes and implied behavioral elasticities.

3.2 Background and Literature Review

Understanding how households choose where to live and where to work is central to explaining commuting patterns, housing demand, labor market matching, and spatial inequality. Although residential and workplace location decisions have traditionally been modeled separately, a growing body of research suggests that these decisions are fundamentally interdependent through interactions among housing markets, commuting costs, neighborhood characteristics, and employment opportunities (Ioannides & Zabel, 2002; Pagliara et al., 2010; Gimenez-Nadal et al., 2025). Workers do not choose housing independently of employment opportunities, nor do they choose jobs without regard to housing costs, commuting burdens, and neighborhood conditions. This study builds on that literature by estimating a joint residence–work location choice model for Southern California using a multinomial logit framework with sampled alternatives. The review is organized around five themes: random utility theory and discrete choice foundations, residential location choice, commuting and workplace trade-offs, joint residence–work modeling, and estimation with large choice sets.

3.2.1 Random Utility Theory and Discrete Choice Foundations

Modern location choice modeling is grounded in random utility theory, in which decision-makers select the alternative that yields the highest utility, with utility composed of a systematic component based on observed attributes and a stochastic component capturing unobserved influences. This framework underlies the family of discrete choice models used widely in transportation, housing, and land-use research (Train, 2009). Train’s synthesis of logit, nested logit, mixed logit, and simulation-based estimation remains the most relevant methodological foundation for this study, while Greene provides the broader econometric basis for specifying, identifying, and estimating discrete choice models (Greene, 2008).

Within this framework, the multinomial logit model is especially useful when the analyst faces a very large set of alternatives and requires an interpretable closed-form probability expression. Its tractability makes it attractive for large-scale joint location problems, even though the independence of irrelevant alternatives property can be restrictive in some settings. In the present application, the multinomial logit model is adopted not because it is the most flexible member of the discrete choice family, but because it provides a transparent and computationally feasible basis for estimating preferences over thousands of residence–work combinations while preserving a strong behavioral interpretation of coefficients as marginal utilities.

3.2.2 Residence Location Choice Models

Residential location choice models explain where households choose to live as a function of housing costs, dwelling characteristics, neighborhood quality, accessibility, and household attributes. This literature extends classic urban economic insights on bid-rent and accessibility into empirical discrete choice settings in which researchers can estimate the relative importance of price, amenities, and travel costs. Pagliara and Wilson (2010) provide a broad overview of residential location modeling traditions, while Ioannides and Zabel demonstrate the importance of neighborhood selection and endogenous sorting in housing demand (Ioannides & Zabel, 2002). Waddell's work further advances this literature by embedding residential choice in a behavioral, disaggregate land-use framework (Waddell, Ulfarsson, Franklin, & Lobb, 2007).

A consistent limitation of many residence location models, however, is that workplace location is treated as fixed or exogenous. Accessibility is typically represented as a summary measure of reachable jobs rather than as the outcome of an explicit joint home–work decision. As a result, traditional residence models can understate the extent to which households trade off a specific residence against a specific workplace. This limitation is especially important in Southern California, where high housing costs, polycentric employment geography, and long commute times constrain feasible residential options for many workers (Train, 2009).

3.2.3 Commuting Trade-offs and Workplace Considerations

Urban economic theory suggests that households balance commuting costs against housing consumption, wages, and neighborhood amenities within a utility-maximization framework. Accordingly, commuting impedance has long been recognized as a central determinant of residential location choice. Across a wide range of residential location models, empirical evidence consistently demonstrates that longer commute times and distances reduce the attractiveness of residential alternatives, although the magnitude of this effect varies across income groups, occupations, household structures, and regional contexts (Prashker et al., 2008; Schirmer et al., 2014; Pagliara and Wilson, 2010).

For the present study, two empirical contributions are particularly relevant. Prashker et al. (2008) demonstrate that commute distance is a significant determinant of residential locations decisions, providing direct support for including commute impedance within the utility specification estimated in this dissertation. Similarly, Islam and Saphores (2022) show that housing costs, land use patterns, and workplace-area characteristics jointly influence commuting distance and time in Los Angeles County, even after accounting for residential self-selection and automobile use. Their findings provide regional empirical support that housing affordability and employment accessibility interact to shape commuting outcomes rather than operating as independent influences.

Together, these studies reinforce the behavioral premise underlying the joint-residence-work location model developed in this dissertation, that workers evaluate residential alternatives by simultaneously considering housing costs, commuting burden, and access to employment opportunities rather than optimizing any single factor.

3.2.4 Joint Residence-Work Location Choice

Joint residence–work location models represent the household as choosing a pair of locations rather than making a one-sided residential decision with job location held fixed. This approach is more behaviorally realistic because it captures the fact that housing costs, neighborhood amenities, workplace opportunity, and commuting impedance are evaluated together. Waddell's land-use modeling framework and the broader equilibrium sorting literature show how individual location choices aggregate into spatial sorting patterns and, ultimately, into policy-relevant changes in housing demand and accessibility. Klaiber and Kuminoff are particularly important here because they explicitly connect heterogeneous residential preferences, housing prices, amenities, and equilibrium adjustment, thereby providing a conceptual bridge between the behavioral estimation and subsequent policy simulations (Klaiber & Kuminoff, 2012).

Recent work also supports the view that residential and workplace decisions are linked at the household level. Giménez-Nadal and coauthors show that commuting outcomes are tied to job changes and relocation decisions, reinforcing the argument that home and work should not be treated as fully independent domains (Gimenez-Nadal, Molina, & Velilla, 2026). Together, these studies justify estimating a joint residence–work location model for Southern California rather than relying on a conventional residence-only framework.

3.2.5 Housing Constraints, Sorting, and System Context

A joint residence-work location model is particularly well suited for studying regions where housing supply constraints and employment concentration jointly influence feasible residential and workplace choices. Baum-Snow and Duranton (2025) emphasize the role of housing supply restrictions and affordability dynamics in shaping spatial equilibrium, while Martin (1997) provides a classic equilibrium treatment of spatial mismatch and accessibility. Conway (2021) further demonstrates how zoning, residential sorting, and travel behavior are linked within an integrated modeling framework.

Collectively, these studies suggest that commuting outcomes emerge from interactions among housing supply, land-use regulation, and employment geography rather than from household preferences alone.

This perspective is central to my dissertation. In Southern California, job-rich areas frequently coincide with strong housing supply constraints, meaning that observed commuting patterns reflect both household preferences and structural limits on feasible residence locations. The joint model estimated in this chapter is designed to recover those trade-offs behaviorally rather than treat them as purely descriptive outcomes.

3.2.6 Large Choice Sets, Data Strategy, and Estimation Feasibility

A major practical challenge in joint residence–work modeling is the size of the feasible choice set. When workers may choose between hundreds of residential locations and hundreds of workplace locations, the number of possible residence-work combinations becomes prohibitively large for direct set estimation. A standard solution in discrete choice modeling is to estimate the model using a sampled subset of alternatives while always retaining the observed (chosen) alternative. Under appropriate sampling corrections, sampled-alternative estimation produces consistent parameter estimates while substantially reducing computational burden (McFadden, 1978; Train, 2009). The sampled alternative approach adopted in this dissertation follows this established framework.

Because detailed household-level information is rarely available for every potentially relevant residential alternative, residential choice models frequently combine individual survey data with spatially aggregated contextual variables describing housing markets, neighborhood conditions, and employment opportunities. Adjemian and Williams (2009) demonstrate that aggregate census measures can serve as reasonable proxies for otherwise unavailable household-level variables in discrete choice settings. Consistent with this approach, this study combines worker-level observations from the CHTS (2016) with ZIP-level housing, accessibility, and employment characteristics to construct the explanatory variables used in model estimation.

Finally, residential location preferences are known to vary systematically across households and worker groups rather than following a single set of homogeneous preferences. Allowing utility parameters to vary through interaction terms enables the model to capture observed behavioral heterogeneity while maintaining a tractable estimation framework (Train, 2009). Accordingly, this study incorporates interactions between worker characteristics and selected residential and workplace attributes to examine how location preferences differ across occupations and income groups.

3.2.7 Implications for This Study

This study builds on the literature by estimating a joint residence–work location choice model using a multinomial logit specification with sampled alternatives. The model defines each residence–work pair as an integrated alternative and estimates the trade-offs households make among housing costs, neighborhood conditions, workplace opportunity, job accessibility, and commuting impedance.

The primary methodological contribution of this chapter is the estimation of a joint residence-work location choice model that explicitly evaluates residential and workplace decisions within the context of Southern California's constrained housing market. The estimated behavioral parameters quantify how workers trade off housing costs, commuting time, accessibility, and employment opportunities, providing the empirical foundation for the policy simulations developed later in the dissertation.

Literature Review Table for Chapter 3 - Study 2			
Author(s)	**Title**	**Core Contribution**	**Methods / Models**
Train (2009)	*Discrete Choice Models with Simulation*	Establishes the theoretical and econometric foundation for modeling individual choice behavior under uncertainty and preference heterogeneity	Random Utility Models (Logit, Mixed Logit, Simulation-Based Estimation)
Greene, W. H. (2008)	*Discrete Choice Modeling*	Provides full econometric foundation for discrete choice models	Random Utility Models, MLE, logit/probit
Klaiber & Kuminoff (2012)	*Equilibrium Sorting Models of Land Use and Residential Choice*	Residential location choices reflect heterogeneous preferences & jointly determine housing prices & spatial distribution of amenities; enables simulation of policy impacts under general equilibrium and links housing supply constraints to price formation	Equilibrium Sorting Models (RUM + Pure Characteristics Models)
Ioannides, Y. M., & Zabel, J. E. (2002)	*Interactions, Neighborhood Selection and Housing Demand*	Demonstrates importance of modeling neighborhood choice and endogenous sorting	Discrete choice + housing demand model
Pagliara, F., & Wilson, A. (2010)	*The State-of-the-Art in Building Residential Location Models*	Comprehensive review of residential location choice models, behavioral assumptions, and methodological developments	Logit models, spatial interaction, microsimulation, equilibrium models
Waddell, P., Ulfarsson, G. F., Franklin, J. P., & Lobb, J. (2007)	*Incorporating land use in metropolitan transportation planning*	Demonstrates feedback loop between transportation and land use	UrbanSim + travel demand model integration
Waddell, P. (2002)	*UrbanSim: Modeling Urban Development for Land Use, Transportation, and Environmental Planning*	Introduces UrbanSim as a behavioral, disaggregate land-use model	Random utility models, microsimulation
Prashker, J., Shiftan, Y., & Hershkovitch-Sarusi, P. (2008)	*Residential choice location, gender and the commute trip to work in Tel Aviv*	Shows commute distance significantly influences residential choice	Logit model

Islam & Saphores (2022)	*Impact of housing costs on commuting (LA)*	Empirically links housing costs → longer commutes	Generalized Structural Equation Model (GSEM)
Giménez-Nadal, J. I., Molina, J. A., & Velilla, J. (2025)	*Household commuting time and job changes*	Shows commuting decisions are joint household decisions influenced by job and relocation changes	Panel data (PSID), longitudinal analysis
Conway (2021)	*If You Zone It, Who Will Come, and How Will They Travel?*	Links zoning changes → residential sorting → travel behavior	Equilibrium sorting model + microsimulation + activity-based model
Baum-Snow & Duranton (2025)	*Housing Supply and Housing Affordability*	Explains structural housing supply constraints and spatial equilibrium dynamics	General equilibrium, housing production models
Martin (1997)	*Job Decentralization with Suburban Housing Discrimination: An Urban Equilibrium Model of Spatial Mismatch*	Theoretical model of job accessibility and spatial mismatch	Monocentric + equilibrium model
Adjemian & Williams (2009)	*Using census aggregates to proxy for household characteristics: an application to vehicle ownership*	Uses aggregates as proxies for missing household data; validates proxy variables --> micro-level variables	Justifies data fusion approach
Schirmer et al. (2014)	*A role of location in residential location choice models: a review of literature*	Housing price is an important determinant & captures multiple location characteristics	Validates the reduced-form, constraint-based representation of housing supply
Vasanen (2012)	*Beyond stated and revealed preferences: the relationship between residential preferences and housing choices in the urban region of Turku, Finland*	Urban structure and limited new construction mean that housing supply cannot fully adjust to preferences, creating mismatch	Shows that housing supply is slow to change and largely fixed in the short run
Bayer et al. (2004)	*An equilibrium model of sorting in an urban housing market*	Housing supply implicitly captured through prices, not explicitly modeled	Housing markets operate through: fixed housing supply & price adjustments

Balbontin et al. (2015)	*A joint best-worst scaling and stated choice model considering observed and unobserved heterogeneity: An application to residential location choice*	Improves estimation of preferences and heterogeneity in residential choice	Mixed logit + stated choice + best-worst scaling

Table 17 - Principal literature informing the Study 2 modeling framework

Table 17 summarizes the principal literature informing the Study 2 modeling framework, highlighting each study's primary methodological contribution, modeling approach, and relevance to the proposed joint residence-work location model.

3.3 Data and Variables Construction

This section describes the data sources, variable construction, and preprocessing procedures used to estimate the joint residence–work location choice model. The modeling framework integrates individual-level microdata with spatially aggregated ZIP-level attributes and ZIP-to-ZIP commuting impedance measures to construct alternative-specific utility components. ZIP codes are used as the primary spatial analysis unit because they provide a tractable balance between behavioral spatial variation, computational feasibility, and compatibility across multiple regional datasets.

3.3.1 Data Sources

This study integrates multiple datasets spanning transportation behavior, labor markets, housing conditions, and neighborhood characteristics to construct residential and employment attributes for each ZIP-level alternative. Table 18 summarizes the primary data sources, spatial resolution, key variables, and their role in the modeling framework.

Data Source Table				
Data Category	**Source**	**Spatial Level**	**Primary Variables**	**Primary Role**
Travel Behavior	California Household Travel Survey (CHTS), accessed through the Transportation Secure Data Center (TSDC), National Renewable Energy Laboratory (2016): www.nrel.gov/tsdc	Individual worker / trip	Residence ZIP, Workplace ZIP, worker characteristics	Worker observations, residence/workplace choices
Commute Times	Google Maps API KEY	ZIP	AM Peak Hour Travel Times	Construction of ZIP-to-ZIP travel impedance matrix
Job Marketplace Attractiveness	LEHD Workplace Area Characteristics (WAC): lehd.ces.census.gov/data	ZIP-level proxy (derived from regional data)	Industry-specific employment opportunities near job hubs	Work location attractiveness
Job Accessibility	Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LEHD/LODES): lehd.ces.census.gov/data/	ZIP	Job density near home opportunities	Accessibility measures
Geography	Topologically Integrated Geographic Encoding & Referencing (TIGER): www.huduser.gov; ZIP Code Tabulation Area (ZCTA): census.gov/programs-surveys/geography/	ZIP	Boundaries, spatial joins; tract-to-Zip Crosswalk	Spatial joins
Housing	Zillow (ZHVI + Listings): www.zillow.com/research/data; American Community Survey (ACS) Data: https://www.census.gov/programs-surveys/acs/data.html	ZIP	Home values, Housing Capacity	Residential cost variables
Environmental	Public Access Points from California Coastal Commission	ZIP / Distance	Coastal proximity	Amenity proxy
Crime	FBI Crime Data Explorer National Incident-Based Reporting System (NIBRS): cde.ucr.cjis.gov	Local (aggregated to ZIP)	Crime rates	Neighborhood quality; not retained in final preferred specification
Transit	GTFS Data: https://www.transit.land	Stop / ZIP aggregated	Transit access metrics	Accessibility; not retained in final preferred specification

Education	CA Dept. of Education: www.cde.ca.gov	School / ZIP aggregated	Test scores	Tested, not retained in final preferred specification
Wage Proxy	LEHD Workplace Area Characteristics (WAC): lehd.ces.census.gov/data	Regional / ZIP proxy	Earnings	Work utility
Spatial Distribution	Census-based centroids	ZIP	Population-weighted centroids	Travel time calculation

Table 18 – Data Source Table

The table above shows all the sources used to collect the data for this research. Observed behavior in this study reflects both measured variables and unobserved factors. Observable components include spatial and economic attributes such as housing costs, accessibility, and employment opportunities. Unobserved factors, such as individual preferences, constraints, and idiosyncratic considerations, are captured through the stochastic error term in the discrete choice framework (Train, 2009).

3.3.2 Worker Data from CHTS

Worker-level travel behavior data were obtained from the 2016 CHTS, which provides detailed demographic, residential, employment, and travel information for households across California. The survey includes observed home locations, workplace locations, trip patterns, commute behavior, socioeconomic characteristics, and household attributes suitable for discrete choice estimation. Study 2 applies eligibility and model-completeness restrictions required for joint residence-work choice estimation, resulting in a final estimation sample of 1,041 workers.

The unit of observation in the estimation dataset is an individual worker associated with an observed residence ZIP code and workplace ZIP code pair. The analysis sample was restricted to employed workers with identifiable home and workplace locations located within or connected to the Southern California study region. Workers missing key spatial or commute-related variables were excluded from estimation.

To better approximate the household member most likely responsible for residential location decisions, the estimation sample was restricted to the household reference person identified in the CHTS (2016). Throughout this dissertation, the term primary residential decision-maker refers to the CHTS household reference person, which serves as a proxy for the individual most directly associated with residential location decisions.

Observed commute behavior from the CHTS serves as the revealed preference foundation for the joint residence–work location choice model. The observed home–work combinations provide the chosen alternatives used in estimation, while sampled non-chosen residence–work pairs are constructed from the feasible ZIP-to-ZIP opportunity set. Individual worker attributes, including occupation, industry, income, and employment characteristics, are merged with ZIP-level residential and workplace attributes to construct alternative-specific utility components.

The final specification therefore emphasizes parsimonious behavioral interpretation and spatial-economic mechanisms rather than highly segmented demographic preference estimation. This approach is consistent with standard multinomial logit applications emphasizing parsimonious utility specification and computational tractability in large-scale discrete choice settings (Train, 2009; Greene, 2008). Future extensions could incorporate richer preference heterogeneity using mixed logit or latent class frameworks (Balbontin et al., 2015).

Individual worker characteristics, including occupation, industry, and household income, are incorporated into the utility specification through interaction terms where appropriate to capture observed heterogeneity in preferences while maintaining a parsimonious baseline specification.

3.3.3 Choice Set Construction

Recent research has emphasized that choice sets should represent behaviorally realistic search spaces rather than the complete universe of theoretically possible alternatives because individuals narrow feasible opportunities before making a final residential decision (Saini & Pandit, 2025).

Therefore, the objective of this model is not to estimate preferences over every theoretically possible residential-workplace combination within Southern California. Rather, the objective is to estimate preferences among behaviorally plausible residence-work configurations that realistically exist within the regional labor market. Consequently, the choice set was intentionally constructed from empirically observed residence-work ZIP pairs rather than the full Cartesian product of residential and employment ZIP codes.

Consistent with the sampling-of-alternatives literature, each worker's chosen residence-work pair was retained while the remaining alternatives were randomly sampled from the empirical residence-work network. Sampling a subset of alternatives substantially reduces computational burden while preserving consistent estimation when appropriately implemented (Dekker, Bansal, & Huo, 2025). Therefore, for each worker, the chosen alternative consists of the observed residence-work ZIP pair recorded in the CHTS. A random sample of 150 nonchosen alternatives was then drawn from an empirical residence-work network derived from all observed residence-work ZIP pairs within the study region.

The choice set for worker n is defined as:

$$C_i = \{a_i^*, a_1, a_2, \dots, a_K\}$$

Equation 7 - Choice Set Equation

Where,

- C_i denotes the sampled choice set available to worker i
- a_i^* is the observed residence-work ZIP pair for worker i
- a_K represents the sample of feasible residence-work alternative
- $K = 150$ nonchosen alternatives

The observed alternative was coded as $Chosen = 1$, while sampled alternatives were coded as $Chosen = 0$.

Although the empirical residence-work network contains only 1,990 unique O-D pairs, the pairs represent the complete observed set of feasible commuting relationships within the CHTS sample. The multinomial logit model therefore estimates preferences over realistic residential-employment opportunities rather than the much larger universe of mathematically possible ZIP combinations, the vast majority of which would never be considered by actual households. Consequently, every sampled alternative represents a feasible residence-work configuration with observed commuting impedance obtained from the Google Distance Matrix API. This eliminates the need to estimate travel times using Euclidean distance, network approximations, or synthetic routing assumptions while ensuring that all alternatives are supported by observed regional travel behavior.

Several alternative strategies for constructing choice sets were evaluated during model development. These included generating all possible residential and employment ZIP combinations, independently sampling residential and employment ZIPs before forming combinations, filtering alternatives using geographic distance or county boundaries prior to impedance estimation, and generating synthetic candidate pairs using centroid proximity. Although these approaches offered greater theoretical coverage of the alternative universe, they also introduced substantial disadvantages. Many generated residence-work combinations would be behaviorally implausible because certain ZIP codes are almost exclusively residential, industrial, military, airport, university, or commercial land uses and therefore rarely function as realistic home-work systems. Furthermore, these approaches would require estimating travel impedance for a very large number of synthetic alternatives while still requiring subsequent filtering to remove unrealistic combinations.

The adopted approach instead represents the alternative universe as an empirical residence-work network derived from observed commuter flows. Sampling from this network preserves behaviorally realistic alternatives, guarantees that every sampled alternative has consistent observed impedance measurements, substantially reduces computational requirements, and avoids estimating utilities for infeasible residence-work configurations. While this approach may exclude extremely rare or previously unobserved residence-work pairs, the resulting alternative universe more closely represents the opportunities that individuals realistically consider within the Southern California labor market. Accordingly, the model estimates preferences over feasible residential-employment opportunities rather than every mathematically possible ZIP code combination.

3.3.4 Commuting Impedance

Commuting costs are represented using ZIP-to-ZIP peak-period travel times derived from the Google Maps Distance Matrix API using ZIP code centroids. Travel times reflect congestion-adjusted conditions during the morning peak period, capturing realistic commuting conditions faced by workers across the study region. Travel times were obtained for each unique residential ZIP-employment ZIP OD pair within the study region. For workers residing and employed in the same ZIP code, travel time was assigned a minimum impedance of one minute rather than zero to reflect local travel and to avoid undefined logarithmic transformations. The travel impedance is then measured for the observed and sampled feasible alternative set.

To ensure numerical stability and consistency across observations:

- Travel times are bounded below at one minute
- Extreme values are capped at 180 minutes

These thresholds exceed the 99th percentile of observed commute durations and therefore affect only a small fraction of extreme observations. Travel times are expressed in minutes and incorporated into the model in logarithmic form.

The natural logarithm of travel time is used to capture diminishing marginal disutility of commuting, a standard assumption in travel demand and discrete choice modeling. Under this specification, an additional minute of travel imposes a larger marginal burden at shorter commute durations than at longer durations. This functional form reflects well-established behavioral evidence that individuals are more sensitive to incremental increases in travel time when baseline commute times are low, with sensitivity decreasing as commute duration increases (Train, 2009; Small & Verhoef, 2007).

Because travel time directly captures congestion conditions and network performance, it provides a behaviorally richer measure of commuting impedance than straight-line or centroid distance alone. Therefore, distance between ZIP code centroids is retained as a diagnostic variable but excluded from the final utility specification due to its near-perfect correlation with travel time ($\rho \approx 0.997$), which would otherwise introduce multicollinearity. The resulting impedance matrix captures all observed and sampled home-work ZIP alternatives used in estimation, providing a behaviorally meaningful representation of commuting impedance within the modeled choice set.

3.3.5 Variable Specification and Behavioral Interpretation

Prior to model estimation, continuous explanatory variables are transformed where necessary to improve numerical stability and support behavioral interpretation. Positively skewed measures, including commute time, housing price, housing capacity, and workplace earnings, enter the utility specification in logarithmic form. Selected transformed variables are subsequently standardized using z-scores to place variables with different scales on comparable numerical ranges. These transformations also enable the model to represent nonlinear behavioral responses, including declining marginal sensitivity as an attribute's magnitude increases (Small and Verhoef, 2024).

The sampled choice set is designed for model estimation and does not impose a binding housing capacity constraint. Housing capacity enters the utility function as an observed ZIP code attribute, while policy simulations modify this attribute to represent proportional changes in available housing. Accordingly, alternatives are not removed once a fixed number of workers selects a ZIP code, and the resulting probabilities represent expected behavioral responses rather than deterministic household assignments.

Variable Dictionary					
Variable	**Definition**	**Description**	**Original Units**	**Transformation**	**Behavioral Interpretation & Expected Sign**
β_{time}	Log Commute Time; Impedance Variable	Log of peak AM travel time between residence and workplace	Minutes	Natural log	Commuting cost / disutility; Negative
β_{price}	Log Housing Price; Home Attribute	Log of median home price per square foot (ZIP-level)	USD/SQFT	Natural Log + z-score	Residential cost; Negative
$\beta_{capacity}$	Log Housing Capacity; Home Attribute	Housing capacity per ZIP code	Units/ZIP code	Natural Log + z-score	Number of housing units; Positive
$\beta_{density}$	Residential Employment Density; Home Attribute	Total employment concentration within residential ZIPs divided by ZIP land area	Number of jobs per square mile	Natural log	Local employment concentration in residential areas; Positive
β_{jobs}	Workplace Job-Market Attractiveness ; Work Attribute	Total employment located in workplace ZIPs	Total jobs in workplace ZIP	Natural log	Scale & concentration of workplace opportunities; Positive
β_{earn}	Wage Proxy; Work Attribute	Average earnings in workplace ZIP	USD/ month	Natural log	Workplace attribute; Job attractiveness; Positive
$\beta_{inc,TT}$	Income x Log Commute Time Interaction; Heterogeneity	Interaction between standardized household income and logarithm of commuting time	Income Interactio n Term	$Income_z \; x \; ln(TT)$	Allows commute time sensitivity to very with income; Potentially Positive
$\beta_{affordability}$	Housing Affordability Burden; Home Attribute	Annualized modeled housing cost divided by estimated annual income	Ratio / relative housing cost burden	$\frac{AnnualizedHousing}{AnnualHouseholdIn}$	Residential cost constraint; greater burden reduces residential utility; expected negative

β_{Prof}	Professional Worker Interaction Term; Heterogeneity	Interaction between professional worker indicator and workplace professional job share	Interactio n Term	Binary x Share	Workplace Interaction Term - based sorting mechanisms; Positive
β_{ess}	Essential Worker Interaction Term; Heterogeneity	Interaction between essential worker indicator and essential worker/service job share	Interactio n Term	Binary x Share	Workplace Interaction Term - based sorting mechanisms Positive
$\beta_{transit}$	Transit Accessibility; Home Attribute	Density of transit stops (ZIP-level)	Transit stop density per square mile	Natural Log + z-score	Residential Attribute; Transit accessibility / reduced automobile dependence; Positive
β_{scho}	School Ratings; Home Attribute	Composite ZIP-level educational quality index	Composit e standardiz ed school quality index by ZIP code	Z-score	Residential Attribute; Neighborhood educational quality / residential amenities; Positive
β_{crime}	Crime Rates; Home Attribute	ZIP level crime rates derived from city-wide incident data	Crimes per 100,00 residents	Natural Log + z-score	Residential Attribute; Neighborhood safety / residential disamenity; Negative
$\beta_{coastal}$	Coastal Proximity; Home Attribute	Distance from ZIP code population-weighted centroid to nearest public coastal access point	Miles	z-score (log (distance + 0.1))	Residential Attribute; Access to coastal amenities / environmental attractiveness; Negative (as greater distance reduces residential attractiveness

Table 19 – Variable Dictionary

The explanatory variables included in the joint residence–work location choice model and shown in Table 19 above, are intended to represent the multidimensional trade-offs households face when balancing commuting burdens, housing market conditions, workplace accessibility, occupation groups, and neighborhood amenities.

Commuting Costs Variable

The commuting-time coefficient (β_{time}) measures the effect of logged peak-period travel time on systematic utility. A negative coefficient indicates that longer commute times reduce the attractiveness of a residence-workplace alternative. Because commute time enters the utility function logarithmically, a proportional increase in travel time has a larger absolute effect when the initial commute is shorter than when it is already long, reflecting diminishing marginal sensitivity to additional travel time (Train, 2009; Prashker et al., 2008).

Housing Market Variables

The housing price coefficient (β_{price}) measures the marginal disutility associated with housing costs and reflects the affordability constraints faced by households. Higher housing prices are expected to reduce the likelihood that a worker selects a residential location, consistent with standard residential location theory (Pagliara et al., 2010; Klaiber & Kuminoff, 2012). Consistent with recent research describing limitations in available housing supply data, including inconsistent coverage across permitting, census, and parcel-level sources (Marantz, 2026), this study does not rely on a single direct measure of housing-market constraints. Instead, housing-market conditions are represented through two complementary variables: observed housing prices, which reflect the interaction of housing demand, available supply, and other local market conditions (Bayer et al., 2004; Schirmer et al., 2014), and ZIP-level housing capacity, measured using ACS housing-unit counts.

These variables do not impose an explicit capacity constraint on the estimation choice set. Rather, they represent differences in housing costs and the relative availability of residential opportunities across ZIP codes. This approach provides a reduced-form representation of housing-market conditions at the spatial scale of the analysis while avoiding assumptions about parcel-level construction, vacancy, turnover, or the exact number of units available to individual workers.

The housing-capacity coefficient $\left(\beta_{capacity}\right)$represents the relationship between available residential capacity and the attractiveness of a residential ZIP code. The variable is constructed from ACS housing-unit counts, transformed using $\ln(H_h + 1)$, and standardized before estimation. Therefore, its coefficient represents the change in systematic utility associated with a one-standard-deviation increase in logged ZIP-level housing capacity, holding commute time, housing price, workplace characteristics, occupational matching, and other included variables constant. A positive coefficient indicates that workers are more likely to select residence-workplace alternatives involving ZIP codes with greater housing availability.

Job Related Variables

Workplace employment attractiveness is represented using two complementary variables: workplace employment density (β_{jobs}) and workplace wage proxy (β_{earn}). Workplace employment density measures the scale of employment opportunities available within the workplace ZIP code, while the wage proxy reflects differences in average earning across employment centers. Together these variables capture both the size and economic attractiveness of potential workplace destinations.

Income Interaction

Household income is reported categorically in the CHTS and converted to approximate annual income using the midpoint of each reported income category. The open-ended category of $250,000 or more is assigned a representative value of $275,000. Responses coded as “do not know” or “refused” remain missing. The resulting annual-income measure is standardized before estimation and interacted with selected residential attributes.

The final specification retains an income interaction with commute time to evaluate whether commuting sensitivity varies systematically across the income distribution. The conditional effect is formulated as:

$$\beta_{time|income} = \beta_{time} + \beta_{inc,time} Income_z$$

A positive interaction coefficient indicates that the corresponding effect becomes more positive, or less negative, as standardized income increases. In the final model, this means that higher-income workers exhibit less disutility from longer commute times than lower-income workers.

Occupational Matching Variables

The occupational matching variables (β_{prof} and β_{ess}) are interaction terms between each worker's occupational classification and the occupational composition of the workplace ZIP code. For worker i and workplace ZIP code w, the professional matching variable is defined as:

$$Prof_i \times ProfShare_w$$

and the essential matching variable is defined as:

$$Ess_i \times EssShare_w$$

where $Prof_i$ and Ess_i are binary indicators of worker type, and $ProfShare_w$ and $EssShare_w$ represent the corresponding employment shares in workplace ZIP code w.

These interactions allow workplace attractiveness to vary with occupational compatibility. A positive coefficient indicates that workers derive greater utility from workplace ZIP codes containing a larger share of employment aligned with their occupational group. The variables therefore represent occupation-specific spatial sorting rather than general employment density alone.

Residential Amenity Variable

Several residential and accessibility attributes were evaluated during model development, including transit accessibility, school quality, crime, and coastal proximity. Although these variables represent theoretically relevant components of residential attractiveness, they were not retained in the preferred final specification because their effects were statistically weak, unstable across specifications, or difficult to distinguish from broader urban density and housing-market conditions. Their construction is documented here for methodological transparency.

The residential employment density variable (β_{dens}) captures the concentration of employment surrounding each residential ZIP code. Unlike the gravity-based accessibility measure developed in Study 1, which measures cumulative access to employment opportunities throughout the region, residential employment density measures the intensity of local employment surrounding a residential location. Higher residential employment density is expected to increase residential attractiveness by locating households closer to concentrations of employment opportunities and the services, businesses, and economic activity typically associated with major employment centers.

Transit accessibility ($\beta_{transit}$) is intended to represent the contribution of local transportation infrastructure to residential attractiveness, reflecting the role of transit availability in shaping location preferences. Transit accessibility is measured using General Transit Feed Specification (GTFS) data obtained from regional transit agencies across the seven-county Southern California study area. Transit supply indicators are constructed by aggregating stop- and service-level data to the ZIP code level. For each ZIP Code Tabulation Area (ZCTA), transit availability is proxied using measures such as the number of transit stops, stop density (stops per square mile), and, where available, service frequency indicators. These measures are intended to measure both the spatial availability and intensity of transit service within each ZIP code. Transit accessibility was evaluated as a residential attribute using GTFS data obtained from regional transit agencies across the seven-county study area. Higher levels of transit supply are expected to increase the attractiveness of residential locations by improving access to employment opportunities and reducing reliance on private vehicle travel.

The school quality variable (β_{scho}) is measured using data from the California Assessment of Student Performance and Progress (CAASPP), including both CAST and SBAC standardized test scores.

School-level performance metrics are aggregated to the ZIP code level using student population weights. For each ZIP code, a composite school quality index is constructed as a weighted average of subject-specific proficiency measures. This index provides a summary measure of local educational quality and was evaluated as an amenity-based variable in the residential utility specification.

The crime rating variable (β_{crime}) was sourced from the FBI National Incident-Based Reporting System (NIBRS) and aggregated to the city–year level. To align crime measures with ZIP-based modeling, a spatial allocation procedure is implemented to translate city-level crime rates to ZIP codes. ZIP–city crosswalks are constructed using TIGER/Line shapefiles, and spatial intersections are used to compute area and population shares of each ZIP within city boundaries. Crime counts are allocated proportionally based on population-weighted shares, and ZIP-level crime rates are computed per 100,000 residents. Final crime measures include violent, property, and total crime rates, which are standardized within the study region and evaluated as neighborhood quality indicators in the residential location model.

The coastal proximity variable ($\beta_{coastal}$) captures access to coastal amenities, a distance-based measure is constructed using the geographic location of public beach access points obtained from the California Coastal Commission. For each ZCTA, the distance from the population-weighted centroid to the nearest beach access point is calculated using straight-line (Euclidean) distance. Because the marginal utility of proximity to coastal amenities is expected to diminish with distance, both raw and transformed measures are used. The primary specification applies a logarithmic transformation of distance, defined as $\log(\text{distance} + 0.1)$, to reduce skewness and improve interpretability within the discrete choice framework. This transformation allows coefficients to be interpreted as proportional changes in utility with respect to distance.

Housing Affordability

Housing affordability is represented using an affordability-burden measure that relates residential housing costs to the economic resources of the worker or household. Unlike housing price alone, which measures the market cost associated with a residential ZIP code, the affordability measure captures the extent to which that cost represents a constraint for a particular decision-maker. Higher affordability burden therefore represents less favorable housing conditions and is expected to reduce residential utility. This formulation allows workers facing the same residential housing price to experience different effective housing constraints depending on their economic circumstances. The measure is particularly important for the policy simulations developed in Study 3, where employer-sponsored housing subsidies are represented as reductions in the housing-cost burden associated with eligible residence–work alternatives while the estimated preference parameters remain fixed.

Together, these components define a joint utility structure in which individuals balance housing costs, amenities, commuting burdens, labor market opportunities, and accessibility when selecting residence–workplace combinations. The estimated coefficients therefore provide behavioral measures of trade-offs that can be used to interpret observed location patterns and inform policy simulations.

3.4 Methodology

This study estimates a joint residence–work location choice model to examine how households simultaneously select residential and employment locations under housing market constraints and commuting trade-offs. The modeling framework follows a random utility maximization (RUM) approach widely used in discrete choice analysis and urban economics (Train, 2009; Greene, 2008).

The methodological framework proceeds in four stages. First, a conceptual joint utility function is defined to represent the combined evaluation of residential attractiveness, workplace opportunities, and commuting costs. Second, a finite set of feasible residence–work location alternatives are constructed using observed geographic and labor market data. Third, a multinomial logit (MNL) model is estimated using a sampled choice set to reveal behavioral parameters governing location preferences. Finally, the estimated coefficients are used to derive behavioral measures, including willingness to pay and elasticities, which serve as inputs for future policy simulations. This structure aligns with prior work on joint residential–work location choice and integrated land use–transport modeling (Waddell, 2002; Klaiber & Kuminoff, 2012), while maintaining computational tractability for large choice sets.

3.4.1 Conceptual Joint Utility Equations

Throughout the following utility equations, i indexes individuals, h indexes residential locations (home ZIP codes), and w indexes workplace locations (employment ZIP codes). Individuals are assumed to select the residence–work location pair (h, w) that maximizes utility from a finite set of feasible alternatives following the standard random utility framework:

$$U_{i,h,w} = V_{i,h,w} + \epsilon_{i,h,w}$$

Equation 8 - Random Utility Framework

Where $U_{i,h,w}$ represents the utility, $V_{i,h,w}$represents the deterministic component of utility, and $\epsilon_{i,h,w}$ is an independently and identically distributed extreme value error term, consistent with the conditional logit assumption (Train, 2009).

The deterministic component of joint utility is decomposed into three elements:

1. Residence location utility
2. Work location utility
3. Commuting disutility

$$V_{i,h,w} = V_{i,h}^{hom} \; + V_{i,w}^{work} + V_{i,h,w}^{commute}$$

Equation 9 - Total Utility of Alternative (h, w) for worker i

This structure reflects the joint nature of residential and employment decisions, in which individuals simultaneously evaluate housing costs, job opportunities, and commuting burdens.

3.4.2 Empirical Utility Specification

The empirical specification synthesizes established findings from residential location theory, labor market sorting, and transportation behavior research. Each explanatory variable corresponds to a theoretically motivated determinant of residential and /or work location choice documented in prior urban economic and travel behavior literature (Train, 2009).

The systematic utility specification is represented as:

$$V_{i,h,w} = \sum_{k} \beta_k X_{i,h,w,k}$$

Equation 10 – Simplified General Utility Function

where $X_{i,h,w,k}$represents the observed attributes associated with residence–workplace alternative (h, w), and $\beta_k$represents the estimated marginal utility associated with attribute k.

3.4.3 Model Estimation

The model is estimated using a multinomial logit specification implemented in Biogeme. Utility is evaluated over the empirically defined choice set described in Section 3.3.3, Choice Set Construction. For each worker, the observed residence, workplace pair is retained and combined with a sampled set of nonchosen alternatives drawn from the empirical residence-workplace network. The estimation sample is restricted to household heads or primary household decision-makers to better represent residential location decisions within the joint residence-workplace framework.

Alternative discrete choice model structures, including nested logit and mixed logit specifications, were also considered. Nested logit models impose hierarchical decision structures, such as selecting a workplace before choosing a residence, which may not adequately represent the simultaneous and interdependent nature of joint residence-workplace decisions. Mixed logit models provide greater flexibility by allowing preference heterogeneity across individuals, including variation in sensitivities to commute time, housing costs, and labor market characteristics. However, these models require substantially greater computational effort and estimation time because of the large sampled alternative space. Since the primary objective of this study is to develop a stable, interpretable behavioral model for regional policy simulation, the multinomial logit specification is selected as the preferred modeling framework.

3.4.4 Model Validity and Representation of Market Constraints

While the model does not explicitly estimate a full housing market equilibrium, it provides a behaviorally and empirically grounded representation of residential and workplace choice under real-world constraints. The specification integrates observed housing prices, accessibility measures, and commuting costs within a random utility framework, allowing households to reveal preferences through observed choices. Housing market constraints are incorporated in reduced form through spatial variation in prices, which reflect underlying supply–demand conditions, and through the construction of empirically grounded choice sets that limit alternatives to observed and plausible residence–work combinations.

This approach is consistent with a broad class of discrete choice and integrated land-use models, where full supply-side processes are difficult to observe or estimate directly and are instead captured through equilibrium price signals and feasibility constraints (Train, 2009; Waddell, 2002; Bayer et al., 2004).

3.4.5 Model Specification Decisions

The final empirical specification reflects a balance between theoretical completeness, behavioral interpretability, and statistical robustness. Alternative model specifications were evaluated during development, including the inclusion of residential employment density as a proxy for job accessibility, as well as additional neighborhood characteristics such as school quality, crime, and coastal proximity. However, these variables were excluded from the final model due to limited statistical significance or potential redundancy with other key variables.

In particular, job accessibility is represented through a combination of workplace employment concentration and commuting impedance, separating the spatial distribution of opportunities from the cost of accessing them. This avoids double-counting accessibility effects and provides a more behaviorally interpretable structure.

Overall, the final model prioritizes parsimony, ensuring that each included variable contributes distinct behavioral information while maintaining consistency with established discrete choice modeling frameworks.

3.4.6 Data Correlation Impacts

Pairwise Pearson correlation diagnostics were evaluated for the explanatory variables retained in the preferred model specification. Overall, the results indicate relatively low-to-moderate correlations among the final model variables and provide no evidence of severe pairwise multicollinearity. No pairwise correlation exceeded an absolute value of 0.70.

The largest correlation in magnitude occurs between the affordability-burden variable and the income–commute-time interaction term, with a coefficient of approximately −0.59. This relationship is expected given the construction of the two measures. Affordability burden incorporates estimated household income in relation to estimated annual housing costs, while the income–commute interaction combines standardized household income with logged commute time. Consequently, the two variables share an income-related component while representing conceptually distinct behavioral mechanisms: affordability burden captures the economic pressure associated with residential housing costs, whereas the interaction term captures heterogeneity in sensitivity to commuting time across the household income distribution. The magnitude of the correlation remains below conventional thresholds typically associated with severe multicollinearity and does not, by itself, warrant excluding either mechanism from the model.

Several additional moderate relationships are behaviorally interpretable. Affordability burden is positively correlated with residential square footage at approximately 0.37, reflecting the tendency for larger housing units to impose greater housing costs relative to household resources. Residential square footage and lot size exhibit a correlation of approximately −0.30 in the estimation sample, while the professional and essential occupational matching variables exhibit a correlation of approximately −0.37. The latter relationship is expected because workplace occupational composition is represented through distinct professional and essential-worker employment shares.

Housing capacity shows only weak relationships with the remaining variables, with pairwise correlations generally near zero, ranging from approximately ±0.21. Workplace earnings likewise exhibit very low correlations with the other explanatory variables. The Zillow-imputation indicator is also weakly correlated with the behavioral variables, suggesting that the indicator primarily controls for differences associated with the source of residential housing information rather than duplicating another explanatory mechanism.

Taken together, these diagnostics support retaining the final set of model variables. The explanatory variables generally provide complementary information about commuting impedance, housing affordability and quality, housing supply, workplace attractiveness, occupational matching, and income-related preference heterogeneity. The correlation results therefore do not indicate a level of pairwise redundancy that would require modification of the preferred specification.

3.5 Results

This section presents the estimation results of the joint residence–work location choice model. The model is estimated using 1,041 head-of-household workers and a sampled choice set containing 151 residence-work alternatives per chooser. Results are organized into three components: coefficient estimates, behavioral interpretation, and implications for policy simulation.

3.5.1 Final Model Specification

Multiple model specifications were estimated before selecting a final specification with relatively stable coefficient signs and significance levels. The discussion below focuses on the preferred final specification. Earlier specifications are provided in Appendix F – Model Specification Development.

Final Specification Joint Choice Estimate Results

The preferred model specification exhibits strong behavioral plausibility and aligns closely with established findings from residential location and urban economic theory. The preferred utility specification follows the general utility formulation given by Equation 10, from Section 3.4.2 Empirical Utility Specification, with the estimated final specification reproduced below:

$$
\begin{aligned}
V_{i,h,w} = \beta_{time} \cdot \ln\left(tt_{h,w}\right) + \beta_{lotsize} \cdot z_{\ln(lotsize_h)} + \beta_{HouseSF} \cdot z_{HouseSF_h} + \beta_{capaity} \cdot z_{\ln(capacity_h)} \\
+ \beta_{inc,time}(Income_{z,i} \cdot lnTT) + \beta_{affordability}(affordability_{i,h}) + \beta_{prof} \\
\cdot (Prof_i \cdot ProfShare_w) + \beta_{ess} \cdot (Ess_i \cdot EssShare_w) + \beta_{earn} earn_w + \beta_{ImputedZillow} \\
\cdot (ImputeZillow_h)
\end{aligned}
$$

Equation 11 - Final Specification Utility Equation

Brief descriptions of the variables in Equation 11 can be found below:

- $tt_{h,w}$: peak-period commute time between residential location *h* and workplace location w
- $lotsize_h$: natural logarithm of residential lot square footage in residential location h, standardized prior to model estimation
- $HouseSF_h$: interior house square footage in residential location h, standardized prior to model estimation
- $capacity_h$: housing capacity in residential location h, standardized prior to model estimation
- $Income \cdot \ln(TT)$: interaction allowing the marginal disutility of commuting travel time to vary with household income
- $Affordability_h$: annualize cost of housing divided by annual worker income

- $(Prof_i \cdot ProfShare_w)$: indicator of whether a professional worker is choosing a workplace ZIP with a higher concentration of professional employment
- $(Ess_i \cdot EssShare_w)$: indicator of whether a essential worker is choosing a workplace ZIP with a higher concentration of essential employment
- $earn_w$: average earnings in workplace location w
- $ImputedZillow_h$: binary variable showing whether or not the Zillow price data was observed or imputed

The transformations shown in Equation 11 correspond directly to the variables defined in 3.3 Data and Variables Construction and summarized in the Variable Dictionary. For variables that were logarithmically transformed and standardized prior to estimation, the notation $z_{\ln}$ denotes:

$$z_{\ln} = \frac{\ln(x) - \mu_{\ln x}}{\sigma_{\ln}}$$

This log-standardization transformation applies to residential lot size and housing capacity. Interior house square footage is standardized without prior logarithmic transformation. Workplace earnings and commute time enter the utility function in natural-log form without subsequent standardization. The affordability-burden measure enters in its modeled level form, while the professional- and essential-worker terms are interactions between worker-group indicators and workplace occupational composition.

Table 20 summarizes the primary coefficients and their interpretations.

Final Specification Results & Interpretation						
Variable	**Description**	**Coefficient**	**Std. Error**	**t-stat**	**p-value**	**Interpretation**
β_{time}	Commute time	-0.1011	0.0264	-3.8247	<0.001	Very significant. Strong disutility of commute timing
$\beta_{lotsize}$	Property lot size (SF)	0.0191	0.0347	0.5491	0.5829	Not significant; Kept to ensure physical housing attributes are not skewing simulations downstream
$\beta_{HouseSF}$	Interior house size (SF)	0.0298	0.0420	0.7086	0.4786	Not significant; Kept to ensure physical housing attributes are not skewing simulations downstream
$\beta_{capacity}$	Log Housing Capacity per ZIP Code	0.0151	0.1109	0.1365	0.8914	Not significant; retained to support policy simulation despite statistical insignificance
β_{earn}	Log monthly workplace earnings	0.5289	0.2765	1.9132	0.0557	Not significant. Higher work zip wages increase utility
β_{prof}	Professional job match	0.9479	0.2635	3.5977	<0.001	Strongly significant. Strong professional sorting
β_{ess}	Essential worker job match	0.8228	0.3590	2.2917	0.0219	Significant. Occupational matching matters
β_{inc_time}	Standardized Income (from USD/yr) × log travel time interaction term	0.1091	0.0229	4.7553	<0.001	Positive interaction indicating that the disutility of commuting decreases as HH income increases
$\beta_{affordability}$	Annualized cost of housing divided by Annual worker income	-0.1353	0.0461	-2.9345	0.0033	Strongly significant. Strong negative reaction to housing cost burdens

Table 20 - Joint Residence-Work Location Final Model Specification Results

Table 21 reports goodness-of-fit statistics for the preferred model specification. The final log-likelihood improves from −5,210.11 for the null model to −5,174.72 for the estimated specification, corresponding to a likelihood-ratio statistic of 70.79. The model has a McFadden ρ^2 of 0.0068 and an adjusted McFadden ρ^2 of 0.0049. Although these pseudo-R^2 values are modest, the specification is intended to identify systematic behavioral relationships within large worker-specific joint residence–work choice sets rather than to produce deterministic prediction of observed alternatives. AIC and BIC values are 10,369.44 and 10,418.92, respectively, and are used primarily for comparison across alternative specifications estimated on the same sample and choice structure.

Model Fit Statistics	
Statistic	**Value**
Number of estimated parameters	10
Sample size	1041
Initial log likelihood	-5210.11
Final log likelihood	-5174.72
Likelihood ratio test vs. null model	70.79
McFadden rho-square	0.006793
Adjusted McFadden rho-square	0.004874
Akaike Information Criterion (AIC)	10369.44
Bayesian Information Criterion (BIC)	10418.92

Table 21 - Final Model Specification Model Fit Statistics

Key findings – Final Model Specification

The preferred specification retains the strongest behavioral mechanisms identified during model development in addition to variables that are useful (j) for policy simulation and (ii) for addressing omitted variable bias between housing affordability and the choice outcome. Commute time remains one of the strongest behavioral determinants of location choice. The negative and statistically significant commute coefficient indicates that workers experience substantial disutility from longer travel time, while the positive income-commute interaction demonstrates that higher-income households are less sensitive to commuting burdens than lower-income households.

Housing affordability is also a significant determinant of joint residence–work location choice. The affordability-burden coefficient is negative and statistically significant, indicating that workers are less likely to select residential locations where estimated annualized housing costs represent a larger share of their annual income. This result demonstrates that housing costs operate relative to workers' financial resources rather than simply through absolute housing prices and provides empirical support for explicitly incorporating affordability into the subsequent policy simulations.

Workplace earnings and occupational matching remain among the strongest workplace attributes. Workers exhibit greater utility for employment locations that offer higher wages and align with their occupation group, supporting the hypothesis that labor-market structure influences joint residence–work decisions.

Although housing capacity is not statistically significant in the preferred specification, it is retained because it provides the structural basis required for the housing policy simulations developed in the following chapter.

Overall, the preferred model provides a parsimonious yet behaviorally realistic representation of joint residence–work location choice. The estimated parameters demonstrate that commuting costs, housing affordability, workplace opportunities, occupation group, and income jointly influence residential and employment location decisions, providing the behavioral foundation for future policy simulations.

Interpretation of Results

Table 22 summarizes the preferred specification results and interprets each coefficient relative to the transformation applied to its associated explanatory variable. Within the random utility framework, coefficient magnitudes must be interpreted jointly with the scale and units of the corresponding explanatory variables. Accordingly, coefficients on logarithmically transformed variables describe utility changes associated with proportional changes in the underlying attribute, while coefficients on standardized variables describe utility changes associated with a one-standard-deviation change in the transformed attribute. Coefficients on interaction terms similarly reflect changes in utility with respect to the scales of both interacting variables. To facilitate substantive interpretation across variables expressed on different scales, Table 22 therefore reports implied changes in systematic utility for representative changes in each attribute, rather than directly comparing raw coefficient magnitudes.

The table below clearly shows that the strongest coefficients emerge from the occupational interaction variables, indicating substantial occupational sorting behavior within the Southern California labor market. Professional workers derive significantly greater utility from workplace locations characterized by higher concentrations of professional employment, while essential workers similarly prefer locations with stronger concentrations of essential-service occupations. These findings suggest that workers sort not only based on generalized accessibility but also based on compatibility between occupational specialization and workplace employment composition. The table below also reinforces how the positive housing capacity coefficient further suggests that increased housing availability improves residential utility.

Final Model Specification Interpretation				
Variable	**Model Form**	**Real-World Change**	**Model-Implied Utility Effect**	**Interpretation**
Commute time	ln(peak commute minutes) + income interaction	10% longer commute at mean standardized income	−0.00964	Negative values indicate disutility from longer commuting. At mean standardized income, a 10% increase in peak-period commute time reduces systematic utility by approximately 0.0096 utility units. The magnitude of this effect varies with worker income because commute time enters the model jointly with the income × commute-time interaction.
Housing affordability burden	Annualized housing cost / annual worker income	10% reduction in affordability-burden ratio	0.01813	Lower affordability burden increases residential attractiveness. A 10% reduction in the annual housing-cost-to-income burden increases systematic utility by approximately 0.0181 utility units, holding the other modeled attributes constant.
Housing capacity	Standardized ln(housing units)	20% increase in housing units	0.00168	A 20% increase in raw housing units increases the standardized log housing-capacity measure by approximately 0.1112 standard deviations and produces an estimated increase of approximately 0.00168 utility units, holding other modeled attributes constant.
Workplace earnings	ln(monthly workplace earnings)	10% higher workplace earnings	0.05041	Positive values indicate greater workplace attractiveness associated with higher earnings. A 10% increase in monthly workplace earnings increases systematic utility by approximately 0.0504 utility units.

Professional occupational match	Professional-worker indicator × professional employment share	10 percentage-point increase in professional employment share	0.0948	Applies only to professional workers. For a professional worker, a 10 percentage-point increase in the professional-employment share of the workplace location increases systematic utility by approximately 0.0948 utility units; the term is zero for nonprofessional workers.
Essential occupational match	Essential-worker indicator × essential employment share	10 percentage-point increase in essential employment share	0.08228	Applies only to essential workers. For an essential worker, a 10 percentage-point increase in the essential-employment share of the workplace location increases systematic utility by approximately 0.0823 utility units; the term is zero for nonessential workers.
Housing square footage	Standardized ln(square feet)	10% larger dwelling	0.00284	Positive values indicate preference for larger dwelling size. A 10% increase in residential square footage produces an estimated increase of approximately 0.00284 utility units, holding the other modeled attributes constant.
Lot size	Standardized ln(lot size)	10% larger lot	0.00182	Positive values indicate preference for larger residential lots. A 10% increase in lot size produces an estimated increase of approximately 0.00182 utility units, holding the other modeled attributes constant.
Income × commute time	income_z × ln(commute time)	Evaluated jointly with commute time across income levels	Not reported separately	This interaction changes the marginal disutility of commuting as worker income changes. Because its effect depends jointly on both standardized income and commute time, a single stand-alone utility effect is not reported; instead, the interaction is incorporated into the commute-time interpretation at specified income levels.

Zillow imputation indicator	Binary indicator	Observed versus county-imputed Zillow value	−0.03307	Diagnostic/control variable indicating whether the Zillow housing attributes were observed directly or county-imputed. It is retained to control for systematic differences associated with imputation and is not interpreted as a behavioral policy effect.

Table 22 - Final Model Variable Transformations and Implied Utility Effects

Table 22 shows the final model variable transformations and implied utility effects for commute time and housing price are reported at mean standardized income. Also, since commute time interacts with income, its total effect varies across workers and is evaluated separately in the income-conditioned sensitivity analysis in 3.5.2 Behavioral Sensitivity Measures.

3.5.2 Behavioral Sensitivity Measures

Baseline Choice-Probability Diagnostics

Baseline choice probabilities were recalculated from the preferred final utility specification using the multinomial logit probability function:

$$P_{ni} = \frac{\exp(V_{i,h,w})}{\sum_{(h\prime,w\prime)\in C_i} \exp(V_{i,h\prime,w\prime})}$$

Where,

- $P_{i,h,w}$is the probability that worker i selects residence–work alternative defined by residential location h and workplace location w;
- $V_{i,h,w}$ is its estimated systematic utility associated with that residence–work alternative; and
- C_i is the worker-specific choice set containing the available residence–work alternatives

Equation 12 - Choice Probability Formula

Probabilities were calculated using a numerically stabilized grouped softmax transformation. Within each worker's choice set, the resulting probabilities summed to one, with a maximum absolute numerical error of approximately 1.11×10^{-16}, which is at the level of machine precision. This confirms that the grouped softmax calculation normalized the probabilities correctly within each worker's choice set.

Final Model Probability Diagnostics	
Measure	**Value**
Workers	1041
Residence-Work Alternatives	155,265
Mean Choice-Set Size	149.15
Mean Chosen Probability	0.0072
Median Chosen Probability	0.0067
Mean Highest Probability	0.0131
Mean Chosen Prob / Equal Benchmark	1.0769
Median Chosen-Alternative Rank	65
Chosen Alternative Ranked First Share	1.15%

Table 23 – Final Model Baseline Choice-Probability Diagnostics

The final analysis includes 1,041 workers and 155,265 residence–work alternatives. The mean choice-set size is approximately 149 alternatives per worker. The mean probability assigned to the observed alternative is 0.0072, compared with a mean equal-probability benchmark of 0.0067, producing a mean observed-to-equal probability ratio of approximately 1.08. The median observed-to-equal ratio is approximately 1.00. The observed alternative has a median probability rank of 65 within the worker-specific choice set and is ranked first for approximately 1.15 percent of workers.

These diagnostics indicate that the model should not be interpreted as a high-accuracy predictor of each worker's observed residence–work pair. Instead, its primary purpose is explanatory and comparative: the model estimates directional behavioral relationships and evaluates how controlled changes in housing price and capacity redistribute probabilities across alternatives. Random utility models represent choice probabilistically rather than requiring the observed alternative to possess the largest deterministic utility, although the present diagnostics also demonstrate that substantial unobserved heterogeneity remains (Train, 2009).

For this reason, policy outcomes are evaluated using changes relative to the same baseline model. Holding the model specification and choice sets constant allows future policy simulation results to be interpreted as internally consistent comparative probability shifts, even where the baseline model does not strongly predict individual observed choices.

Income-Conditioned Behavioral Sensitivity

The preferred model specification includes an interaction between commute time and standardized household income to evaluate whether sensitivity to commuting burden varies systematically across the income distribution. Because this interaction modifies the commute-time coefficient, its effect must be interpreted conditionally rather than by examining the base and interaction coefficients independently.

For worker n, the income-conditioned coefficient is calculated as:

$$\beta_{time,i}^{\text{conditional}} = \beta_{time} + \beta_{inc\times time}\ln(Income)_i$$

Where,

- $Income_i$ is the standardized estimated annual household income of worker i.

Equation 13 - Income-Conditioned Coefficient Formula

A positive income-interaction coefficient therefore indicates that the commute-time effect becomes more positive, or less negative, as household income increases.

To evaluate preference heterogeneity at substantively meaningful points in the observed income distribution, conditional commute-time coefficients were calculated at the 25th, 50th, and 75th percentiles of worker-level standardized household income.

This approach follows the established interpretation of multiplicative interaction terms, under which the effect of one variable must be evaluated at substantively meaningful values of the modifying variable rather than interpreting the base and interaction coefficients independently (Brambor, Clark, & Golder, 2005).

Because commute time enters the utility function in logarithmic form, the modeled utility change associated with a 10 percent increase in commute time is:

$$\Delta V_{time,n}^{10\%} = \beta_{time,n}^{\text{conditional}} \ln(1.10)$$

Equation 14 - Modeled Utility Change w/ 10% Increase in Commute Time

The 10 percent increase is used as a common proportional change for interpretation rather than as an estimated policy threshold. These conditional utility effects indicate how the modeled disutility from a proportional increase in commuting varies with household income levels. In the multinomial logit framework, resulting changes in choice probability depend on the complete utility vector and the utilities of all competing residence–work alternatives.

Income-Conditioned Behavioral Sensitivity			
Income Group	**Income z-score**	**Conditional Commute-Time Coefficient**	**Utility Change from 10% Longer Commute**
Lower income (25th percentile)	-0.23174	-0.12638	-0.01205
Median income	0.20203	-0.07907	-0.00754
Higher income (75th percentile)	0.66184	-0.02893	-0.00276

Table 24 - Income-Conditioned Behavioral Sensitivity of Commute Time

Table 24 shows the income-conditioned heterogeneity in modeled commute-time sensitivity. The preferred specification estimates a negative base commute-time coefficient and a positive income–commute interaction coefficient. At the 25th, 50th, and 75th percentiles of standardized household income, the resulting conditional commute-time coefficients are −0.12638, −0.07907, and −0.02893, respectively. A 10 percent increase in commute time therefore produces modeled utility changes of approximately −0.01205, −0.00754, and −0.00276 at these respective income levels. Commute time remains a source of disutility at all three evaluated points in the income distribution, but the magnitude of that disutility declines as household income increases. The positive interaction should therefore be interpreted as an attenuation of commute-time sensitivity among higher-income workers rather than as evidence that higher-income households prefer longer commutes.

Elasticities

To supplement the coefficient and conditional-sensitivity interpretations, direct choice-probability elasticities were calculated for the continuous attributes retained in the preferred model specification. Elasticities provide a scale-independent measure of behavioral responsiveness by estimating the proportional change in an alternative's choice probability associated with a proportional change in an explanatory attribute, holding the remaining alternatives and attributes constant.

Using the equation from Train (2009) and the chain rule, for residence-work alternative (h, w) in worker i's choice set, the direct elasticity of choice probability $P_{i,h,w}$ with respect to attribute $x_{i,h,w}$ is defined as:

$$E_{P_{i,h,w}, x_{i,h,w}} = \frac{\partial P_{i,h,w}}{\partial x_{i,h,w}} \frac{x_{i,h,w}}{P_{i,h,w}}$$

Within the multinomial logit model, when an attribute affects the systematic utility of its own alternative, the derivative of probability is:

$$\frac{\partial P_{i,h,w}}{\partial x_{i,h,w}} = P_{ni}(1 - P) \frac{\partial V_{i,h,w}}{\partial x_{i,h,w}}$$

Therefore:

$$E_{P_{i,h,w}, x_{i,h,w}} = \left(1 - P_{i,h,w}\right) x_{i,h,w} \frac{\partial V_{i,h,w}}{\partial x_{i,h,w}}$$

The appropriate elasticity expression consequently depends on the transformation used for each explanatory variable. For variables entering the utility function in natural-log form, such as commute time and workplace earnings, the direct elasticity simplifies to:

$$E_{P_{i,h,w}, x_{i,h,w}} = \beta_x \left(1 - P_{i,h,w}\right)$$

Several residential attributes in the final model specification are both logarithmically transformed and standardized. For an attribute represented as:

$$z_{\ln x} = \frac{\ln(x) - \mu_{\ln x}}{\sigma_{\ln x}}$$

The application of the chain rule gives:

$$\frac{\partial V_{i,h,w}}{\partial x_{i,h,w}} = \frac{\beta_x}{\sigma_{\ln}}(1 - P_{i,h,w})$$

Therefore, the direct probability elasticity becomes:

$$E_{P_{i,h,w},x_{i,h,w}} = \frac{\beta_x}{\sigma_{\ln x}}(1 - P_{i,h,w})$$

This adjustment is important because the estimated coefficient on a standardized logarithmic variable is not itself an elasticity. The coefficient represents the utility effect of a one-standard-deviation change in the transformed attribute, while the chain-rule adjustment converts that coefficient back into a proportional response with respect to the underlying physical variable.

Commute-time elasticity additionally incorporates the income interaction retained in the preferred specification. Because systematic utility includes both logged commute time and its interaction with standardized household income, the direct commute-time elasticity for worker $i$choosing residence–work alternative $(h, w)$is:

$$E_{P_{i,h,w},tt_{i,h,w}} = (\beta_{time} + \beta_{inc,time} Income_{z,i})(1 - P_{i,h,w})$$

Therefore, commute-time elasticity varies across workers according to household income. This formulation is consistent with the conditional sensitivity results reported above: commute-time responsiveness remains negative over the evaluated income distribution, while its magnitude decreases as household income increases.

Affordability burden enters the preferred model as a bounded housing-cost-to-income burden measure rather than as a logarithmically transformed attribute. Its direct own-alternative elasticity is therefore calculated as:

$$E_{P_{i,h,w},A_{i,h}} = \beta_{affordability} A_{i,h}(1 - P_{i,h,w})$$

Where,

- $A_{i,h}$ denotes the affordability-burden value associated with residential location h for worker i

Equation 15 - Elasticity Derivation

Because affordability burden is a constructed housing-cost-to-income ratio, the resulting elasticity should be interpreted as local responsiveness of modeled choice probability to proportional changes in the affordability-burden measure rather than as a direct monetary elasticity.

Elasticities are calculated using the reconstructed baseline probabilities from the preferred model utility specification. The Zillow-imputation indicator is excluded from the elasticity analysis because it is binary; changes in binary variables are more appropriately evaluated using discrete probability changes. Likewise, occupational matching terms are retained primarily as interaction-based sorting mechanisms and are interpreted through their estimated utility and probability effects rather than as conventional continuous elasticities.

Attribute	Model form	Own probability elasticity	Mean Own Elasticity – All Alternatives	Mean Own Elasticity – Chosen Alternatives
Commute time	ln(TT) + income interaction	$(\beta_{time} + \beta_{inc,time} Income_z)(1 - P)$	-0.10036	-0.10032
Affordability burden	Housing-cost-to-income burden ratio	$\beta_{afford} A(1 - P)$	-0.18021	-0.1614
Square footage	standardized ln(SF)	$\frac{\beta_{SF}}{\sigma_{\ln SF}}(1 - P)$	0.08442	0.08437
Lot size	standardized ln(Lot)	$\frac{\beta_{lot}}{\sigma_{\ln lot}}(1 - P)$	0.00605	0.00605
Housing capacity	standardized ln(Capacity)	$\frac{\beta_{capacity}}{\sigma_{\ln capacity}}(1 - P)$	0.00918	0.00917
Workplace earnings	ln(Earnings)	$\beta_{earn}(1 - P)$	0.52539	0.52511

Table 25 – Direct Own-Alternative Probability Elasticities for the Preferred Model Specification

Table 25 summarizes the direct own-alternative probability elasticities calculated from the preferred model specification. The reported elasticities measure the proportional change in the modeled probability of selecting a residence–work alternative associated with a one-percent change in the corresponding continuous attribute, holding the remaining attributes constant. For log-transformed and standardized variables, the estimates incorporate the appropriate chain-rule adjustment so that the resulting values are expressed relative to changes in the underlying attribute rather than the transformed model variable.

The elasticity estimates reinforce the behavioral patterns identified in the coefficient results. Workplace earnings exhibit the largest positive elasticity, with a mean own-alternative elasticity of approximately 0.525 for chosen alternatives. Thus, holding other attributes constant, a one-percent increase in workplace earnings is associated with an approximately 0.53-percentage-point increase in the probability of selecting the corresponding residence–work alternative. This comparatively strong response is consistent with workplace earnings serving as an important measure of labor-market attractiveness.

The affordability burden yields the largest negative elasticity, with a mean elasticity of approximately −0.161 across the chosen alternatives. This indicates that increases in the modeled housing-cost burden reduce the relative attractiveness of residential alternatives. Commute time also produces a negative elasticity of approximately −0.100, confirming that longer commuting remains an important source of disutility in the joint residence–work choice process.

Housing square footage has a positive but more moderate elasticity of approximately 0.084, indicating that larger residential units increase alternative attractiveness, while lot size and housing capacity exhibit substantially smaller positive elasticities of approximately 0.006 and 0.009, respectively. These small elasticity magnitudes are consistent with the weaker coefficient estimates for these variables and suggest that they operate primarily as secondary residential attributes rather than as dominant behavioral drivers.

The similarity between elasticities calculated across all alternatives and those calculated only for observed chosen alternatives further suggests that the estimated response patterns are not being driven by a small subset of extreme alternatives. Overall, the elasticity results support the interpretation that workers respond most strongly to workplace economic opportunity, housing affordability, and commuting burden, while physical housing characteristics and regional housing supply exert smaller marginal effects within the estimated choice framework.

Robustness Analysis

Additional model diagnostics and specification checks are provided in Appendix E – Robustness Check. These analyses were used to evaluate the numerical stability, behavioral consistency, and multicollinearity of the preferred joint residence–work choice specification. The diagnostics include comparisons with alternative model specifications developed during model refinement, pairwise correlation analysis, Variance Inflation Factor (VIF) diagnostics, baseline choice-probability diagnostics, and income-conditioned behavioral sensitivity analysis.

Across these checks, the primary behavioral relationships remain consistent. Commute time and housing affordability remain negatively associated with residential–workplace utility, while workplace earnings and occupation-specific workplace matching remain positively associated. The preferred specification also preserves the expected income-related heterogeneity in commute-time sensitivity: commute disutility remains negative across the evaluated income distribution but becomes smaller in magnitude as household income increases. Pairwise-correlation and VIF diagnostics provide no evidence of problematic multicollinearity among the retained explanatory variables.

Taken together, these diagnostics support use of the final model as the preferred specification for interpretation and subsequent policy simulation. They demonstrate that the principal coefficient signs, interaction effects, numerical behavior, and policy-relevant relationships are reasonably stable under the diagnostic tests performed.

Choice-Set Size Sensitivity Analysis

To evaluate whether the final model estimates were sensitive to the number of sampled nonchosen alternatives included in each worker's choice set, the final specification was re-estimated using $K = 10$, $K = 30$, and $K = 50$, while retaining $K = 150$as the primary specification. The same 1,041-worker estimation sample and utility specification were maintained across models. The estimated coefficients were generally stable across choice-set sizes, particularly for affordability burden, peak commute time, the income–commute-time interaction, and the professional- and essential-worker employment-match variables. Parameters that were statistically weak in the primary model, including housing capacity, lot size, square footage, and the Zillow-imputation indicator, remained small and generally insignificant across alternative values of K. These results indicate that the primary behavioral findings are not materially driven by the selected number of sampled alternatives.

Choice-Set Size Sensitivity Test					
Final Model Parameters	**K=10**	**K=30**	**K=50**	**K=150 Final**	**Robustness Interpretation**
Affordability burden	-0.1331	-0.1378	-0.1419	-0.1353	Extremely stable
Housing capacity	0.0286	-0.0077	-0.004	0.0151	Small changes, insignificant throughout
Essential-worker match	0.8754	0.8129	0.8717	0.8228	Stable positive effect
Income × commute time	0.1078	0.1121	0.1093	0.1091	Exceptionally stable
Lot size	0.0286	0.0226	0.0275	0.0191	Small, insignificant throughout
Professional-worker match	0.9643	0.9276	0.9524	0.948	Exceptionally stable
Home square footage	0.0373	0.0269	0.0357	0.0298	Small, insignificant throughout
Peak commute time	-0.0971	-0.0934	-0.1031	-0.1011	Extremely stable
Work earnings	0.3462	0.568	0.5083	0.5289	Positive; significance varies
Zillow-imputation indicator	-0.011	-0.0189	-0.0429	-0.0331	Small, insignificant throughout

Table 26 - Choice-Set Size Sensitivity Analysis

3.5.3 Evaluated but Excluded Variables

Several additional residential and neighborhood attributes were evaluated during model development, including school quality, crime, coastal proximity, transit availability, residential employment density, and additional housing characteristics. These variables were not retained in the preferred specification when their estimated effects were statistically weak, unstable in magnitude or sign across alternative specifications, or did not provide a sufficiently robust and interpretable contribution to the preferred joint residence–work location model.

Housing-quality characteristics received particular attention during specification development. Bedroom and bathroom counts, living area, lot size, housing price, and related Zillow listing attributes were evaluated as potential measures of residential quality. The final specification retains residential square footage and lot size because they provide continuous measures of dwelling and parcel characteristics while avoiding an unnecessarily large collection of highly related housing variables. Bedroom and bathroom counts were therefore treated as candidate quality indicators rather than retained as separate explanatory variables. This parsimonious specification also reduces the risk that multiple measures of essentially the same underlying housing characteristics compete for explanatory power.

Transit availability remained statistically significant in some intermediate specifications; however, its estimated magnitude and behavioral interpretation were insufficiently stable throughout the specification development process to justify its retention in the preferred model. In particular, its contribution became less consistent after accounting for commute impedance, housing characteristics, housing capacity, workplace earnings, and occupational matching. Transit availability was therefore retained as an evaluated alternative explanatory variable but excluded from the preferred specification on the basis of coefficient stability and interpretability rather than statistical significance in any single intermediate model.

The exclusion of these variables should not be interpreted as evidence that schools, crime, transit accessibility, coastal amenities, or detailed dwelling characteristics are unimportant to residential location choice. Rather, the preferred specification emphasizes variables that yielded the clearest and most stable behavioral interpretation within the available data, sampled-choice framework, and the geographic scale of this study. The evaluated variables and alternative specifications are retained in Appendix E – Robustness Check for methodological transparency.

3.6 Discussion

This section interprets the estimated joint residence–work location choice model within a broader theoretical and policy context. The findings highlight the interconnected roles of commuting costs, labor market opportunity, and housing constraints in shaping residential sorting and commuting patterns in Southern California, consistent with established frameworks in urban economics and discrete choice modeling (Train, 2009; Waddell, 2002).

3.6.1 Labor Market Opportunity and Spatial Sorting

Workplace characteristics play a central role in shaping residential location decisions. The estimated model indicates that workers respond more strongly to workplace earnings and occupational employment composition than to generalized measurement of employment density. These findings are consistent with urban economic theory, which suggests that larger employment centers provide greater job opportunities, improved labor market matching, and higher wages (Klaiber & Kuminoff, 2012; Martin, 1997).

The strongest behavioral effects in the preferred specification emerge from the occupational matching variables. Professional workers derive greater utility from workplace locations with higher concentrations of professional employment, while essential workers similarly prefer employment centers with higher concentrations of essential occupations. These findings indicate that workplace composition and occupational compatibility influence residential sorting beyond generalized measures of employment opportunity.

Collectively, these results suggest that residential location decisions are shaped not only by commuting costs and housing affordability, but also by the spatial organization of labor markets. Workers appear to value locations that provide employment opportunities aligned with their occupations, reinforcing differences in commuting patterns across worker groups.

3.6.2 Housing Constraints and Spatial Mismatch

The joint residence-work location framework provides insight into the mechanisms underlying spatial mismatch between housing and employment. Although households are attracted to employment-rich locations, housing affordability constraints limit the set of feasible residential alternatives. Because housing supply adjusts slowly and remains relatively fixed in the short run, residential decisions occur within a constrained housing market, creating persistent separation between housing and employment (Vasanen, 2012).

The preferred specification estimates a positive, although statistically insignificant, coefficient for residential housing capacity. While this estimate alone does not establish an independent behavioral effect, its direction is consistent with theories suggesting that greater housing availability increases the attractiveness of residential alternatives. More importantly, housing capacity is the structural variable required to evaluate housing supply interventions in the policy simulations developed in Study 3.

These findings are consistent with equilibrium sorting models, in which housing supply constraints influence residential prices, residential opportunities, and ultimately commuting patterns (Bayer et al., 2004). When housing availability remains constrained near major employment centers, households increasingly trade residential proximity for affordability, resulting in longer commuting distances and greater travel burdens (Baum Snow & Duranton, 2025; Martin, 1997).

Collectively, these results support the broader argument that housing market constraints contribute to persistent jobs-housing imbalance and regional commuting burdens throughout Southern California.

3.6.3 Behavioral Trade-offs and Policy Relevance

The estimated coefficients reveal clear behavioral trade-offs among commuting costs, housing affordability, housing availability, workplace earnings, and occupational composition. Households evaluate residential alternatives by balancing these competing factors, consistent with random utility maximization theory (Train, 2009; Greene, 2008).

The income interaction term further demonstrates that commuting costs affect households differently across income groups. Lower income households exhibit greater sensitivity to longer commuting times, while higher income households are comparatively less sensitive to these costs. These findings suggest that policies affecting housing affordability or commuting conditions may produce different responses across socioeconomic groups.

The positive housing capacity coefficient, although not statistically significant, provides the structural mechanism needed to evaluate housing supply policies within the simulation framework. Together, these estimated behavioral relationships establish a consistent foundation for comparing employer-sponsored housing subsidies and office-to-residential housing expansion scenarios developed in Study 3.

3.6.4 Implications for Policy Simulation

The preferred model provides the behavioral foundation for evaluating housing and transportation policy scenarios. By quantifying household trade-offs among commuting costs, housing affordability, housing availability, workplace earnings, and occupational matching, the estimated coefficients allow residential choice probabilities to be recalculated after policy-induced changes to the explanatory variables.

The estimated behavioral relationships are directly incorporated into the simulation framework developed in Study 3. Employer-sponsored housing subsidies modify effective housing prices for eligible workers, while office-to-residential conversion scenarios modify housing capacity and apply a literature-informed housing price response. These adjustments are introduced into the estimated utility function, after which residence-work choice probabilities are recalculated using the multinomial logit framework.

The preferred specification demonstrates three important characteristics that support the policy simulations. First, the model produces behaviorally reasonable and statistically coherent estimates that are consistent with established residential location choice theory. Second, the retained variables represent policy-responsive mechanisms. Housing prices, housing capacity, and commuting costs can all be modified under alternative policy assumptions while preserving the estimated behavioral relationships between residential and workplace choices. Finally, the estimated coefficients provide a consistent behavioral basis for comparing policy scenarios. Rather than predicting exact household relocations, the simulations evaluate how changes in housing affordability and housing availability alter the relative attractiveness of competing residential alternatives, allowing expected commuting outcomes to be compared across policy strategies.

A limitation concerns the temporal context of the CHTS data used to estimate worker location-choice behavior. The survey predates the COVID-19 pandemic and therefore does not fully capture subsequent changes in telework, hybrid work arrangements, or workplace attendance patterns. These changes may alter the relative importance of commute time and workplace proximity for occupations with greater flexibility to work remotely. The estimated relationships should therefore be interpreted as reflecting the behavioral structure observed during the underlying survey period rather than as a complete representation of post-pandemic work arrangements. This limitation may be less consequential for occupations requiring regular on-site presence, but future research using post-pandemic travel-survey data could evaluate whether residential and workplace location preferences have changed as hybrid and remote work have become more prevalent.

3.7 Conclusion

This study examines how households jointly select residential and workplace locations using a discrete choice framework that integrates housing costs, housing capacity, workplace opportunities, and commuting constraints. By modeling these decisions simultaneously, the analysis captures the interdependence between residential and employment geography.

The results identify three principal behavioral mechanisms. First, commute time remains a negative and statistically significant determinant of residence–work utility, indicating that longer travel times reduce the attractiveness of an alternative. Second, housing price has the expected negative effect, while the income–price interaction indicates that price sensitivity varies across household income levels. Third, the positive occupational-match coefficients indicate that professional and essential workers derive greater utility from workplace locations whose employment composition more closely corresponds to their occupational group. Workplace earnings also increase modeled utility, reinforcing the importance of labor-market opportunity in residence–work sorting.

The housing-capacity coefficient is positive but not statistically significant. It is therefore not interpreted as conclusive evidence of an independent behavioral effect. Nevertheless, the variable is retained because it provides the structural basis for evaluating housing-supply interventions for future simulations.

Collectively, the results indicate that residence–work choices arise from interacting commuting, housing-market, income, workplace-earnings, and occupational-sorting considerations. In constrained housing markets, these competing forces can contribute to persistent jobs–housing imbalance and longer commuting burdens.

The joint modeling framework developed in this study provides the behavioral foundation for the policy simulations presented in Study 3. The estimated parameters are used to evaluate changes in the relative attractiveness of residence–work alternatives under employer-sponsored housing subsidies, office-to-residential housing-capacity expansion, and a combined intervention scenario. These simulations are intended to assess comparative behavioral responses rather than to forecast parcel-level development or exact household relocation outcomes.

Chapter 4 - Study 3: Housing Policy Scenario Analysis and Commuting Outcomes

4.1 Overview

The long-distance commuting patterns documented in Study 1 and the residential and workplace location preferences estimated in Study 2 provide a basis for evaluating how selected housing policies may influence residence-work location choices and commuting outcomes. This chapter uses a scenario-based simulation framework to examine how changes in housing costs, residential capacity, and housing allocation priorities affect the relative attractiveness of the residence–work alternatives included in each worker's choice set.

The simulations apply the behavioral parameters estimated in the final joint residence–work location choice model developed in Chapter 3. The model includes alternative-specific measures of peak-period travel time, housing price, housing capacity, workplace earnings, and occupational matching for professional and essential workers. It also includes interactions between worker income and both travel time and housing price, allowing the sensitivity to these attributes to vary across the income distribution. These estimated parameters are used to calculate the systematic utility and choice probability associated with each available residence–work alternative.

A baseline scenario is first established using the observed values of all model attributes and the final Study 2 coefficient estimates. Each policy scenario then modifies one or more relevant attributes while holding the remaining model inputs constant. The resulting utilities and probabilities are compared with the baseline to evaluate changes in predicted residential location, residence–work pair selection, commute time, and the prevalence of long-distance commuting. The analysis is intended to represent short- to medium-term behavioral responses within the observed and sampled choice environment, rather than a complete housing market or land-use equilibrium.

Two policy mechanisms are considered. The first reduces the effective housing cost in selected residential ZIP codes to eligible occupation groups. The second increases the available housing capacity in selected ZIP codes located near major employment centers to represent an expansion in residential supply. Together, the scenarios provide a structured comparison of how housing affordability, supply, and allocation mechanisms may alter predicted residence–work choices and commuting outcomes.

The primary contribution of this chapter is to connect the worker-level behavioral relationships estimated in Study 2 with policy-relevant changes in housing attributes. Rather than estimating the effects of zoning regulations, permitting processes, or other institutional constraints directly, the simulations isolate the modeled effects of changes in housing price, housing capacity, and allocation rules. The results therefore provide evidence about the direction and relative magnitude of predicted behavioral responses under the specified scenarios, while remaining bounded by the variables and choice alternatives represented in the model.

4.1.1 Research Questions

Below are the research questions this Chapter is intended to address:

1. How would reducing housing costs near major job hubs affect residential location probabilities and commute burdens?
2. How do incremental housing supply increases near job centers influence long-distance commuting outcomes?
3. Which occupational groups benefit most from increased housing affordability near employment hubs?
4. How would office-to-residential conversions shift accessibility and commute outcomes in SCAG and SANDAG Metropolitan Planning Organizations (MPOs)?

This chapter applies the behavioral parameters estimated in Chapter 3 within a scenario-based simulation framework to evaluate how alternative housing policies influence residential location choices and commuting outcomes. The simulations modify selected housing attributes while holding all other model inputs constant, allowing direct comparison of the behavioral responses associated with different policy interventions.

4.2 Literature Review

Evaluating housing policies in high-cost metropolitan regions requires integrating insights from residential location choice, accessibility, land use–transport interaction (LUTI) modeling, and spatial equilibrium theory. While prior research has examined individual components of these systems, such as housing affordability, commuting behavior, or land-use regulation, fewer studies have combined behavioral modeling and spatial simulation to evaluate how policy interventions reshape residential patterns, commuting flows, and accessibility outcomes (Klaiber & Kuminoff, 2012; Waddell, 2002). This chapter builds on that literature by synthesizing behavioral and system-level approaches to evaluate the effectiveness of housing policy interventions under realistic structural constraints.

4.2.1 Residential Location, Accessibility, and Equity Implications of Housing Policy

Housing policy is often evaluated based on unit production or affordability outcomes; however, a growing body of research emphasizes that the *location* of housing is equally critical in determining accessibility and equity outcomes. Accessibility-based frameworks demonstrate that housing located far from employment centers or transit networks may reduce nominal housing costs while simultaneously increasing commute burdens and limiting access to jobs and essential services (Wang et al., 2024).

Empirical research shows that housing policies can produce uneven accessibility outcomes depending on where new supply is introduced and which populations can access it. Accessibility-based equity frameworks highlight that improvements in housing affordability do not necessarily translate into improved access to opportunity if housing is located in areas with weak job connectivity or limited transit access (Fan et al., 2025). These findings underscore the importance of evaluating housing policies using accessibility and commuting metrics rather than affordability indicators alone.

This perspective directly motivates the simulation framework adopted in this study, which evaluates housing policy scenarios by their ability to alter residential location patterns to reduce commute distances, travel times, and vehicle miles traveled (VMT), while improving access to employment opportunities.

4.2.2 Joint Residential and Workplace Decision-Making as a Behavioral Foundation

Because commuting is a derived outcome of the spatial relationship between residence and workplace, modeling frameworks increasingly recognize that residential and employment location decisions cannot be treated independently (Train, 2009; Ioannides & Zabel, 2002). Households adjust commuting burdens through a combination of residential relocation, job changes, or both, although relocation decisions often occur less frequently due to higher adjustment costs (Giménez-Nadal et al., 2025).

Joint residence–work location choice models address this limitation by explicitly modeling the trade-offs households make among housing costs, commuting time, job accessibility, and neighborhood characteristics (Pagliara and Wilson, 2010; Waddell, 2002). These models provide behaviorally grounded estimates of how households respond to changes in housing affordability and location-specific opportunities, enabling the simulation of policy-induced shifts in residential patterns.

This behavioral foundation is critical for policy evaluation. By estimating preference parameters governing residential and workplace choices, the modeling framework used in this study enables counterfactual analysis of how housing policies, such as cost reductions, supply increases, or targeted allocation mechanisms, affect household location decisions and, ultimately, commuting outcomes.

4.2.3 Land Use–Transport Interaction Models and Policy Simulation

Scenario-based policy simulation has a long history in land use–transport interaction (LUTI) modeling, where integrated frameworks are used to evaluate how land-use changes affect transportation outcomes and vice versa (Waddell et al., 2007). These models range from aggregate spatial interaction approaches to disaggregate microsimulation and agent-based systems.

UrbanSim represents one of the most influential LUTI frameworks, explicitly designed to evaluate land-use and transportation policies within a behaviorally grounded simulation environment (Waddell, 2002).

Within this broader tradition, recent research emphasizes the importance of transparent, disaggregate simulation approaches that allow policymakers to compare alternative scenarios under uncertainty (Conway, 2021). These frameworks often integrate residential location models with accessibility measures and spatial interaction models to translate household-level decisions into regional travel outcomes.

The approach adopted in this study aligns with this tradition but focuses on short- to medium-run behavioral responses rather than full long-run equilibrium dynamics. By combining estimated behavioral parameters with scenario-based policy inputs, the framework enables systematic comparison of policy impacts across consistent metrics, including commute time, VMT, and accessibility.

4.2.4 Structural Constraints, Housing Supply, and Policy Effectiveness

A central insight from the literature is that the effectiveness of housing policies depends critically on underlying structural constraints, including zoning regulations, land availability, and the spatial distribution of employment centers (Baum-Snow & Duranton, 2025). In high-demand metropolitan regions, limited housing supply elasticity leads to rising prices and outward displacement of households, increasing commute distances and reducing accessibility.

Research consistently shows that policies aimed at improving affordability or increasing housing supply can have heterogeneous effects depending on where supply is added and which populations benefit. Empirical evidence from California demonstrates that rising housing costs in job-rich areas directly increase commuting distances, particularly for workers with fewer residential options (Mitra & Saphores, 2019; Islam & Saphores, 2022).

Zoning policy further reinforces these dynamics by shaping both residential location choices and travel behavior. Conway (2021) shows that zoning regulations act as binding constraints on access to high-opportunity neighborhoods, while zoning reforms that increase housing supply in these areas can reduce commute distances and improve accessibility outcomes.

4.2.5 Office-to-Residential Conversions and Feasibility Constraints

Office-to-residential conversions have gained increasing attention as a strategy for expanding housing supply in employment-dense areas. However, the feasibility of such conversions is highly dependent on building characteristics, location, and financial considerations (Geraedts et al., 2017; Peiser et al., 2024).

Research shows that not all office buildings are suitable for residential reuse, with conversion potential constrained by factors such as structural design, floor plate configuration, regulatory requirements, and cost feasibility. These constraints imply that policy interventions based on conversion strategies must be targeted and context-specific rather than assumed to produce uniform supply increases.

These findings inform the modeling approach used in this study, where office-to-residential conversions are represented as targeted changes in housing supply or effective housing costs in selected areas

4.2.6 Equity, Population Heterogeneity, and Distribution Impacts

An important theme in the literature is that housing and transportation policies do not affect all populations equally. Differences in income and worker characteristics can influence responses to residential location and the distribution of policy (Giménez-Nadal et al., 2025). This study reflects these differences by evaluating policy outcomes across income groups and occupational categories represented within the estimated joint residence-work location model.

Essential workers and lower-income households often face greater housing affordability constraints and limited residential mobility, increasing their exposure to long commute times and reduced access to employment opportunities (Mitra & Saphores, 2019). As a result, policies that improve accessibility for these groups can yield disproportionate benefits.

This study incorporates these considerations by evaluating policy impacts across demographic and occupational groups, highlighting distributional differences in accessibility and commuting outcomes.

4.3 Policy Simulation Framework

4.3.1 Overview of Policy Framework

This study evaluates two housing policy interventions designed to improve residential proximity to employment centers and reduce long-distance commuting burdens in Southern California. The policies reflect mechanisms frequently discussed in workforce housing policy debates and represent distinct intervention channels within the housing system: housing cost subsidies for eligible workers and housing supply expansion.

Each policy scenario modifies attributes of residential alternatives within the estimated Joint Residence–Work Location Choice Model. Workers respond behaviorally to these changes through updated residential and work location choices. The resulting residential-work location distributions are then translated into commuting flows.

All scenarios are stylized policy experiments intended to evaluate behavioral sensitivity to housing interventions, rather than literal forecasts of parcel-level development.

Target locations for the policy interventions are defined as job-center ZIP codes, identified using employment density and regional job accessibility metrics. Some targeted ZIP codes in Ventura County appear visually large due to the geographic size of suburban and exurban ZIP code polygons relative to denser urban ZIPs in Los Angeles and Orange Counties. The mapped area does not necessarily indicate greater employment magnitude; rather, it reflects the spatial extent of the ZIP code boundaries.

Note that military workers are excluded from the essential-worker priority category because military housing decisions may be governed by different institutional constraints, including base assignment, on-base/off-base housing availability, housing allowances, and installation-specific school/work arrangements. As a result, their residential location behavior may not respond to civilian housing subsidies or priority-housing policies in the same way as other essential-worker groups.

Professional & Essential Worker Definitions

Worker Bin	Description	Typical Occupations	Workers in Final CHTS Sample
Professional Workers	High-skill knowledge economy workers concentrated in major employment hubs and often priced out of nearby housing	engineers, software developers, finance professionals, researchers, architects, lawyers, scientists	54.8%
Essential Workers	Workers providing critical services who often have lower wages relative to housing costs in job-rich regions	healthcare staff, teachers, first responders, transportation operators, utilities workers, public services	30.8%
Other Workers	Remaining occupations not specifically targeted by the policies	retail, hospitality, construction, manufacturing, logistics, administrative support	14.4%

Table 27 - Professional and Essential Worker Descriptions

4.3.2 Policy Details

Two housing-policy interventions are evaluated relative to a status quo scenario. Policy 1 is an employer-sponsored housing subsidy that reduces the effective cost of housing for eligible workers in targeted residential locations. Policy 2 represents an increase in residential housing capacity within selected employment-center ZIP codes. Together, the scenarios test whether localized housing-cost reductions or housing-supply expansion increase the probability that workers select residence–work alternatives associated with major employment centers and whether those changes improve expected commuting outcomes.

Policy 1 (P1): Employer-Sponsored Housing Incentives

Employer-sponsored housing programs are represented as reductions in effective housing costs for professional and essential workers who select residential alternatives near their workplaces. The intervention is evaluated at three subsidy levels (5%, 10%, and 20%) and three workplace-proximity thresholds (5, 15, and 30 minutes). A residential alternative is eligible when it is located within the designated employment-center geography and its modeled peak-period commute time from the worker's workplace does not exceed the applicable threshold.

The resulting nine scenarios test how the magnitude and geographic reach of an employer-sponsored housing incentive affect joint residence–work location probabilities and expected commute outcomes. Professional and essential workers are evaluated separately in the results to preserve differences in occupational geography and modeled responses.

Policy 2 (P2): Office-to-Residential Conversions

Post-pandemic shifts toward hybrid and remote work have increased vacancy rates in many central business districts, creating opportunities for adaptive reuse of commercial buildings. Therefore, the second policy scenario examines the potential impact of converting these underutilized office spaces into residential housing units within employment-dense areas to examine whether the increase in housing supply near these major employment areas would alter the probability that a worker would choose to live closer to work.

In this policy framework, office-to-residential conversions are represented as incremental percent increases in housing capacity reflecting prior studies on vacant, conversion-eligible, office spaces within major employment centers. Prior research demonstrates that vacant office buildings vary substantially in their suitability for residential conversion because feasibility depends on market conditions, location, building configuration and condition, and other physical and institutional characteristics (Geraedts, van der Voordt, & Remoy, 2017). A parcel- or building-level feasibility assessment of office conversion potential within the selected Southern California employment centers is beyond the scope of this dissertation; Policy 2 therefore represents a stylized expansion of residential housing capacity within the 16 employment-center ZIP codes rather than an estimate of physically convertible office inventory. Baseline residential capacity is measured using ACS five-year total housing-unit estimates. For each scenario, the existing housing stock in every targeted ZIP code is increased proportionally by 5%, 10%, or 20%. Consequently, the absolute number of units added varies by ZIP code according to its baseline housing stock. The policy-adjusted housing-unit totals are log-transformed and standardized using the baseline Study 2 scaling parameters before being entered into the residential-location utility calculation.

These increases expand the availability of residential units near employment centers, enabling additional households to relocate closer to workplaces. The scope of this research is meant to be a partial-equilibrium counterfactual, rather than a housing-market equilibrium model; therefore, it does not include an analysis of how increasing capacity will affect the cost of housing in the area.

Because the simulation operates at the ZIP-code level rather than at the parcel level, these conversions are modeled as aggregate increases in housing capacity at the ZIP-code level.

Scenarios include:

- Scenario 2A: 5% increase of housing stock representing conversion of vacant office floor area to residential use in major employment centers
- Scenario 2B: 10% increase of housing stock representing conversion of vacant office floor area to residential use in major employment centers
- Scenario 2C: 20% increase of housing stock representing conversion of vacant office floor area to residential use in major employment centers
- Sensitivity analyses at 50% and 90% increase in housing in major employment centers

These scenarios represent stylized supply expansions intended to assess whether concentrated housing additions in selected areas can increase the probability that workers choose to live in those locations.

4.4 Simulation Methodology

Policy scenarios are evaluated using a behavioral simulation framework that applies the joint residence–work location choice model estimated in Chapter 3 to counterfactual housing conditions. The simulation modifies selected residential attributes, including housing costs and housing capacity, or applies group-specific housing-capacity adjustments for targeted workforce allocation scenarios. Residential choice probabilities are then recomputed using the estimated utility function to evaluate resulting changes in residential location patterns, commuting outcomes, and regional accessibility.

4.4.1 Behavioral Simulation Framework

Residential location decisions are modeled using a joint residence–work location choice framework estimated in Chapter 3, grounded in random utility theory (McFadden, 1978; Train, 2009). In this framework, each worker i selects a residential location h that maximizes indirect utility, given by:

$$U_{ihw}^{w} = V_{ihw}^{s} + \epsilon_{ihw}$$

$$\mathrm{V}_{\mathrm{ihw}}^{\mathrm{s}} = \sum_{k=1}^{K} \hat{\beta}_k \, X_{kihw}^{s}$$

Equation 16 – Random Utility Specification of Joint Residence-Work Location Choice

Where:

- i is the worker;
- h is the residential alternative;
- w is the workplace alternative;
- s is the policy scenario;
- $\mathrm{V}_{\mathrm{ihw}}^{\mathrm{s}}$ is the systematic utility under scenario s;
- k indexes the explanatory variables included in the final model specification;
- K is the total number of estimated attributes;
- $\hat{\beta}_k$ is the fixed coefficient from the final model specification;
- X_{kihw}^{s} is the value of attribute k for worker i, residence h, and workplace w under scenario s
- $\in_{ihw}$ is an idiosyncratic error term assumed to follow an independently and identically distributed extreme value distribution

Equation 16 represents a simplified conceptual representation of the utility framework. The full empirical specification estimated in Study 2 additionally includes workplace earnings, occupational matching variables, affordability burdens, and housing-capacity measures. The coefficients associated with each variable quantify the marginal contribution of each attribute type to overall utility.

The simulation population consists of the final Study 2 estimation sample of 1,041 workers from the California Household Travel Survey (CHTS), restricted to the seven-county Southern California study region. Rather than constructing a synthetic regional population, the simulation recalculates residential choice probabilities for the observed workers under alternative policy scenarios. Each worker evaluates the same sampled residential-workplace choice set used during model estimation, ensuring consistency between the estimated behavioral parameters and the policy simulations.

Under standard assumptions of random utility maximization, the probability that worker i selects residential location h is given by the multinomial logit form:

$$P_{ihw}^{s} = \frac{\exp(V_{ihw}^{s})}{\sum_{(h\prime w\prime)\epsilon C_n} \exp(V_{ih\prime w\prime}^{s})}$$

Equation 17 – Multinomial Logit Choice Probability Equation

Where C_i is the sampled choice set for worker i.

The status-quo scenario preserves the baseline attributes used in the final model specification. Each policy scenario then modifies only the attributes directly affected by that intervention. Policy 1 reduces the affordability burden associated with eligible worker–residence alternatives through an employer-sponsored housing subsidy. Policy 2 increases the standardized housing-capacity attribute within the designated employment-center ZIP codes and incorporates the associated supply-induced housing-price response. Scenario 3 applies both interventions simultaneously. All remaining individual, workplace, transportation, and location attributes are held at their baseline values.

For each scenario, the modified attributes are entered into the utility specification using the coefficients estimated in Study 2. Systematic utilities and multinomial-logit probabilities are then recalculated across each worker's choice set. Differences between baseline and policy probabilities therefore represent changes in the relative attractiveness of residence–work alternatives attributable to the simulated policy intervention, conditional on the estimated behavioral relationships and fixed choice-set structure.

Finally, the resulting probabilities are used to calculate probability-weighted expected outcomes, including expected commute duration, commute-threshold outcomes, affordability outcomes where applicable, and the probability of selecting policy-targeted residential alternatives. This framework provides a consistent counterfactual comparison across the status quo and policy scenarios while isolating the effects of the modeled policy changes from re-estimation of the underlying behavioral parameters.

4.4.2 Policy Scenario Implementation

Policy 1: Employer-Sponsored Housing Cost Subsidy

Subsidy Adjustment Strategy

Policy 1 represents an employer-sponsored housing subsidy intended to reduce the housing-cost burden associated with residential alternatives that place eligible workers within a specified commute-time threshold of their workplace. The policy does not assume that a subsidized worker automatically relocates. Instead, it changes the relative attractiveness of qualifying residence-work alternatives within the worker’s existing choice set, after which the residential-workplace choice probabilities are recalculated using the estimated model utility function.

$$C_{ihw}^{p1} = C_h(1 - \delta \cdot I_{ih}^{p1})$$

$$I_{ih}^{p1} = 1[G_i \in \{Professional, Essential\} \wedge (t_{ihw} \leq \tau_s)]$$

Equation 18 - Employer-Sponsored Housing Price Adjustment Equation

Where,

- I_{ih}^{p1} is the eligibility indicator;
- G_i is the worker group;
- i is the worker;
- h is the residential alternative;
- w is the workplace alternative;
- s is the policy scenario;
- τ_s is the applicable commute time threshold for the policy scenario s;
- t_{ihw} is the commute time for worker i with home location h and worker location w;
- C_h is the baseline housing price for residential alternative h;
- δ is the proportional subsidy rate;
- C_{ihw}^{p1} is the effective housing price faced by worker i for residential housing alternative h and workplace alternative w under Policy 1.

The eligibility indicator equals 1 when the worker is classified as either a professional or an essential worker occupational group and the corresponding residence–work alternative satisfies the policy's geographic targeting criterion. Otherwise, the indicator equals 0 and the baseline housing price remains unchanged.

This formulation intentionally leaves the underlying market housing price unchanged. The policy instead represents the portion of the housing cost paid by the employer, thereby reducing the effective cost faced by the worker.

Adjustment to the Final Model Specification Affordability Variable

The preferred model specification represents housing cost through a worker-specific affordability-burden measure rather than through housing price alone. The baseline affordability burden for worker i and residential alternative h is defined as:

$$A_{ih} = \frac{C_h}{Y_i}$$

$$C_h = 12[L_h \frac{r_m(1 + r_m)^N}{(1 + r_m)^N - 1}]$$

Where,

- A_{ih} is the baseline affordability burden
- C_h is the baseline housing price for residential alternative h;
- Y_i is the worker's annual income from CHTS
- $L_h = 0.80R_h$ which represents the amount of a home loan after a 20% down payment towards the price of the house h
- $r_m = \frac{0.065}{12}$ which represents the assumed interest rate of a home loan
- N represents the assumed life of a home loan

Equation 19 - Baseline Affordability Burden Equation

Because the employer subsidy reduces the cost borne by the worker but does not change the worker income, the policy-adjusted affordability burden becomes:

$$A_{ihw}^{P1} = A_{ih}(1 - \delta_s I_{ihw}^{P1})$$

Accordingly, the change in affordability burden produced by the policy is:

$$\Delta A_{ihw}^{P1} - A_{ih} = -\delta_s I_{ihw}^{P1} A_{ih}$$

Equation 20 - Policy-Adjusted Affordability Burden

This formulation directly corresponds to the affordability variable used in the final model specification.

Policy-Specific Choice Probabilities

Policy-specific probabilities are calculated by applying the utility change to the baseline probabilities in the final model specification. For alternative $j = (h, w)$ in worker i's choice set,

$$P_{ij}^{pl,s} = \frac{P_{nj}^0 \exp(\Delta V_{nj}^{pl,s})}{\sum_{j' \in C_i} P_{ij'}^0 \exp(\Delta V_{il}^{pl,s})}$$

Equation 21 - Policy-Specific Choice Probability Reweighting Equation

where P_{ij}^{0} is the baseline model specification probability and C_i is worker i's residence–work choice set.

This exact multinomial-logit reweighting approach preserves the estimated preference structure of the final model specification while isolating the behavioral effect of the policy intervention. Probabilities continue to sum to one within each worker's choice set, and untreated alternatives retain their baseline attributes while competing against alternatives whose affordability burden has been reduced by the subsidy.

Policy 2: Office-to-Residential Conversion Housing Supply Expansion

Baseline Housing Capacity

Baseline residential housing capacity is represented using total housing-unit estimates from ACS 2024 five-year Table B25001. Housing-unit counts are merged onto the fixed Study 2 ZIP-code universe and transformed using:

$$\ln(H_h + 1)$$

where,

- H_h is the number of housing units in residential ZIP code h

The log-transformed measure is standardized before inclusion in the joint residence–work location choice model.

Raw Capacity Expansion

Under Policy 2, housing capacity is increased proportionally within the 16 targeted ZIP codes. For scenario s, the policy-adjusted capacity is:

$$H_h^s = \begin{cases} H_h(1 + r_s), & h \in \mathcal{T} \\ H_h, & h \notin \mathcal{T} \end{cases}$$

Where,

- r_s is the scenario-specific capacity expansion rate
- $\mathcal{T}$ denotes the set of targeted ZIP codes

Equation 22 - Scenario-Specific Housing-Capacity Expansion

Standardized Capacity Adjustment

Because the estimated model uses standardized log capacity rather than raw housing-unit counts, the corresponding policy adjustment is:

$$z_{H,h}^{s} = z_{H,h} + I(h \in \mathcal{T}) \frac{\ln(1 + r_s)}{\sigma_{\ln H}}$$

Where,

- $z_{H,h}$ is the baseline standardized log-capacity value
- $\sigma_{\ln H}$ is the standard deviation used to construct the capacity variable

Equation 23 - Policy-Adjusted Standardized Housing Capacity

Housing Price Response Assumption

The simulation also incorporates a housing-price response to increased supply. Using a price–supply elasticity ϵ_{PH}, the implied policy-adjusted housing price is:

$$P_h^s = P_h(1 + r_s)^{\epsilon_{PH}}$$

In logarithmic form:

$$\ln P_h^s = \ln P_h + \epsilon_{PH} \ln(1 + r_s)$$

Equation 24 - Implied Housing-Price Response to Capacity Expansion

Where,

- $\epsilon_{PH} = -0.19$, informed by Mense (2025), who estimates that a 1% increase in new housing supply reduces average rents by approximately 0.19%.
- Applied only when $h \in \mathcal{T}$; all other ZIP codes retain their baseline price values.

The supply-induced rent response is represented using a literature-informed parameter of −0.19, based on Mense (2025), who estimates that a 1% increase in annual new housing supply reduces average rents by approximately 0.19%. Mense's analysis uses housing-market data from 94 planning regions in Germany rather than Southern California. Accordingly, the −0.19 parameter is not interpreted as a locally estimated Southern California elasticity; it is applied as a literature-informed sensitivity assumption to represent the direction and approximate magnitude of the potential housing-cost response to increased supply.

Standardized Price Adjustment

Because housing price enters the estimated model as a standardized logarithmic variable, the policy-adjusted price measure becomes:

$$z_{P,h}^{S} = z_{P,h} + I(h \in \mathcal{T}) \frac{\epsilon_{PH} \ln(1 + r_s)}{\sigma_{\ln}}$$

Where,

- $z_{p,h}^{S}$ is the standardized price adjustment;
- $z_{p,h}$ is the initial standardized price from Zillow
- $I(h \in \mathcal{T})$ is the binary indicator that the residence in question lies within one of the altered ZIP codes
- ϵ_{PH} is the implied housing elasticity factor (introduced in Equation 24)
- $r_s$is the scenario-specific capacity expansion rate
- σ_{lnP} is the standard deviation

Equation 25 - Policy-Adjusted Standardized Housing Price

Interpretation and Limitations

The 5%, 10%, and 20% housing-stock increases are stylized sensitivity levels rather than forecasts of expected office-conversion production. Additionally, 50% and 90% increases are calculated to test the sensitivity. The graduated scenarios are used to evaluate whether simulated residential and commuting outcomes respond proportionally to increasingly substantial housing-capacity additions. This approach is consistent with scenario-based adaptive-reuse studies that evaluate multiple conversion intensities rather than assuming a single deterministic development outcome. These scenario magnitudes are stylized representations of incremental housing-supply expansion rather than forecasts of realized office-conversion production since conversion feasibility and unit yield vary considerably by building geometry, construction cost, regulation, and market conditions (Horowitz & Kansal, 2025). Accordingly, the analysis should be interpreted as a regional behavioral sensitivity assessment that can help identify whether additional investigation of office-to-residential conversion strategies is warranted. A subsequent feasibility analysis would require parcel- and building-level information regarding structure type, vacancy, construction cost, regulatory constraints, ownership, and market conditions.

This dual mechanism reflects both quantity and price effects of supply expansion. This formulation represents a reduced-form approximation of localized housing-market responses to increased supply rather than a fully endogenous housing-price equilibrium model.

4.4.3 Simulation Scenarios

Although Policies 1 and 2 are defined separately, the simulation design also evaluates their coordinated implementation. The analysis therefore includes a status-quo condition, two standalone policy scenarios, and one combined scenario. Scenario 3 is not a separate policy; it applies the housing-cost adjustment from Policy 1 and the housing-capacity and price adjustments from Policy 2 within a common simulation framework. The simulated scenarios are as follows:

- Scenario 0 (S0): Status Quo
- Scenario 1 (S1): Housing Cost Intervention (Subsidy Only – Policy 1):
  - Employer-sponsored housing subsidies are applied to eligible workers in employment-proximate locations, reducing effective housing costs and influencing residential choice through the utility function
- Scenario 2 (S2): Housing Supply Expansion (Capacity Increase – Policy 2):

    - Housing capacity is increased in targeted job-center locations through office-to-residential conversion, allowing additional households to locate in high-demand areas.
- Scenario 3 (S3): Combined Policy Intervention (Subsidy + Capacity)
    - A combined intervention incorporating:
        - Housing cost subsidies (Policy 1)
        - Housing supply expansion (Policy 2)
    - This scenario reflects coordinated housing strategies in which increased affordability for eligible workers and increased housing capacity in major employment are addressed simultaneously

This structure allows for comparison of:

- **Current Condition,** status quo
- **Isolated policy effects** (Scenarios 1 and 2), and
- **Combined policy impacts** (Scenario 3), capturing potential synergies across interventions

Scenario	Policies Included	Target Population	Mechanism	Description
S0	None	All workers	Status quo	No change
S1	Policy 1	Eligible workers (professional & essential)	Price reduction	Eligible professional and essential workers receive a housing-price reduction for qualifying residential alternatives within the specified commute shed
S2	Policy 2	All workers (location-based)	Supply expansion	Housing capacity and the associated literature-informed price response are adjusted in the 16 target ZIP codes for all workers
S3	Policy 1 + 2	All workers; additional subsidy for eligible workers	Integrated (price + supply)	Policy 2 capacity and price adjustments are applied in the target ZIP codes, and eligible professional and essential workers also receive the Policy 1 subsidy for qualifying alternatives.

Table 28 - Policy Integration into Scenarios

4.4.4 Outcome Metrics

Policy outcomes are evaluated primarily using probability-weighted measures calculated from the complete distribution of modeled residence–work location choice probabilities. Probability-weighted measures are used because they represent expected behavioral responses across all available alternatives rather than relying on a single simulated assignment for each worker.

The primary outcome measures are:

- Expected commute time: The probability-weighted peak-period commute time implied by workers' simulated residence–work choice probabilities.

- Expected long-commute shares: The probability-weighted shares of workers assigned to alternatives with commute times of at least 45, 60, and 75 minutes. The 75-minute threshold is also reported as the supercommuter measure.
- Expected target-location probability: The expected probability that a worker selects a residence–work alternative satisfying the relevant policy eligibility condition. For Policy 1, this represents an eligible residential alternative within the specified commute-time threshold. For Policy 2, it represents a residence located within a capacity-expansion ZIP code.
- Change from the status quo: For each metric, the policy result is compared with its corresponding baseline expectation. Changes in commute shares and probabilities are reported in percentage points.
- Workers with increased target probability: The percentage of workers whose summed probability of selecting a policy-targeted alternative increases relative to the baseline.
- Worker-group outcomes: Expected commute and target-location outcomes are calculated separately for essential, professional, and, where applicable, other workers to identify heterogeneous policy responses.
- Change in Consumer Welfare: Changes in consumer welfare are measured using the change in the multinomial-logit logsum, which represents the change in expected maximum utility across a worker's sampled residence–work choice set. To improve interpretability, logsum changes are additionally converted into two welfare-equivalent measures: (1) a commute-time-equivalent welfare gain, representing the reduction in commute time that would generate an equivalent modeled utility improvement; and (2) a housing-cost-equivalent welfare gain, representing the reduction in annual housing cost that would generate an equivalent modeled utility improvement at the worker's estimated income. These are welfare-equivalent measures rather than predictions of literal commute-time reductions or monetary transfers.

Together, these measures distinguish changes in modeled behavior from changes in welfare. A policy may generate relatively small changes in regional commute patterns or residential choice probabilities while still improving the attractiveness of workers' available residence-work alternatives and therefore increasing expected utility.

4.5 Simulation Results

This section presents the results of the policy simulations described in 4.4.2 Policy Scenario Implementation through 4.4.4 Outcome Metrics. Each policy is presented independently before comparing the combined effects across scenarios.

4.5.1 Scenario 1 (Policy 1) Results – Employer-Sponsored Housing Subsidies

Policy Overview and Simulation Design

Policy 1 evaluates employer-sponsored housing subsidies for professional and essential workers who select eligible residential alternatives near their workplaces. Eligibility requires that the worker belongs to one of the two designated occupational groups, that the residential alternative lies within a targeted employment-center ZIP code, and that the modeled commute time between the residential and workplace alternatives do not exceed the scenario-specific threshold.

The simulation evaluates subsidy rates of 5%, 10%, and 20% under maximum eligible commute-time thresholds of 5, 15, and 30 minutes. The subsidy reduces the effective housing price associated with each eligible worker–residence alternative. The adjusted price is transformed using the same logarithmic and standardization parameters applied in Study 2, after which the income–housing-price interaction, systematic utility, and residence–work choice probabilities are recalculated. Alternatives that do not satisfy the occupational, geographic, and commute-time conditions retain their baseline values.

Figure 21 displays the 16 employment-center ZIP codes used to define the geographic component of the targeted policy scenarios. These ZIP codes were intentionally selected to represent concentrated employment opportunities within the study region rather than to provide comprehensive geographic coverage. The targeted geography reflects the underlying policy question of whether increasing access to housing near major employment concentrations can alter residential-location probabilities and reduce commuting burdens. Accordingly, ZIP codes outside these designated employment centers are not directly treated by the policy. For Policy 1, geographic targeting is combined with worker eligibility and the scenario-specific commute-time threshold, which is evaluated separately for each worker–residence–workplace alternative.

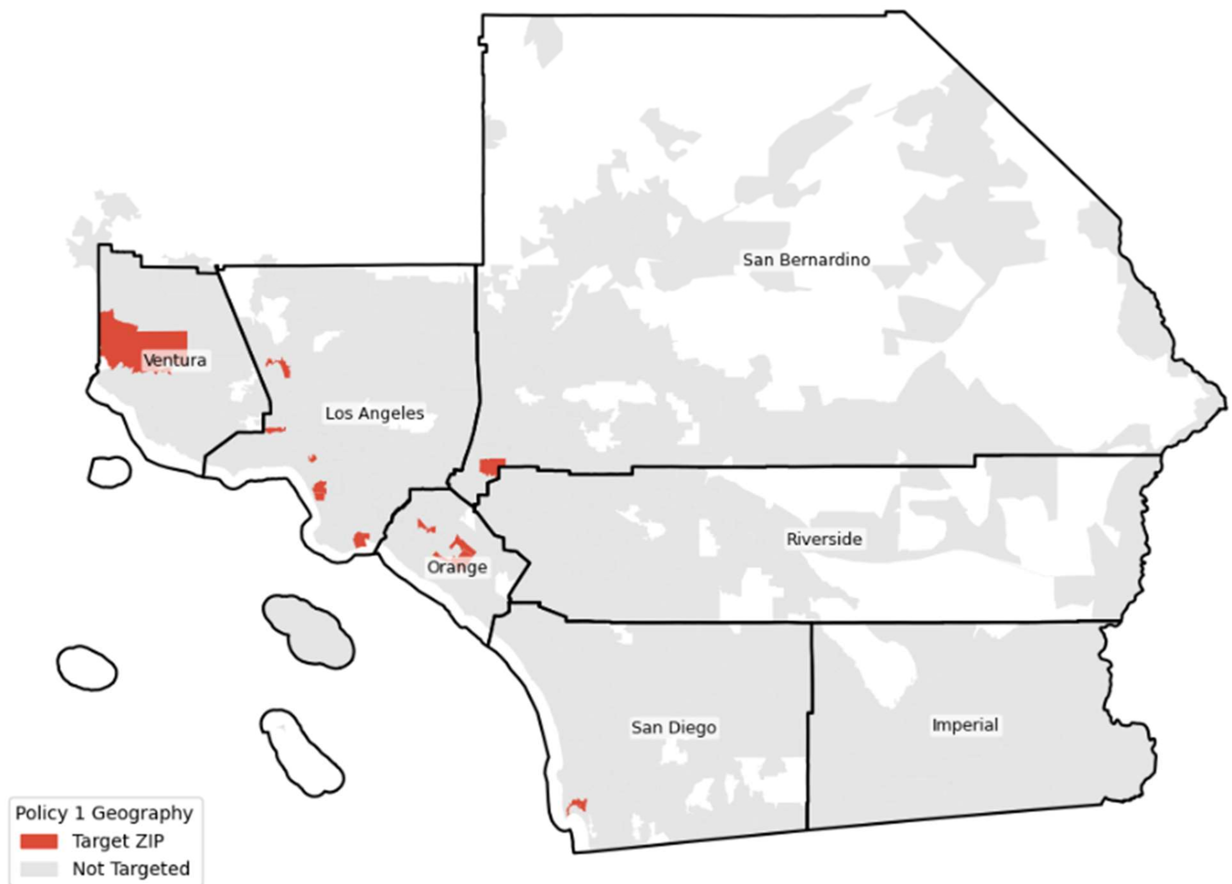

Figure 21 – ZIP Codes Meeting Policy 1 Employment Center Selection Criteria

Table 29 summarizes the number of eligible alternatives, workers, occupational-group members, and residential ZIP codes associated with each threshold. The eligible choice set expands as the threshold increases. The 5-minute threshold contains 574 eligible residence–work alternatives involving 446 workers and seven residential ZIP codes. The 15-minute threshold contains 1,074 alternatives involving 667 workers and eight ZIP codes. The 30-minute threshold contains 2,774 alternatives involving 880 workers and 14 ZIP codes.

The number of eligible alternatives remains constant across subsidy rates within a given threshold because the subsidy magnitude changes the effective housing price but does not alter the geographic or commute-time eligibility rule.

Scenario 1 Design and Eligible Alternatives							
Scenario	**Subsidy**	**Target Commute**	**Eligible Residence-Work Alternatives**	**Eligible Workers**	**Professional Workers**	**Essential Workers**	**Eligible Residential ZIPs**
S1 - 5% Subsidy; 5 Min. Commute	5%	5 minutes	574	446	287	159	7
S1 - 10% Subsidy; 5 Min. Commute	10%						
S1 - 20% Subsidy; 5 Min. Commute	20%						
S1 - 5% Subsidy; 15 Min. Commute	5%	15 minutes	1074	667	441	226	8
S1 - 10% Subsidy; 15 Min. Commute	10%						
S1 - 20% Subsidy; 15 Min. Commute	20%						
S1 - 5% Subsidy; 30 Min. Commute	5%	30 minutes	2774	880	560	320	14
S1 - 10% Subsidy; 30 Min. Commute	10%						
S1 - 20% Subsidy; 30 Min. Commute	20%						

Table 29 – Scenario 1 Eligible Residence-Work Location Alternatives Available within Target Commute Thresholds

Expected Commute Outcomes

Table 30 compares probability-weighted expected commute outcomes under each Policy 1 scenario with the status quo. Under the baseline simulation, the expected commute is approximately 31.74 minutes. Across the Policy 1 scenarios, expected commute time decreases as either the subsidy rate or the commute-time eligibility threshold increases.

The largest reduction among the primary scenarios occurs under the 20% subsidy with a 30-minute eligibility threshold, where expected commute declines to approximately 31.46 minutes, a reduction of approximately 0.280 minutes, or 0.96%, relative to baseline. Under the 5-minute threshold, expected commute reductions range from approximately 0.032 minutes under the 5% subsidy to 0.130 minutes under the 20% subsidy.

The relatively modest aggregate changes do not indicate that the policy has no effect. Policy 1 modifies the relative attractiveness of only those residence–work alternatives that satisfy both the worker eligibility criteria and the applicable commute-time threshold, while the reported expected commute measure reflects probability-weighted outcomes across each worker's complete modeled choice set. Consequently, localized changes in the attractiveness of eligible alternatives translate into comparatively smaller changes in regionwide expected commute outcomes.

Policy 1 - Expected Commute Outcomes					
Subsidy (%)	**Commute Threshold (min)**	**Avg. Treated Alternatives**	**Expected Commute (min)**	**Δ Expected Commute (min)**	**Change from Baseline (%)**
5	5	12.41	31.704	-0.032	-0.12
10	5	12.41	31.672	-0.064	-0.23
20	5	12.41	31.606	-0.130	-0.48
5	15	32.09	31.683	-0.052	-0.19
10	15	32.09	31.631	-0.105	-0.37
20	15	32.09	31.524	-0.212	-0.75
5	30	79.35	31.666	-0.070	-0.24
10	30	79.35	31.596	-0.140	-0.48
20	30	79.35	31.456	-0.280	-0.96

Table 30 – Policy 1 Expected Commute Outcomes

Expected Outcomes by Occupation Group

Table 31 reports expected outcomes separately for professional and essential workers. The results indicate that Policy 1 affects both occupational groups, although the magnitude of the response differs. Across the primary scenarios, essential workers generally experience somewhat larger reduction in commute time and larger increases in target-alternative probability than professional workers.

Under the 20% subsidy with a 30-minute eligibility threshold, the expected commute for essential workers declines from approximately 30.778 to 30.430 minutes, a reduction of about 0.349 minutes, or 1.25%. For professional workers, expected commute time declines from approximately 32.319 to 32.082 minutes, a reduction of approximately 0.237 minutes, or 0.79%. The associated target-alternative probability increases from approximately 58.20% to 59.13% for essential workers, an increase of approximately 0.93 percentage points, compared with an increase from approximately 54.98% to 55.63% for professional workers, or approximately 0.64 percentage points.

Policy 1 - Expected Commute Outcomes by Worker Group							
Subsidy (%)	**Commute Threshold (min)**	**Worker Group**	**Policy Expected Commute (min)**	**Δ Expected Commute (min)**	**Baseline Target Probability (%)**	**Policy Target Probability (%)**	**Δ Target Probability (% pts)**
5	5	Essential	30.734	-0.044	13.03	13.16	0.13
5	5	Professional	32.295	-0.024	10.16	10.23	0.07
10	5	Essential	30.689	-0.089	13.03	13.30	0.27
10	5	Professional	32.271	-0.049	10.16	10.31	0.15
20	5	Essential	30.598	-0.180	13.03	13.58	0.55
20	5	Professional	32.221	-0.099	10.16	10.46	0.3
5	15	Essential	30.710	-0.068	26.87	27.08	0.21
5	15	Professional	32.277	-0.042	23.83	23.96	0.13
10	15	Essential	30.640	-0.138	26.87	27.29	0.43
10	15	Professional	32.234	-0.085	23.83	24.09	0.26
20	15	Essential	30.500	-0.278	26.87	27.73	0.86
20	15	Professional	32.147	-0.172	23.83	24.36	0.53
5	30	Essential	30.691	-0.087	58.20	58.43	0.23
5	30	Professional	32.260	-0.059	54.98	55.14	0.16
10	30	Essential	30.603	-0.175	58.20	58.66	0.47
10	30	Professional	32.201	-0.119	54.98	55.30	0.32
20	30	Essential	30.430	-0.349	58.20	59.13	0.93
20	30	Professional	32.082	-0.237	54.98	55.63	0.64

Table 31 - Scenario 1 Expected Commute Outcomes by Occupation Group

This pattern is also visible across the lower subsidy levels and shorter commute thresholds. The results therefore suggest that essential workers are somewhat more responsive to the modeled subsidy within the available choice sets. This difference reflects the combined influence of the estimated occupational matching effects, affordability relationships, workplace geography, and the set of eligible residential alternatives available to each worker.

Expected Probability Response

Table 32 presents the baseline and policy expected probabilities of selecting a subsidy-eligible residence–work alternative. Because eligibility expands with the commute threshold, baseline target probability differs substantially across the 5-, 15-, and 30-minute scenarios.

Under the 5-minute threshold, baseline target probability is approximately 11.22%. It increases to approximately 11.32%, 11.42%, and 11.62% under the 5%, 10%, and 20% subsidy scenarios, respectively. These changes correspond to increases of approximately 0.10, 0.19, and 0.39 percentage points.

Under the 15-minute threshold, baseline target probability is approximately 24.95%, increasing to approximately 25.11%, 25.27%, and 25.60% as the subsidy rises from 5% to 20%. Under the 30-minute threshold, baseline target probability is approximately 56.18% and increases to approximately 56.37%, 56.55%, and 56.93% under the primary subsidy scenarios. The corresponding increase under the 20% subsidy is approximately 0.75 percentage points, or about 1.28% relative to baseline.

Policy 1 - Final Model Probability Response						
Subsidy (%)	**Commute Threshold (min)**	**Avg. Treated Alternatives**	**Baseline Target Probability (%)**	**Policy Target Probability (%)**	**Δ Target Probability (% pts)**	**Relative Change in Target Probability (%)**
5	5	12.41	11.22	11.32	0.1	0.65
10	5	12.41	11.22	11.42	0.19	1.32
20	5	12.41	11.22	11.62	0.39	2.67
5	15	32.09	24.95	25.11	0.16	0.57
10	15	32.09	24.95	25.27	0.33	1.14
20	15	32.09	24.95	25.6	0.66	2.31
5	30	79.35	56.18	56.37	0.19	0.32
10	30	79.35	56.18	56.55	0.38	0.64
20	30	79.35	56.18	56.93	0.75	1.28

Table 32 - Policy 1 Probability Response under the Final Model Specification

These results confirm that the model responds in the expected direction. Larger subsidies increase the probability of selecting eligible residence–work alternatives, and broader commute thresholds increase the share of the choice set eligible for the subsidy. At the same time, the magnitude of the probability shifts remains moderate, reflecting the fact that housing affordability is only one component of residential choice and competes with commute time, housing characteristics, workplace attributes, occupational matching, and other modeled factors.

Sensitivity Analysis

Table 33 through Table 35 presents upper-bound sensitivity scenarios in which eligible professional and essential workers receive housing-cost subsidies of 50% and 90% for qualifying alternatives within 30 minutes of their workplaces. These scenarios are intended as stress tests rather than proposed program designs and evaluate whether substantially larger subsidy levels materially alter the response observed under the primary scenarios.

Under the 50% subsidy, expected commute decreases from approximately 31.736 to 31.038 minutes, a reduction of approximately 0.698 minutes, or 2.39%. Target-alternative probability increases from approximately 56.18% to 58.05%, an increase of approximately 1.87 percentage points, or 3.20% relative to baseline. Under the 90% subsidy, expected commute falls to approximately 30.481 minutes, a reduction of approximately 1.255 minutes, or 4.28%, while target-alternative probability increases to approximately 59.54%, a gain of approximately 3.36 percentage points, or 5.75% relative to baseline.

Policy 1 - Expected Commute Outcomes Sensitivity Analysis					
Subsidy (%)	**Commute Threshold (min)**	**Avg. Treated Alternatives**	**Expected Commute (min)**	**Δ Expected Commute (min)**	**Change from Baseline (%)**
50	30	79.35	31.038	-0.698	-2.39
90	30	79.35	30.481	-1.255	-4.28

Table 33 - Policy 1 Expected Commute Outcomes Sensitivity Analysis

The occupational results show the same directional pattern. Under the 90% stress test, essential workers experience an expected commute reduction of approximately 1.545 minutes compared with approximately 1.076 minutes for professional workers. Target-alternative probability increases by approximately 4.11 percentage points for essential workers and 2.89 percentage points for professional workers.

Policy 1 - Expected Commute Outcomes by Worker Group Sensitivity Analysis with a 30 Minute Commute Threshold							
Subsidy (%)	Worker Group	Avg. Eligible Alternatives	Policy Expected Commute (min)	Δ Expected Commute (min)	Baseline Target Probability (%)	Policy Target Probability (%)	Δ Target Probability (% pts)
50	Essential	79.40	29.913	-0.865	58.20	60.5	2.31
50	Professional	79.31	31.725	-0.594	54.98	56.59	1.6
90	Essential	79.40	29.233	-1.545	58.20	62.31	4.11
90	Professional	79.31	31.243	-1.076	54.98	57.88	2.89

Table 34 - Policy 1 Expected Outcomes by Occupation Group Sensitivity Analysis

Although these upper-bound scenarios produce larger changes than the primary 5%, 10%, and 20% scenarios, the resulting effects remain moderate at the regional level. This finding suggests that subsidy magnitude contributes to the modeled response but does not fully determine residential relocation patterns. Even very large housing-cost reductions operate within a constrained residential choice environment shaped by workplace geography, commute time, occupational matching, and other attributes represented in the final choice model.

Policy 1 - Final Model Probability Response Sensitivity Analysis						
Subsidy (%)	Commute Threshold (min)	Avg. Treated Alternatives	Baseline Target Probability (%)	Policy Target Probability (%)	Δ Target Probability (% pts)	Relative Change in Target Probability (%)
50	30	79.35	56.18	58.05	1.87	3.2
90	30	79.35	56.18	59.54	3.36	5.75

Table 35 – Policy 1 Probability Response Sensitivity Analysis

Affordability Burden Effects

Policy 1 produces consistent reductions in expected housing affordability burden across all employer-sponsored housing subsidy scenarios. The magnitude of the reduction increases with both the subsidy rate and the allowable commute threshold, indicating that larger subsidies and broader geographic eligibility provide workers with access to a wider set of financially attractive residential alternatives. Under the primary scenarios, as shown in Table 36, expected affordability burden decreases from approximately 0.49% under the 5% subsidy with a 5-minute eligibility threshold to approximately 10.86% under the 20% subsidy with a 30-minute threshold. The negative changes reported in Table 33 represent improvements in affordability because the burden measure is defined as the annualized housing cost relative to annual worker income; therefore, a lower value indicates a smaller housing-cost burden.

The results also indicate that the affordability effects are broadly distributed among eligible workers rather than being driven by a small subset of the sample. Approximately 99.9% to 100% of eligible workers experience an improvement in expected affordability across the simulated scenarios. Importantly, however, the magnitude of the improvement varies substantially with policy intensity. For example, under the 20% subsidy and 30-minute eligibility threshold, the expected affordability burden declines from the baseline by approximately 0.133, corresponding to a 10.86% reduction in the expected housing-cost burden. The sensitivity scenarios reinforce this pattern: the 50% subsidy reduces expected burden by approximately 28.2%, while the 90% stress-test scenario produces a reduction of approximately 53.8%. These higher subsidy levels are not intended to represent preferred policy recommendations; rather, they demonstrate that the model responds monotonically and directionally as expected when the magnitude of the intervention is increased.

Policy 1 Affordability Burden Table						
Subsidy (%)	Commute Threshold (min)	Expected Affordability Burden	Delta Affordability Burden	Baseline Target Probability (%)	Policy Target Probability (%)	Delta Target Probability (% pts)
5	5	1.1550	-0.0079	11.22	11.32	0.1
10	5	1.1468	-0.0162	11.22	11.42	0.19
20	5	1.1290	-0.0339	11.22	11.62	0.39
5	15	1.1471	-0.0159	24.95	25.11	0.16
10	15	1.1306	-0.0323	24.95	25.27	0.33
20	15	1.0960	-0.0669	24.95	25.60	0.66
5	30	1.1307	-0.0323	56.18	56.37	0.19
10	30	1.0977	-0.0652	56.18	56.55	0.38
20	30	1.0298	-0.1331	56.18	56.93	0.75
50	30	0.8091	-0.3539	56.18	58.05	1.87
90	30	0.4702	-0.6927	56.18	59.54	3.36

Table 36 - Policy 1 Affordability Burden Changes Amongst Eligible Workers

Changes in the probability of selecting a policy-targeted residential alternative are more modest. For the 30-minute scenarios, the baseline expected probability of selecting a qualifying alternative is approximately 56.18%. This increases to 56.37%, 56.55%, and 56.93% under the 5%, 10%, and 20% subsidy scenarios, respectively. Thus, the 20% primary scenario produces an increase of approximately 0.75 percentage points in target-alternative probability. The substantially larger affordability improvements relative to the changes in residential choice probability suggest an important distinction: Policy 1 may provide meaningful financial benefits to workers even when it produces relatively modest changes in residential location probabilities. This finding indicates that the policy's principal benefit may operate through reduced housing-cost burden rather than large-scale residential relocation.

Mean Annual Housing-Cost and Mean Commute Time Equivalents

Table 37 reports changes in expected maximum utility, or logsum, associated with each Policy 1 scenario and translates those changes into commute-time and housing-cost equivalents. In a random utility framework, the logsum summarizes the expected utility available to a worker across the modeled residence–workplace alternatives, accounting for both the attractiveness of individual alternatives and the probability of selecting them. The welfare measure therefore captures changes in the overall choice set rather than changes in expected commute time alone. A worker may experience an improvement in expected welfare even when the associated change in expected commute time is small if the policy increases the attractiveness or availability of residence–workplace alternatives through improved housing affordability, housing characteristics, workplace earnings, occupational compatibility, or other modeled attributes.

All Policy 1 scenarios produce positive average and median logsum changes relative to the baseline, indicating improvements in modeled expected utility. Among the primary scenarios, the average logsum change increases from approximately 0.0011 under the 5% subsidy and 5-minute eligibility threshold to approximately 0.0174 under the 20% subsidy and 30-minute threshold. The corresponding commute-time and housing-cost equivalents similarly increase with the intensity and geographic reach of the intervention. Under the 20% subsidy and 15-minute threshold, for example, the average welfare change corresponds to approximately 2.24 minutes of commute-time-equivalent gain or approximately $3,004 in annual housing-cost-equivalent gain.

The distribution of modeled welfare effects is heterogeneous across workers. Under the 20% subsidy and 30-minute threshold, the average logsum improvement is approximately 0.0174, while the maximum worker-level improvement approaches 0.2031. This variation reflects differences in workers' baseline choice sets and exposure to qualifying alternatives. Workers whose existing residence–workplace alternatives are already comparatively attractive may experience little change, whereas workers for whom the subsidy makes a previously less-attractive alternative more competitive can experience substantially larger modeled gains.

The upper-bound sensitivity scenarios reinforce this pattern. At the 30-minute eligibility threshold, increasing the subsidy to 50% raises the average logsum change to approximately 0.0450, while the 90% stress-test scenario produces an average change of approximately 0.0848.

Because utility is measured on an arbitrary scale, the commute-time and housing-cost equivalent transformations provide interpretable measures of relative welfare magnitude by expressing the modeled utility change in units of commute time or housing cost.

Policy 1 - Scenario 1 Equivalents					
Subsidy / Commute Radius	**Average Change in Expected Commute (min)**	**Mean Delta Logsum**	**Mean Commute-Time Equivalent Gain (min)**	**Mean Annual Housing-Cost Equivalent Gain ($)**	**Mean Monthly Housing-Cost Equivalent Gain ($)**
5% / 5min	-0.0316	0.00108	0.246	314.13	26.18
10% / 5min	-0.0637	0.00218	0.492	633.03	52.75
20% / 5min	-0.1296	0.00448	0.988	1285.91	107.16
5% / 15min	-0.0523	0.00213	0.571	739.5	61.62
10% / 15min	-0.1051	0.00429	1.134	1486.58	123.88
20% / 15min	-0.2121	0.00874	2.235	3004.36	250.36
5% / 30min	-0.0700	0.00428	1.259	1657.95	138.16
10% / 30min	-0.1399	0.00860	2.461	3327.16	277.26
20% / 30min	-0.1399	0.01740	4.704	6700.45	558.37
50% / 30min	-0.6977	0.04499	10.309	17122.51	1426.88
90% / 30min	-1.2547	0.08485	15.744	31853.75	2654.48

Table 37 - Policy 1 Scenario Equivalents

Spatial Redistribution Effects

Figure 22 presents the probability-weighted expected net residential redistribution under the 20% subsidy and 30-minute eligibility-threshold scenario. The map compares the expected number of residents assigned to each ZIP code under Policy 1 with the corresponding status-quo expectation.

The modeled redistribution remains spatially dispersed rather than concentrated in a single employment center. Several ZIP codes containing subsidy-eligible alternatives gain expected residents, while other eligible and nearby substitute locations experience small expected losses. This pattern occurs because reducing the effective housing price of an alternative changes its probability relative to every other available alternative in the worker's residence–work choice set. Eligibility therefore does not guarantee a gain for every treated ZIP code; the resulting effect depends on the relative attractiveness of all competing alternatives.

The mapped values represent probability-weighted expected changes rather than deterministic household movements. They describe the average modeled redistribution across workers' residential choice probabilities and should not be interpreted as a forecast that a specific number of observed households will relocate.

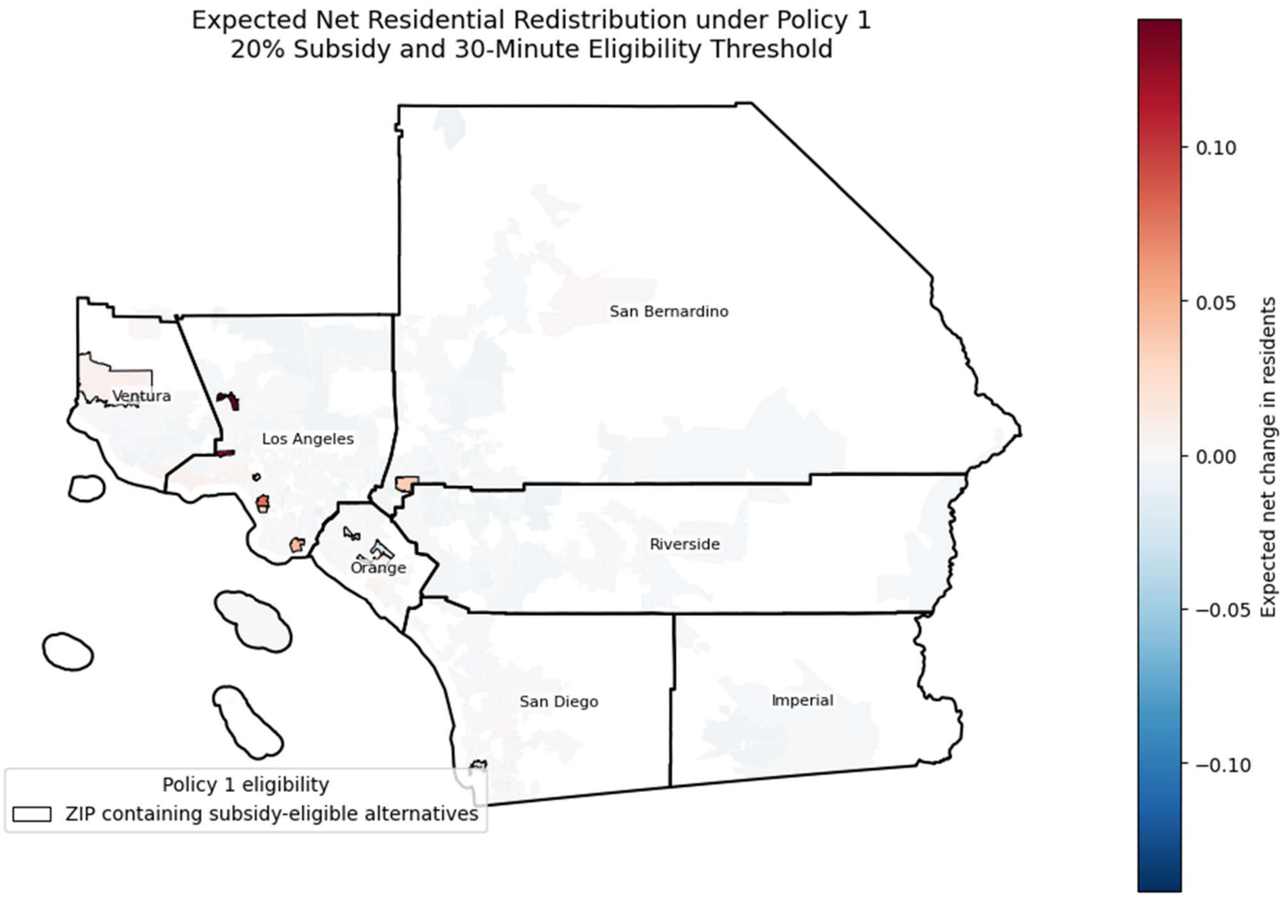

Figure 22 – Probability-Weighted Expected Net Residential Redistribution under Policy 1

Summary

Policy 1 produces consistent behavioral responses across the modeled scenarios. Employer-sponsored housing subsidies increase the attractiveness of qualifying residence–work alternatives, reduce expected housing affordability burden, increase the probability that eligible professional and essential workers select qualifying residential alternatives, and generate positive consumer welfare effects. Across the primary scenarios, the magnitude of these responses generally increases with both subsidy level and the breadth of the commute-time eligibility threshold.

The effects on regional commuting patterns are comparatively modest. Under the strongest primary scenario, a 20% subsidy with a 30-minute eligibility threshold, expected commute time declines by approximately 0.280 minutes, or 0.96%, while the expected probability of selecting a qualifying alternative increases by approximately 0.75 percentage points, or 1.28% relative to baseline. The occupational analysis indicates somewhat greater responsiveness among essential workers: under this scenario, their expected commute decreases by approximately 0.349 minutes, compared with 0.237 minutes for professional workers, while their target-alternative probability increases by approximately 0.93 and 0.64 percentage points, respectively.

The policy produces more substantial changes in housing affordability. Under the 20% subsidy and 30-minute threshold, mean affordability burden declines by approximately 10.86% relative to baseline, indicating that the intervention can materially improve the housing-cost conditions associated with workers' modeled residence–work alternatives even when changes in regional commute outcomes remain relatively small. This distinction demonstrates that commute reduction alone does not capture the full effect of the policy.

The consumer welfare results provide additional evidence of this broader policy response. All modeled scenarios produce positive average logsum changes, with the average welfare effect increasing from approximately 0.0011 under the smallest primary intervention to approximately 0.0174 under the 20% subsidy and 30-minute threshold. The positive logsum response indicates an improvement in the expected utility associated with workers' residence–work choice sets, reflecting the combined effects of affordability, commuting, housing characteristics, workplace attributes, and occupational compatibility.

The upper-bound sensitivity tests further demonstrate that behavioral responses increase with policy intensity. Under the 90% subsidy stress test, expected commute time decreases by approximately

1.255 minutes (4.28%), while target-alternative probability increases by approximately 3.36 percentage points (5.75% relative to baseline). The average logsum change simultaneously rises to approximately 0.0848. Although these scenarios are not intended as realistic program designs, they demonstrate that increasing subsidy magnitude generates progressively larger responses while also showing that even very large affordability interventions do not fundamentally restructure regional commuting patterns.

Overall, the results suggest that employer-sponsored housing subsidies are more effective as a targeted housing-affordability and residential-opportunity intervention than as a stand-alone regional commute-reduction strategy. The policy improves affordability, increases the attractiveness of qualifying residence–work alternatives, and generates positive expected welfare effects, but its ability to substantially alter regional commuting patterns remains constrained by the geography of employment and housing, the availability of qualifying residential alternatives, and the multiple competing attributes represented in the joint residence–work location model.

4.5.2 Scenario 2 (Policy 2) Results – Office-to-Residential Conversions

Policy Overview and Simulation Design

Policy 2 evaluates an office-to-residential conversion strategy by increasing estimated residential housing capacity within selected employment-rich ZIP codes across the seven-county Southern California study region. Unlike Policy 1, which modifies effective housing costs through employer-sponsored subsidies, Policy 2 modifies the modeled housing-capacity variable within the joint residence–work location choice model. The policy therefore tests whether increasing housing availability near major employment centers can produce stronger residential sorting responses and reduce regional commuting burdens without creating new employment centers.

Figure 23 illustrates the ZIP codes targeted for residential-capacity expansion under Policy 2 which represent employment-oriented urban corridors where underutilized office or commercial space could plausibly be converted into residential inventory. The geographic concentration of targeted ZIP codes within major metropolitan corridors reflects the policy objective of increasing housing availability near existing employment centers rather than redistributing employment itself.

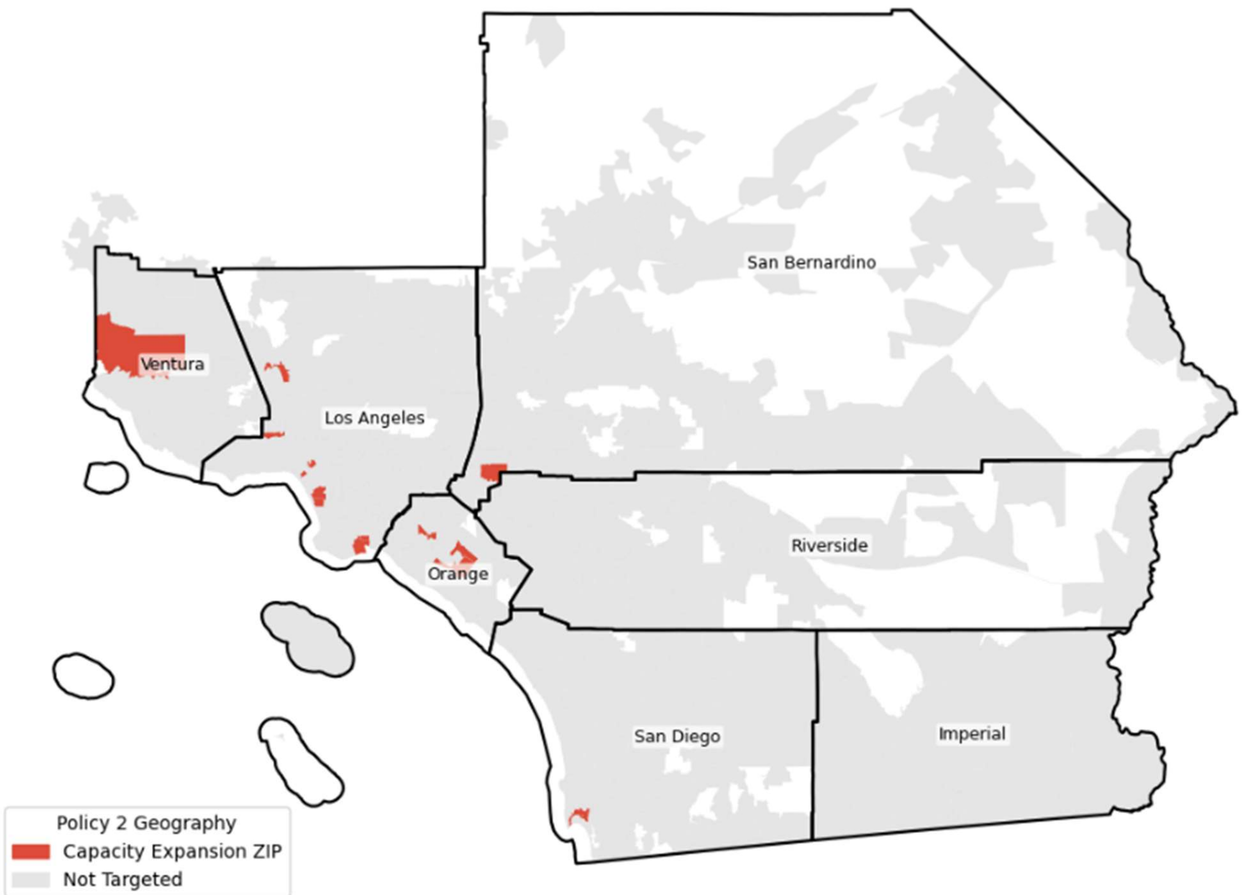

Figure 23 - ZIP Codes Targeted for Policy 2 Housing-Capacity Expansion

The simulation begins with the ACS-derived ZIP-level housing capacity dataset developed in Study 2. Residential capacity within sixteen employment-oriented ZIP codes is increased prior to recomputing the logged and standardized housing-capacity measure using the original Study 2 scaling parameters. Three policy scenarios were evaluated representing 5%, 10%, and 20% increases in residential capacity within the targeted ZIP codes.

As summarized in Table 38, the modeled interventions add housing units and price shifts for each scenario. Although the proportional increases are moderate, the absolute number of added units is substantial because the selected ZIP codes represent highly urbanized employment corridors with large existing residential inventories. Implied price change (%) represents the reduced-form percentage change in the housing-price attribute associated with the modeled increase in housing capacity. Negative values indicate an assumed reduction in housing prices as housing supply expands. These values are sensitivity assumptions rather than locally estimated forecasts. The standardized price shift converts the implied housing-price response into the same standardized log-price units used in the joint-residence-work location choice model. This value is applied to the housing-price attribute when recalculating choice probabilities under each policy scenario.

Scenario 2 Capacity Expansion Scenarios					
Capacity Increase	**Total Units Added**	**Max Units Added in Single ZIP**	**Standardized Capacity Shift**	**Implied Price Change (%)**	**Standardized Price Shift**
5%	13,520	1,730	0.02975	-0.92273	-0.01962
10%	27,041	3,461	0.05812	-1.79460	-0.03833
20%	54,081	6,921	0.11118	-3.40480	-0.07332

Table 38 - Policy 2 Capacity Expansion Scenarios

The policy framework is intended to approximate the potential redevelopment of underutilized office or commercial space into residential inventory within employment-accessible urban areas. Rather than subsidizing existing housing choices, Policy 2 directly expands the set of feasible residential opportunities available near major job centers. Consequently, the intervention evaluates whether relaxing housing supply constraints can produce measurable changes in regional residential sorting behavior.

Policy 2 Capacity Expansion Stress Tests						
Scenario	**Capacity Increase**	**Total Units Added**	**Max Units Added in Single ZIP**	**Standardized Capacity Shift**	**Implied Price Change (%)**	**Standardized Price Shift**
S2 - 50% Housing Increase	50%	135,203	17,302	0.24725	-7.41457	-0.16306
S2 - 90% Housing Increase	90%	243,365	31,144	0.39139	-11.48094	-0.25812

Table 39 - Capacity Expansion Stress Tests for Scenario 2

Table 39 presents two stress-test scenarios in which residential capacity in the 16 targeted ZIP codes is increased by 50% and 90%. These scenarios are not intended to represent anticipated office-to-residential production levels. Instead, they test whether the direction and magnitude of the modeled response change when the housing-supply intervention is increased substantially beyond the primary 5%, 10%, and 20% scenarios. The stress tests add approximately 135,203 and 243,365 housing units, respectively, and generate implied housing-price reductions of approximately 7.4% and 11.5%. Because the price response is modeled using an elasticity-based reduced-form relationship, the percentage price reduction increases less than proportionally as housing capacity expands. Results from these scenarios are interpreted as model-sensitivity evidence rather than forecasts of likely development outcomes.

Expected Commute Outcomes

Table 40 compares probability-weighted expected commute outcomes under each Policy 2 housing-capacity scenario with the status quo. Under the baseline simulation, mean expected commute time is approximately 31.5924 minutes. Increasing housing capacity within the 16 targeted employment-center ZIP codes produces only very small changes in this regional average. Under the primary scenarios, expected commute time increases to approximately 31.5932, 31.5938, and 31.5951 minutes under the 5%, 10%, and 20% capacity expansions, respectively. Thus, even under the largest primary scenario, the change in regional expected commute time is only approximately 0.0026 minutes.

Although Policy 2 increases residential capacity in major employment centers, greater proximity to employment concentrations does not necessarily imply shorter commutes for every worker. Employment-center ZIP codes are embedded within interconnected metropolitan labor markets, and workers selecting housing in these locations may continue to commute to workplaces distributed throughout the region. In addition, residential location choice reflects multiple dimensions of utility—including housing affordability, housing characteristics, workplace earnings, occupational compatibility, and commute time—rather than commute minimization alone. Increasing housing availability in employment centers can therefore make those residential locations more attractive without necessarily reducing the regionwide expected commute.

Policy 2 - Expected Outcomes vs Status Quo			
Scenario	**Capacity Increase (%)**	**Expected Mean Commute (min)**	**Change in Expected Commute (min)**
S0_Status_Quo	0	31.5924	0
S2_05	5	31.5932	0.0007
S2_10	10	31.5938	0.0014
S2_20	20	31.5951	0.0026

Table 40 - Policy 2 Commute Outcomes

This finding suggests that housing-capacity expansion and commute reduction should be treated as related but distinct policy objectives. Policy 2 can alter residential location probabilities by expanding housing opportunities in employment-rich areas, but the simulations provide little evidence that capacity expansion alone is sufficient to materially reduce average regional commute times.

Expected Probability Outcomes

Table 41 reports the expected probability that a worker selects a residence–work alternative located within one of the 16 employment-center ZIP codes targeted by Policy 2. For each worker, probabilities are first calculated across all available alternatives in the modeled choice set and then summed across alternatives located within the targeted ZIP codes. The resulting worker-level probabilities are subsequently averaged across the sample. Unlike a single simulated residential assignment, this probability-weighted measure represents the expected behavioral response implied by the estimated joint residence–work location choice model.

Policy 2 - Expected Probability Outcomes vs Status Quo				
Capacity Increase (%)	**Baseline Probability - Target ZIP (%)**	**Scenario Probability - Target ZIP (%)**	**Change in Probability (% pts)**	**% Change from Baseline**
0	3.68436	3.68436	0	0
5	3.68436	3.692242	0.007882	0.213929
10	3.68436	3.699734	0.015373	0.417261
20	3.68436	3.713684	0.029323	0.795888

Table 41 - Expected Probability of Selecting a Policy 2 Target ZIP Code

Under the status quo, the average probability of selecting a residential alternative within a targeted employment-center ZIP code is approximately 3.684%. The probability increases monotonically as modeled housing capacity expands. A 5% capacity increase raises the expected probability to approximately 3.692%, a gain of 0.008 percentage points, or approximately 0.21% relative to baseline. Under the 10% scenario, the probability increases to approximately 3.700%, while the 20% primary scenario raises it to approximately 3.714%. The 20% expansion therefore produces an increase of approximately 0.029 percentage points, or 0.80% relative to baseline.

Policy 2 produces a detectable residential-location response even though the corresponding change in regional expected commute time is negligible. This distinction demonstrates that increased housing availability near employment concentrations can influence residential sorting without necessarily generating proportional changes in regionwide commuting outcomes.

Expected Probability by Occupation Group

Table 42 disaggregates the expected probability of selecting a targeted employment-center ZIP code by occupational group. Baseline probabilities differ across professional, essential, and other workers, reflecting differences in the residence–work alternatives represented within their respective choice sets and the attributes associated with those alternatives. Under the status quo, professional workers have the highest average probability of selecting a targeted ZIP at approximately 3.84%, followed by all workers at 3.68%, essential workers at 3.49%, and workers classified as other at approximately 3.42%.

Policy 2 increases the expected probability of selecting a targeted ZIP across all occupational groups and at every modeled capacity level. Under the 5% capacity expansion, the probability increases from approximately 3.84% to 3.86% for professional workers, from 3.49% to 3.50% for essential workers, and from 3.42% to 3.44% for other workers. The corresponding relative increases are approximately 0.44% for each group. As capacity expands, the magnitude of the response increases monotonically. Under the 20% primary scenario, target probability rises to approximately 3.91% for professional workers, 3.55% for essential workers, and 3.48% for other workers, representing relative increases of approximately 1.66–1.67% across groups.

The similarity of the relative probability response across occupational groups is an important result. Although the groups begin with different baseline probabilities of selecting housing within the targeted employment centers, their proportional response to additional housing capacity are nearly uniform. This suggests that the modeled capacity intervention does not disproportionately increase the relative attractiveness of targeted ZIP codes for one occupational group. Instead, expanding residential capacity increases the attractiveness of these locations broadly across professional, essential, and other workers.

Policy 2 - Expected Probability of Selecting a Target ZIP						
Scenario	**Worker Group**	**Workers**	**Baseline Target Probability (%)**	**Policy Target Probability (%)**	**Δ Probability (percentage points)**	**Change from Baseline (%)**
Status Quo	All Workers	1,041	3.68	3.68	0	0
	Professional	588	3.84	3.84	0	0
	Essential	336	3.49	3.49	0	0
	Other	117	3.42	3.42	0	0
S2 – 5%	All Workers	1,041	3.68	3.7	0.016	0.44
	Professional	588	3.84	3.86	0.017	0.44
	Essential	336	3.49	3.5	0.016	0.44
	Other	117	3.42	3.44	0.015	0.44
S2 – 10%	All Workers	1,041	3.68	3.71	0.032	0.87
	Professional	588	3.84	3.87	0.033	0.87
	Essential	336	3.49	3.52	0.03	0.87
	Other	117	3.42	3.45	0.03	0.87
S2 – 20%	All Workers	1,041	3.68	3.74	0.061	1.67
	Professional	588	3.84	3.91	0.064	1.66
	Essential	336	3.49	3.55	0.058	1.67
	Other	117	3.42	3.48	0.057	1.67
S2 – 30%	All Workers	1,041	3.68	3.77	0.089	2.41
	Professional	588	3.84	3.93	0.092	2.4
	Essential	336	3.49	3.57	0.084	2.41
	Other	117	3.42	3.5	0.083	2.41

Table 42 - Policy 2 Expected Probability of Selecting a Residential Alternative within the Target Employment-Center ZIP Codes

This finding differs from Policy 1, where subsidy eligibility and occupational characteristics produce more differentiated responses between professional and essential workers. Policy 2 operates through the residential alternative itself, by increasing modeled housing capacity within targeted employment centers, rather than through a worker-specific financial incentive. The relatively uniform proportional response across occupational groups is therefore consistent with the intervention’s design and suggests that housing-supply expansion may have broader, less occupationally targeted effects on residential-location than employer-sponsored housing subsidies.

Sensitivity Analysis

The sensitivity analysis evaluates whether substantially larger increases in residential capacity produce materially different outcomes from the primary Policy 2 scenarios. Two upper-bound scenarios increase modeled housing capacity in the 16 targeted employment-center ZIP codes by 50% and 90%. These scenarios serve as stress tests rather than forecasts of expected office-to-residential production and are intended to evaluate the model's responsiveness to substantially larger capacity changes.

Policy 2 - Expected Outcomes vs Status Quo Sensitivity Analysis			
Scenario	**Capacity Increase (%)**	**Expected Mean Commute (min)**	**Change in Expected Commute (min)**
S2_50	50	31.5982	0.0058
S2_90	90	31.6014	0.0090

Table 43 – Policy 2 Expected Commute Outcomes Sensitivity Analysis

The probability response continues to increase monotonically with housing capacity. Under the 50% scenario, the average probability of selecting a targeted ZIP increases from approximately 3.684% to 3.749%, an increase of approximately 0.065 percentage points, or 1.76% relative to baseline. Under the 90% scenario, target probability increases to approximately 3.786%, representing an increase of approximately 0.102 percentage points, or 2.76% relative to baseline. These results extend the pattern observed in the primary scenarios and demonstrate that increasingly large capacity expansions progressively increase the relative attractiveness of residential alternatives within the targeted employment centers.

Policy 2 - Expected Outcomes vs Status Quo Sensitivity Analysis					
Scenario	**Capacity Increase (%)**	**Baseline Probability - Target ZIP (%)**	**Scenario Probability - Target ZIP (%)**	**Change in Probability (% pts)**	**% Change from Baseline**
S2_50	50	3.68436	3.749088	0.064728	1.756835
S2_90	90	3.68436	3.786012	0.101652	2.759014

Table 44 – Policy 2 Expected Probability Sensitivity Analysis

The occupational analysis produces a similar pattern. Under the 50% scenario, target probabilities increase to approximately 3.98% for professional workers, 3.62% for essential workers, and

3.55% for other workers, corresponding to relative increases of approximately 3.74% to 3.76%. Under the 90% scenario, probabilities increase to approximately 4.07%, 3.70%, and 3.63%, respectively, representing increases of approximately 5.98% to 6.01% relative to each group's baseline. The similarity of these proportional responses reinforces the primary finding that the modeled housing-capacity intervention increases the attractiveness of targeted residential locations broadly rather than concentrating its effects within a particular occupational group.

Policy 2 - Expected Probability of Selecting a Target ZIP						
Scenario	**Worker Group**	**Workers**	**Baseline Target Probability (%)**	**Policy Target Probability (%)**	**Δ Probability (percentage points)**	**Change from Baseline (%)**
S2 – 50%	All Workers	1,041	3.68	3.82	0.138	3.74
	Professional	588	3.84	3.98	0.144	3.74
	Essential	336	3.49	3.62	0.131	3.76
	Other	117	3.42	3.55	0.128	3.75
S2 – 90%	All Workers	1,041	3.68	3.9	0.22	5.99
	Professional	588	3.84	4.07	0.23	5.98
	Essential	336	3.49	3.7	0.209	6.01
	Other	117	3.42	3.63	0.205	6.00

Table 45 - Policy 2 Expected Probability by Worker Group Sensitivity Analysis

Despite these larger residential-choice responses, expected regional commute outcomes remain comparatively stable. Expected mean commute increases by approximately 0.0058 minutes under the 50% scenario and 0.0090 minutes under the 90% scenario relative to baseline. Thus, even an intentionally extreme 90% increase in modeled housing capacity produces less than a 0.01-minute change in the regional probability-weighted mean commute. The sensitivity analysis therefore reinforces the distinction between residential-location response and commuting response: substantially increasing housing capacity within employment-center ZIP codes can measurably increase their attractiveness as residential locations without, by itself, producing meaningful reductions in regionwide expected commute times.

Mean Annual Housing-Cost and Mean Commute Time Equivalents

The Policy 2 results indicate comparatively modest welfare-equivalent gains from increasing residential capacity alone. As simulated capacity increases from 5% to 90%, the mean commute-time-equivalent gain rises from approximately 0.03 to 0.37 minutes, while the mean annual housing-cost equivalent increases from approximately $40 to $510. The monotonic increase across scenarios indicates that expanding residential capacity near employment centers improves the modeled opportunity set, although the magnitude of the effect remains relatively small when compared with the targeted subsidy scenarios evaluated under Policy 1. This result is consistent with the mechanism represented by Policy 2: additional housing capacity expands the availability of residential alternatives but does not directly reduce the housing costs faced by individual workers.

Policy 2 - Scenario 2 Equivalents				
Increased Capacity	**Average Change in Expected Commute (min)**	**Mean Delta Logsum**	**Mean Commute-Time Equivalent Gain (min)**	**Mean Monthly Housing-Cost Equivalent Gain ($)**
5%	0.0007	0.00008	0.029	3.31
10%	0.0014	0.00016	0.057	6.46
20%	0.0026	0.00031	0.108	12.31
50%	0.0058	0.00068	0.238	27.13
90%	0.0090	0.00106	0.371	42.51

Table 46 - Policy 2 / Scenario 2 Equivalents

Spatial Redistribution Effects

Figure 24 represents the expected net residential redistribution under the Policy 2 – 20% capacity-expansion scenario. Red areas indicate ZIP codes gaining expected residential probability mass relative to the status quo, while blue areas indicate net losses. Changes represent probability-weighted expected residential assignments rather than realized household counts or parcel-level development forecasts. Black outlines identify the 16 ZIP codes in which housing capacity was directly increased.

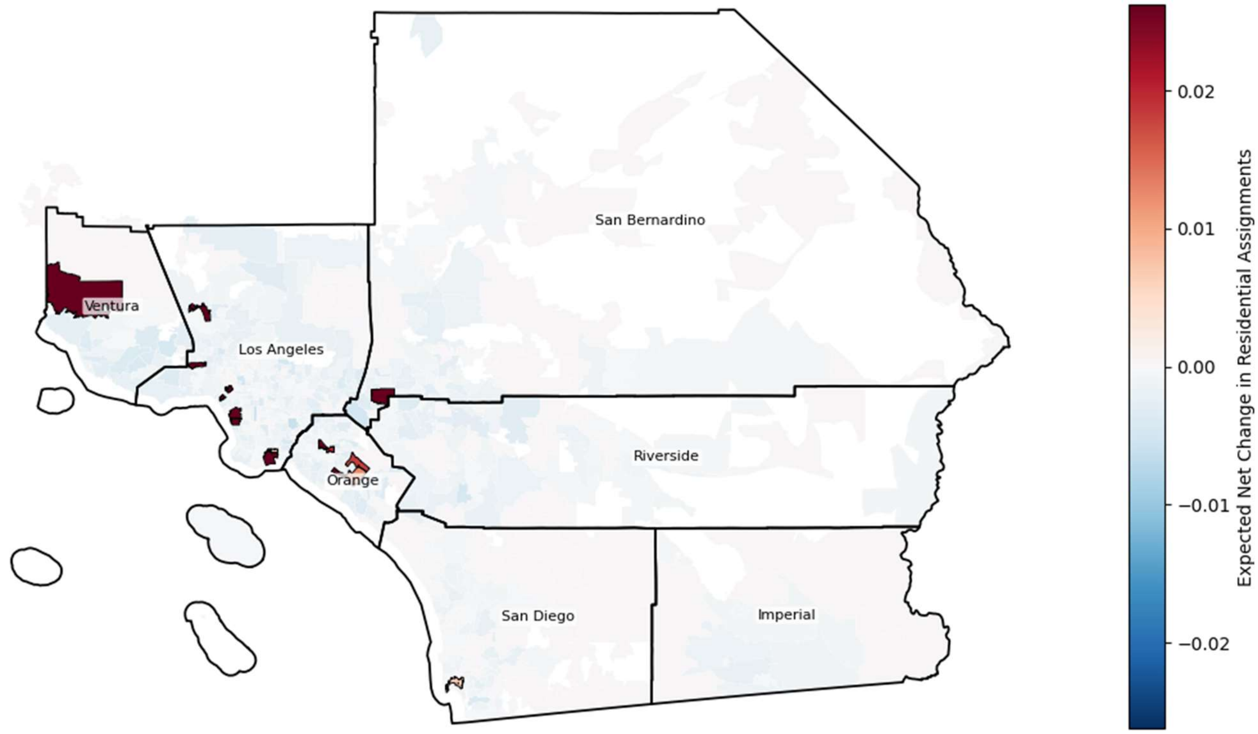

Figure 24 – Expected Net Residential Redistribution under Policy 2 – 20% Capacity Expansion

Although Policy 2 directly increases residential capacity in only sixteen ZIP codes, the resulting behavioral effects propagate across a much broader regional geography. This occurs because residential alternatives compete probabilistically within the location choice model. Increasing the attractiveness of a subset of residential alternatives changes the relative competitiveness of nearby and substitute locations, producing secondary equilibrium effects throughout the broader metropolitan housing system.

These redistribution dynamics conceptually resemble housing vacancy-chain and residential filtering processes commonly discussed in urban economics, in which housing-supply changes in one location indirectly reshape residential opportunities and sorting behavior elsewhere in the regional system. The Policy 2 results therefore demonstrate that localized housing-capacity interventions can generate broader regional residential adjustments even when policy changes are geographically concentrated.

At the same time, the redistribution patterns remain spatially heterogeneous and comparatively diffuse, indicating that workers do not uniformly relocate toward the nearest employment-accessible locations. Instead, residential preferences continue reflecting the combined influence of commute burdens, occupational geography, housing availability, and regional accessibility constraints.

Summary

Overall, Policy 2 demonstrates that increasing residential housing capacity within employment-center ZIP codes increases the expected probability that workers select residential alternatives in those locations. The intervention expands modeled housing availability in 16 targeted ZIP codes and, through the assumed housing supply–price relationship, also produces modest reductions in effective housing prices. Larger capacity increases generate progressively larger standardized capacity shifts, implied price reductions, and expected probabilities of selecting a targeted residential location.

The spatial results indicate that the effects extend beyond the directly targeted ZIP codes. Because residential alternatives compete within each worker's choice set, increasing the attractiveness of selected locations redistributes probability across a broader regional geography. The resulting pattern is spatially heterogeneous and does not reflect uniform movement toward a single employment center. The occupational results further show that professional, essential, and other workers respond in the same direction, with similar proportional increases in the probability of selecting a targeted ZIP across occupational groups. Thus, Policy 2 operates primarily as a place-based housing-capacity intervention rather than one that disproportionately affects a particular occupational group.

Despite these residential-choice effects, regional commute outcomes remain comparatively stable. Expected mean commute time changes by only approximately 0.003 minutes under the largest primary scenario, while even the 50% and 90% capacity stress tests produce changes of only approximately 0.006 and 0.009 minutes, respectively. These results indicate that substantially increasing housing capacity within employment-center ZIP codes can alter residential-location probabilities without producing corresponding reductions in regionwide expected commute time.

The sensitivity analysis reinforces this distinction. Larger capacity expansions produce progressively larger increases in the probability of selecting targeted residential locations, demonstrating that the behavioral response strengthens with the magnitude of the intervention. Nevertheless, even the upper-bound scenarios generate negligible changes in expected regional commute outcomes. Housing availability near employment centers therefore represents one component of the jobs–housing relationship, while commuting outcomes continue to reflect dispersed workplace geography, occupational characteristics, housing-market conditions, transportation-system conditions, and the availability of substitute residential alternatives throughout Southern California.

Overall, Policy 2 provides evidence that housing-supply expansion can increase the relative attractiveness of residential opportunities within major employment centers and influence residential sorting, while also demonstrating that housing-capacity interventions alone are unlikely to substantially reduce long-distance commuting at the regional scale. The findings support evaluating housing-capacity policies as part of a broader package of land-use, housing-affordability, employment-location, and transportation strategies rather than as a stand-alone solution to the regional jobs–housing mismatch.

4.5.3 Scenario 3 (Policy 1 + Policy 2) Results: Capacity + Eligible Subsidies

Simulation Design

Scenario 3 analyzes whether combining Policies 1 and 2 will increase the probability that more workers will choose to relocate. Therefore, this scenario runs the simulation that employer-sponsored housing subsidies for eligible workers will be added to the expanded housing capacity framework and analyze any additional commute-related benefits.

Scenario 3 Structure			
Scenario	Capacity Expansion	Eligible-worker Subsidy	Commute Threshold (min)
S3–5%	5%	5%	30
S3–10%	10%	10%	
S3–20%	20%	20%	
Stress 1	50%	50%	
Stress 2	90%	90%	

Table 47 - Scenario 3 Structure

This combined mechanism for Scenario 3 is:

- Capacity increases in the 16 target ZIP codes for all workers
- The capacity increase generates the Policy 2 implied price response for all alternatives in those ZIP codes
- Professional and essential workers receive an additional employer subsidy when the target residence is within 30 minutes of their workplace
- Capacity, price, and income x price are all updated before probabilities are recalculated

Combined Effects on Commuting

Table 48 summarizes expected regional commute outcomes under the combined housing-capacity expansion and employer-sponsored housing subsidy scenarios. Across the primary 5%, 10%, and 20% intervention levels, expected mean commute time remains close to the status-quo value of approximately 31.592 minutes. Expected mean commute time declines to approximately 31.590 minutes under the 5% scenario, 31.587 minutes under the 10% scenario, and 31.581 minutes under the 20% scenario. These changes correspond to mean reductions of approximately 0.003, 0.006, and 0.012 minutes, respectively.

Although the aggregate changes are small, the direction of the response is consistent across the primary scenarios. The share of eligible workers experiencing any reduction in expected commute time increases from approximately 69.4% under the 5% scenario to 70.1% under the 20% scenario. However, the magnitude of these individual improvements remains modest: none of the primary scenarios produces a reduction of at least one minute for a meaningful share of workers, and the maximum worker-level reduction reaches approximately 0.50 minutes under the 20% scenario.

These findings indicate that the combined intervention changes residential-location probabilities without substantially altering regionwide expected commute outcomes under the primary scenarios. Housing-capacity expansion increases the relative attractiveness of residential alternatives within the targeted employment-center ZIP codes, while the employer-sponsored subsidy further increases the attractiveness of qualifying alternatives for eligible workers. Nevertheless, workers continue to evaluate alternatives within the broader residence–work choice environment represented by the model, including commute time, housing affordability, workplace earnings, occupational compatibility, housing characteristics, and the availability of competing residential locations. Consequently, improvements in housing affordability and residential choice do not translate one-for-one into reductions in commuting.

Scenario 3 - Combined Policy Effects on Commuting						
Capacity Increase (%)	Subsidy (%)	Baseline Expected Commute (min)	Policy Expected Commute (min)	Mean Commute Reduction (min)	Eligible Workers with Reduced Commute (%)	Maximum Reduction (min)
5	5	31.592	31.59	0.003	69.36	0.113
10	10	31.592	31.587	0.006	69.55	0.233
20	20	31.592	31.581	0.012	70.12	0.496

Table 48 – Combined Policy Effects on Commuting

Combined Policy Effects on Housing Affordability

Table 49 reports changes in expected housing affordability burden under the combined-policy scenarios. Unlike the comparatively small commute response, affordability improves consistently and progressively as the magnitude of the intervention increases. The baseline expected affordability-burden ratio is approximately 1.202. Under the 5% combined scenario, the expected burden declines to approximately 1.200, representing a reduction of approximately 0.15%. The 10% scenario reduces the burden by approximately 0.30%, while the 20% primary scenario reduces it by approximately 0.60%.

These results are consistent with the mechanisms represented in the combined-policy simulation. Policy 2 increases modeled housing capacity within the 16 targeted employment-center ZIP codes and incorporates a supply-induced housing-cost response, while Policy 1 reduces the effective housing cost of qualifying alternatives for eligible workers through the employer-sponsored subsidy. The two mechanisms therefore operate through complementary channels: one changes the modeled housing-market conditions of targeted locations, while the other directly reduces the effective housing cost faced by eligible workers selecting qualifying alternatives.

Scenario 3 - Combined Policy Effects on Housing Affordability					
Capacity Increase (%)	Subsidy (%)	Baseline Expected Affordability Burden	Policy Expected Affordability Burden	Δ Affordability Burden	Change in Burden (%)
5	5	1.202	1.2	-0.0016	-0.15
10	10	1.202	1.198	-0.0033	-0.3
20	20	1.202	1.195	-0.0068	-0.6

Table 49 - Combined Policy Effects on Housing Affordability

The results should not be interpreted as forecasts of realized household expenditures or market-wide housing-price reductions. Rather, the affordability-burden measure represents the expected housing-cost burden implied by the residential alternatives and choice probabilities generated by the model. The progressive decline across scenarios nevertheless provides evidence that the combined intervention shifts expected residential choices toward alternatives associated with lower modeled housing-cost burdens.

Combined Policy Effects on Consumer Welfare

Table 50 presents changes in consumer welfare using the expected logsum, or inclusive value, generated by the joint residence–work location choice model. The logsum summarizes the utility associated with the complete set of residential–work alternatives available to a worker. An increase therefore indicates that the policy improves the overall attractiveness of the worker's modeled choice set after accounting simultaneously for the attributes represented in the utility function.

Average logsum changes are positive under every combined-policy scenario and increase with policy magnitude. The average welfare gain rises from approximately 0.0003 under the 5% scenario to 0.0006 under the 10% scenario and 0.0012 under the 20% primary scenario. Median changes are also positive, increasing from approximately 0.0002 to 0.0007 across these scenarios. Moreover, the results indicate positive welfare changes for 100% of eligible workers under each scenario.

Scenario 3 - Combined Policy Effects on Consumer Welfare					
Capacity Increase (%)	**Subsidy (%)**	**Average Δ Logsum**	**Median Δ Logsum**	**Eligible Workers with Welfare Improvement (%)**	**Maximum Δ Logsum**
5	5	0.0003	0.0002	100	0.0071
10	10	0.0006	0.0004	100	0.0147
20	20	0.0012	0.0007	100	0.0313
50	50	0.0030	0.0016	100	0.0956
90	90	0.0057	0.0028	100	0.2227

Table 50 – Combined Policy Effects on Consumer Welfare

These logsum changes should not be interpreted directly as minutes, dollars, or percentage changes in welfare. Instead, they provide a utility-based measure of whether the modeled choice environment becomes either more or less favorable following the intervention. Their primary value is comparative: larger positive values indicate larger improvements in expected choice-set utility under the same estimated model. In practical terms, the positive changes indicate that eligible workers have access to a more attractive combination of housing cost, location, commute, employment, and housing characteristics after the combined policy is introduced, even when the resulting change in average commute duration is small.

This distinction is important for interpreting the policy. A worker can experience a welfare improvement without experiencing a substantial commute-time reduction because commuting represents only one component of residential–work utility. The combined intervention can improve welfare through lower effective housing burdens and more attractive residential opportunities while workers continue to trade these improvements against workplace location, housing characteristics, occupational compatibility, and commute conditions. The positive logsum results therefore provide a broader measure of policy benefit than commute time alone.

Sensitivity Analysis

The upper-bound sensitivity scenarios test whether substantially larger combined interventions generate materially different behavioral responses. These scenarios should be interpreted as stress tests of model responsiveness rather than plausible near-term policy forecasts.

Scenario 3 - Combined Policy Effects on Commuting Sensitivity Analysis						
Capacity / Subsidy Increase (%)	**Baseline Expected Commute (min)**	**Policy Expected Commute (min)**	**Mean Commute Reduction (min)**	**Eligible Workers with Reduced Commute (%)**	**≥1-min Reduction (%)**	**Maximum Reduction (min)**
50 / 50	31.592	31.56	0.033	71.66	0.1	1.467
90 /90	31.592	31.526	0.067	74.54	0.58	3.196

Table 51 – Combined Policy Effects on Commuting Sensitivity Analysis

The results show that increasing both housing capacity and subsidy magnitude strengthens the response in the expected direction. Under the 50% scenario, expected mean commute time declines by approximately 0.033 minutes, while approximately 71.7% of eligible workers experience some commute reduction. Under the 90% scenario, the mean reduction increases to approximately 0.067 minutes and approximately 74.5% of eligible workers experience an improvement. The maximum worker-level reduction reaches approximately 1.47 minutes under the 50% scenario and 3.20 minutes under the 90% scenario. Even under these deliberately large interventions, however, only approximately 0.10% and 0.58% of workers, respectively, experience commute reductions of at least one minute. Thus, substantially increasing policy magnitude strengthens the commute response but does not produce large regionwide commuting effects.

Scenario 3 - Combined Policy Effects on Housing Affordability Sensitivity Analysis					
Capacity Increase (%)	Subsidy (%)	Baseline Expected Affordability Burden	Policy Expected Affordability Burden	Δ Affordability Burden	Change in Burden (%)
50	50	1.202	1.182	-0.0194	-1.55
90	90	1.202	1.158	-0.0434	-2.99

Table 52 - Combined Policy Effects on Housing Affordability Sensitivity Analysis

Affordability responds more strongly. The expected affordability burden declines by approximately 1.55% under the 50% scenario and 2.99% under the 90% scenario. Consumer welfare follows the same pattern: the average logsum gain increases to approximately 0.0030 under the 50% scenario and 0.0057 under the 90% scenario, while the maximum individual logsum gain reaches approximately 0.0956 and 0.2227, respectively. Positive welfare changes continue to occur among all eligible workers.

Combined Policy Effects on Consumer Welfare Sensitivity Analysis					
Capacity Increase (%)	Subsidy (%)	Average Δ Logsum	Median Δ Logsum	Eligible Workers with Welfare Improvement (%)	Maximum Δ Logsum
50	50	0.0030	0.0016	100	0.0956
90	90	0.0057	0.0028	100	0.2227

Table 53 – Combined Policy Effects on Consumer Welfare Sensitivity Analysis

Taken together, the sensitivity tests demonstrate that the modest primary-scenario results are not attributable to a lack of behavioral responsiveness in the simulation framework. Increasing policy magnitude produces progressively larger affordability, residential-choice, welfare, and commute responses. However, the relative magnitude of those responses differs considerably: affordability and consumer welfare improve more visibly, while regional commute time remains comparatively resistant to change. This suggests that the limited commute effects reflect structural features of the modeled Southern California residence–work system rather than simply insufficient policy intensity.

Mean Annual Housing-Cost and Mean Commute Time Equivalents

The combined Policy 1 and Policy 2 scenarios produce larger welfare-equivalent gains than the corresponding capacity-expansion scenarios under Policy 2 alone. As increased capacity rises from 5% to 90%, the mean commute-time-equivalent gain increases from approximately 0.09 to 1.54 minutes, while the mean annual housing-cost equivalent increases from approximately $126 to $2,139. The larger gains under the combined intervention indicate that expanding housing capacity can produce greater modeled benefits when paired with measures that also improve housing affordability for eligible workers. At the same time, the magnitude of the combined effects remains dependent on the intensity of the simulated intervention, with relatively modest gains under the lower-capacity scenarios and progressively larger gains under the upper-bound sensitivity scenarios.

Combined Policy 1 + 2 - Scenario 3 Equivalents					
Increased Capacity	**Average Change in Expected Commute (min)**	**Mean Delta Logsum**	**Mean Commute-Time Equivalent Gain (min)**	**Mean Annual Housing-Cost Equivalent Gain ($)**	**Mean Monthly Housing-Cost Equivalent Gain ($)**
5%	-0.0028	0.00029	0.094	125.74	10.48
10%	-0.0057	0.00058	0.185	249.70	20.81
20%	-0.0117	0.00117	0.365	493.24	41.10
50%	-0.0325	0.00300	0.878	1202.58	100.22
90%	-0.0669	0.00574	1.537	2138.65	178.22

Table 54 - Combined Policy 1 & 2 Scenario 3 Equivalent

Spatial Redistribution Effects

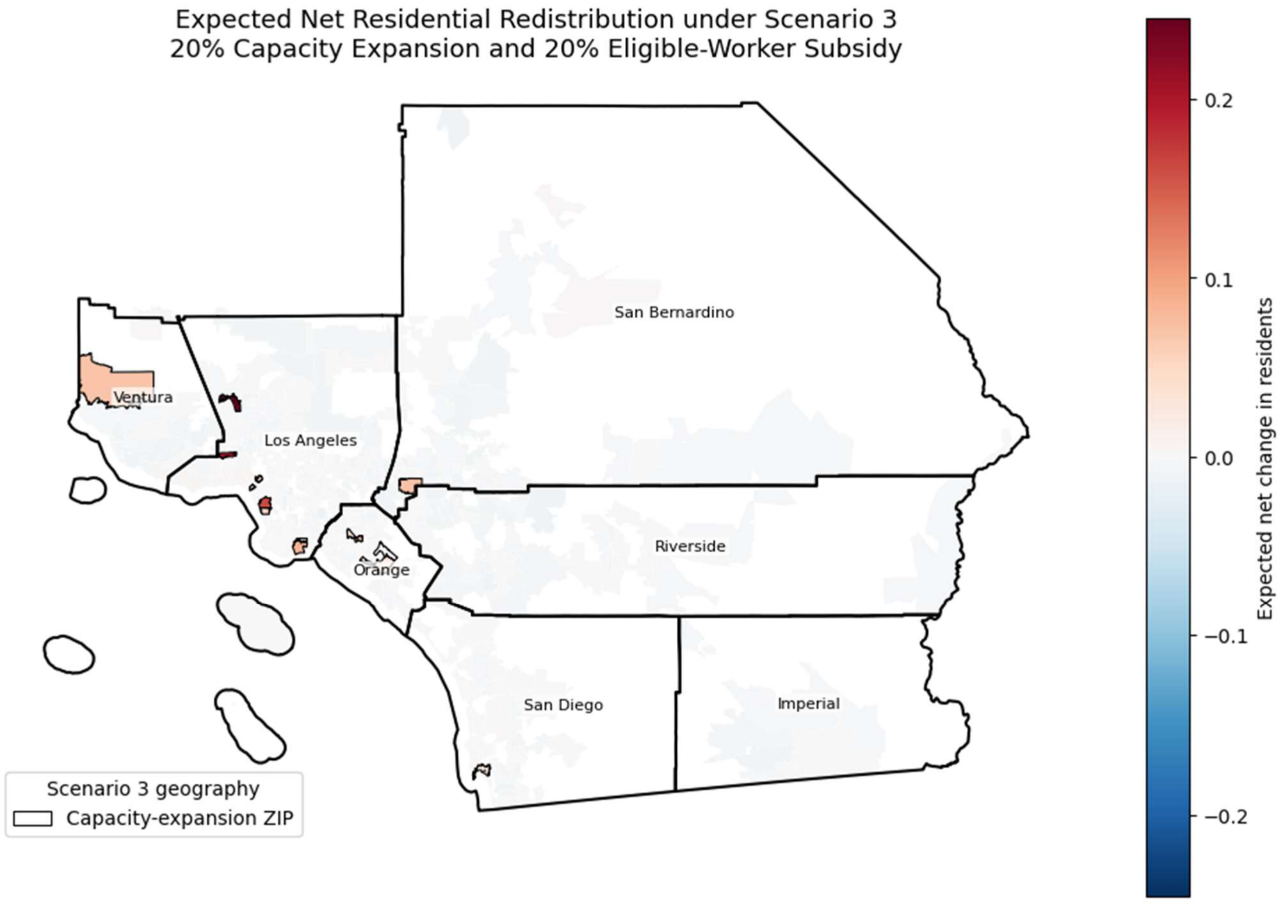

Figure 25 - Expected Net Residential under Scenario 3

Figure 25 presents the probability-weighted expected net residential redistribution under the combined 20% housing-capacity expansion and 20% eligible-worker subsidy scenario. The map compares each ZIP code's expected residential assignment under Scenario 3 with its corresponding status-quo expectation.

The combined policy produces a broader and larger localized redistribution than the standalone employer-sponsored subsidy. Expected gains are concentrated primarily within and near the capacity-expansion ZIP codes, although effects extend to surrounding locations through competition among residential alternatives. Some targeted ZIP codes gain expected residents, while others experience little change or small losses because the newly expanded and subsidized alternatives compete with one another as well as with untreated alternatives throughout each worker's choice set.

The spatial pattern remains heterogeneous. The combined intervention does not cause workers to converge uniformly on a single employment center. Instead, probability mass is redistributed across multiple metropolitan submarkets, reflecting differences in commute time, housing price, housing capacity, workplace earnings, worker–job matching, and the income-specific responses represented in the estimated model.

Relative to either standalone policy, the combined policy produces larger expected changes in residential choice probabilities and spatial redistribution. This result indicates that affordability incentives become more influential when additional housing capacity is simultaneously introduced in employment-accessible locations.

Summary

The combined-policy experiment demonstrates that housing-capacity expansion and employer-sponsored housing assistance can generate complementary improvements in residential choice, housing affordability, and consumer welfare, but these improvements do not necessarily produce proportionately large reductions in regional commuting. Across the primary scenarios, increasing intervention magnitude consistently reduces expected affordability burden, increases the attractiveness of targeted and qualifying residential alternatives, and produces positive expected welfare changes among eligible workers. These responses strengthen further under the upper-bound sensitivity scenarios.

The commuting results are substantially more modest. Although a majority of eligible workers experience some reduction in expected commute time, the individual reductions are generally very small and mean regional commute time remains nearly unchanged under the primary scenarios. Even the 50% and 90% stress tests produce only limited changes in aggregate commuting. The combined intervention therefore appears substantially more effective at improving the housing and residential-choice dimensions of worker utility than at restructuring regional commute patterns.

This divergence is itself an important policy finding. It indicates that improving housing availability and affordability near employment centers can make workers' feasible residential alternatives more attractive without necessarily relocating households sufficiently, or in the particular spatial directions required, to produce large reductions in regional commute duration. Residential location decisions remain jointly conditioned by workplace geography, housing characteristics, occupational compatibility, income, transportation conditions, and the distribution of alternative housing opportunities across the region.

Accordingly, the Scenario 3 results support a coordinated rather than singular approach to the jobs–housing mismatch. Housing-capacity expansion and employer-sponsored housing assistance may provide meaningful benefits through improved affordability, expanded residential opportunities, and higher expected consumer welfare. However, achieving substantial reductions in long-distance commuting likely requires complementary strategies that address the spatial distribution of employment and housing, transportation accessibility, and the alignment between workers, workplaces, and available housing opportunities. The combined-policy results therefore reinforce the broader conclusion of this dissertation: housing affordability, residential location, and commuting are interconnected outcomes, but improvements in one dimension should not be assumed to generate equivalent improvements in the others.

4.6 Discussion

This chapter evaluates how alternative housing policy interventions influence residential location patterns and commuting outcomes within Southern California using the behavioral simulation framework developed in Chapter 4. By modifying housing prices, housing availability, and workforce targeting while holding estimated behavioral preferences constant, the simulations isolate the mechanisms through which different housing policies influence residential choice and regional commuting outcomes.

Policy 1 demonstrates that employer-sponsored housing subsidies increase the attractiveness of residential alternatives near employment centers for eligible workers. Although the subsidy increases residential utility and the probability of selecting qualifying housing alternatives, overall relocation responses remain modest. These results suggest that affordability incentives alone are insufficient to substantially reduce regional commuting burdens when housing availability near employment centers remains constrained.

Policy 2 demonstrates that increasing housing supply near employment centers produces larger changes in residential location behavior than housing subsidies alone. By expanding housing availability in employment-accessible ZIP codes, workers gain additional feasible housing options near major job centers. However, regional reductions in commute time and the prevalence of long commutes remain comparatively modest, indicating that housing supply expansion alone does not fully offset the broader influence of employment geography, transportation networks, and occupational sorting on commuting behavior.

Scenario 3 evaluates the combined implementation of Policy 1 and Policy 2, integrating targeted employer-sponsored housing subsidies with housing-capacity expansion in employment-oriented ZIP codes. The combined intervention produces consistent improvements in housing affordability and consumer welfare, while its effects on regional commuting remain modest. As the magnitude of the combined intervention increases, expected affordability burden declines and consumer welfare, measured through changes in the model logsum, increases. Expected mean commute time also declines, but by only a small amount at the regional scale. These findings indicate that combining additional housing capacity with targeted affordability assistance improves the residential choice environment for eligible workers more clearly than it changes aggregate commuting outcomes. Regional commuting patterns remain influenced by the broader spatial distribution of workplaces, housing opportunities, occupational matching, and transportation accessibility.

Collectively, the Policy 1, Policy 2, and combined Scenario 3 simulations demonstrate that commuting patterns are shaped by the interaction of housing availability, housing affordability, employment geography, transportation accessibility, and occupational specialization. Even substantial housing interventions produce gradual rather than dramatic regional changes because residential location decisions remain constrained by the broader spatial organization of Southern California's housing and labor markets. The results therefore support coordinated housing, land use, and transportation strategies rather than isolated housing interventions alone.

4.7 Conclusion

This chapter evaluates how these two housing policy scenarios influence residential location choices and commuting outcomes within Southern California using the behavioral simulation framework developed from the joint residence and work location choice model. The simulations modify housing affordability, housing availability, and access to additional housing while holding the other model attributes constant. The results show that each policy affects residential choice through a different mechanism and produces a different combination of localized and regional outcomes.

Policy 1, the employer-sponsored housing subsidy, increases the attractiveness of qualifying housing options for eligible professional and essential workers. The subsidy scenarios produce measurable increases in the probability of selecting housing near employment locations and modest reductions in expected commuting burdens. However, the overall regional effects remain limited because reducing the effective price of housing does not increase the number of available residential opportunities near employment centers. The Policy 1 results therefore indicate that affordability assistance may improve access to existing housing opportunities, but its broader effectiveness remains constrained when housing availability is limited.

Policy 2, the office to residential housing capacity expansion, produces larger changes in the spatial distribution of expected residential assignments. By increasing housing availability in 16 employment-oriented ZIP codes, the policy expands the number and relative attractiveness of residential options near major job centers. The simulations generate measurable increases in expected residential selection within the targeted locations. Regional changes in mean commute time and long commute shares remain modest, however, because employment geography, transportation conditions, occupational specialization, and existing residential patterns continue to influence household location choices.

Scenario 3 evaluates Policy 1 and Policy 2 in combination, simultaneously expanding housing capacity within employment-oriented ZIP codes and reducing effective housing costs for eligible workers. The combined intervention produces improvements in expected housing affordability and consumer welfare, while reductions in expected commute time remain comparatively small. As intervention intensity increases, affordability burden declines and the expected logsum increases, indicating improvement in the overall attractiveness of the residential–work choice set. The commute response moves in the expected direction but remains modest even under the upper-bound sensitivity scenarios. These findings demonstrate that combining housing supply expansion with targeted affordability assistance can improve workers' residential opportunities and welfare without necessarily producing proportionately large changes in regional commuting patterns.

Across Policy 1, Policy 2, and the combined Scenario 3 simulations, regional commuting outcomes remain relatively resistant to rapid transformation. Even under higher intensity scenarios, reductions in expected commute time and in the prevalence of long commutes remain incremental. This demonstrates that commuting behavior is shaped by a broader regional system involving employment concentration, wages, housing affordability, occupational matching, transportation networks, and the existing distribution of residential development.

Three broader conclusions emerge from the analysis. First, affordability interventions alone are unlikely to substantially change regional commuting patterns when housing supply remains limited near major employment centers. Second, increasing housing availability in employment-accessible locations increases the attractiveness of those residential alternatives, although housing-supply expansion alone may not resolve regional commuting inefficiencies. Third, combining housing-capacity expansion with targeted affordability assistance produces the broadest set of modeled benefits, improving housing affordability and consumer welfare while also producing small reductions in expected commuting burdens.

Overall, the findings support the conclusion that Southern California's jobs-and-housing imbalance reflects an interconnected regional system rather than a single housing shortage. Meaningful reductions in long-distance commuting therefore require coordinated strategies that address housing production and affordability, employment geography, land-use planning, and transportation accessibility. Housing interventions alone do not fully resolve regional commuting inefficiencies, but policies that strategically expand housing opportunities near employment centers may play an important role in improving workforce accessibility and reducing commuting burdens over time.

4.8 Policy Implications

The findings provide several practical implications for metropolitan regions seeking to reduce long-distance commuting and improve workforce accessibility.

First, the results demonstrate that the location of new housing is as important as the total amount of housing constructed. Moderate increases in residential capacity located near major employment centers produce larger behavioral responses than equivalent housing added in locations with lower employment accessibility. This finding suggests that planning strategies emphasizing housing production near major job centers may be more effective than policies focused exclusively on increasing regional housing supply.

Second, affordability interventions implemented in isolation appear to have limited regional impacts. Although employer-sponsored housing subsidies increase the attractiveness of employment-proximate residential alternatives, relocation responses remain constrained when sufficient housing is unavailable near employment centers. Price-based policies therefore appear most effective when accompanied by additional housing supply.

Third, the combined results for Scenario 3 demonstrate the potential value of coordinating housing-supply and affordability strategies. Expanding housing capacity increases the availability of residential opportunities near employment centers, while targeted employer-sponsored subsidies improve affordability for eligible workers. When implemented together, these mechanisms improve expected housing affordability and consumer welfare, even though changes in regional commute duration remain modest. This distinction is important for policy evaluation because the benefits of coordinated housing interventions should not be assessed solely through changes in average commute time.

Fourth, the findings reinforce the importance of integrating housing policy with land use and transportation planning. Traditional transportation investments often seek to reduce commuting burdens by expanding roadway or transit capacity. The results presented here suggest that complementary housing strategies that improve residential access to major employment centers may provide an additional mechanism for reducing regional commuting burdens.

Finally, the study demonstrates the importance of evaluating housing policies using accessibility-based and behavioral outcome measures rather than relying solely on housing production totals or regional commute reductions. Changes in residential-location probabilities, housing affordability, and consumer welfare provide important information about how housing interventions affect workers even when aggregate commuting patterns remain comparatively stable.

Chapter 5 – Dissertation Conclusion

5.1 Summary of Key Findings

This dissertation examines how housing conditions, employment geography, worker characteristics, and transportation accessibility interact to shape residential location decisions and commuting burdens in Southern California. Across three related studies, the analysis progresses from identifying where commuting and accessibility pressures are concentrated to estimating the behavioral trade-offs underlying residence–work location choices and, finally to evaluating how targeted housing interventions may alter those choices. Taken together, the findings demonstrate that Southern California's jobs–housing imbalance is not attributable to a single constraint. Rather, it reflects the interaction among housing affordability and availability, the spatial concentration of employment opportunities occupational specialization, and the transportation costs that connect workers to jobs.

Study 1 establishes the spatial and demographic context for these relationships. The analysis documents substantial geographic variation in commute duration, long-distance commuting, housing costs, and access to employment opportunities across Southern California. The Worker Stress Zone framework further identifies locations where multiple pressures, including high housing costs, limited access to relevant employment, and elevated long-distance commuting, occur simultaneously. These conditions are not distributed uniformly across the region or across worker groups. Professional and essential workers experience different spatial patterns of housing and employment pressure, demonstrating that aggregate measures of jobs–housing balance can obscure important differences in the constraints facing particular segments of the workforce. Study 1 therefore establishes that commuting burden should be understood as part of a broader accessibility problem rather than as an isolated transportation outcome.

Study 2 examines the behavioral mechanisms underlying these observed spatial patterns through a joint residence–work location choice model. The results show that commute time remains a strong source of disutility: workers prefer residence–work combinations that reduce travel burden, all else equal. However, commute time is only one component of location choice. Housing affordability also meaningfully affects residential utility, while workplace earnings, housing characteristics, and occupational compatibility influence the relative attractiveness of alternative residence–work combinations. The income–commute interaction further indicates that sensitivity to commuting burden varies with worker income, reinforcing the importance of accounting for heterogeneity in how workers evaluate housing and employment opportunities.

The occupational matching results provide additional evidence that workers do not respond simply to the total number of jobs available in a location. Professional and essential workers exhibit stronger preferences for workplace locations that contain greater concentrations of employment relevant to their respective occupational groups. This distinction is important because it suggests that proximity to employment alone does not necessarily represent meaningful job accessibility. The composition and suitability of available employment opportunities matter alongside their geographic accessibility. Similarly, the positive relationship between housing capacity and residential utility indicates that housing availability contributes to the attractiveness and feasibility of residential locations, even though the estimated capacity coefficient is imprecise. Together, the Study 2 findings demonstrate that residence–work location decisions reflect simultaneous trade-offs among commute burden, housing affordability and availability, employment opportunity, occupational compatibility, and worker characteristics.

Study 3 translates these estimated behavioral relationships into policy simulations. Policy 1 evaluates employer-sponsored housing subsidies for eligible professional and essential workers residing within specified commute thresholds of their workplaces. The simulations consistently show that reducing effective housing costs increases the probability that eligible workers select qualifying residential alternatives. The response becomes larger as subsidy levels increase and as broader commute thresholds expand the set of eligible alternatives. Housing affordability improves correspondingly, and the positive changes in consumer welfare indicate that workers gain access to a more attractive set of feasible residence–work alternatives. Regional reductions in expected commute time, however, remain modest because the subsidy changes the relative affordability of existing residential opportunities without increasing the underlying supply or geographic distribution of housing.

Policy 2 evaluates housing-capacity expansion within selected employment-oriented ZIP codes. Increasing capacity raises the expected probability that workers select residential alternatives within the targeted locations, demonstrating that additional housing availability near employment centers can influence residential sorting. The supply-induced affordability mechanism also improves the relative attractiveness of these locations. Nevertheless, regional commute outcomes again change only incrementally. This result indicates that placing additional housing near major employment centers can improve residential accessibility without necessarily producing equivalent reductions in commuting because workers continue to evaluate opportunities across a broader regional labor and housing market.

Scenario 3 evaluates Policies 1 and 2 in combination, simultaneously expanding housing capacity in employment-oriented locations and reducing effective housing costs for eligible workers. The combined simulations produce consistent improvements in expected housing affordability and consumer welfare and small reductions in expected commute burden. These results demonstrate the complementary roles of housing supply and affordability: increasing capacity expands the set of residential opportunities available near employment centers, while targeted subsidies improve eligible workers' ability to access those opportunities. At the same time, the persistence of relatively small aggregate commute effects, even as affordability and welfare improve, demonstrates that regional commuting patterns cannot be substantially altered through housing interventions alone.

A central finding therefore emerges across all three studies: improving housing access near employment is valuable, but proximity alone does not determine commuting behavior or worker welfare. Workers choose among residence–work combinations based on multiple competing attributes, including housing costs, housing availability, workplace earnings, occupational compatibility, commute burden, and the distribution of alternatives throughout the region. Policies can consequently produce meaningful improvements in affordability, residential choice, accessibility, and consumer welfare without generating proportionately large reductions in average regional commute time.

Taken together, these findings characterize Southern California's jobs–housing imbalance as an interconnected regional accessibility problem. Study 1 identifies where the pressures are concentrated and which workers experience them; Study 2 demonstrates the behavioral mechanisms through which workers respond to housing, employment, and transportation conditions; and Study 3 shows how those mechanisms shape responses to housing-policy interventions. The results suggest that meaningful improvements in workforce accessibility will require coordinated strategies that address both sides of the residence–work relationship: expanding feasible and affordable housing opportunities near employment while also considering the spatial distribution and occupational composition of employment opportunities and the transportation networks connecting workers to them. Housing policy is therefore an important component of reducing jobs–housing mismatch, but its effectiveness depends on how it is integrated with broader land-use, employment, and transportation planning.

5.2 Major Contributions

This dissertation makes several contributions to the literature on urban economics, transportation, and land-use planning, spanning conceptual, methodological, empirical, and policy domains.

Conceptual Contribution

This research develops an integrated framework linking housing affordability, labor-market opportunity, and commuting behavior. By treating commuting as an endogenous component of both residential and workplace location decisions, the dissertation advances the conceptual understanding of how spatial structure emerges in constrained housing markets. The findings emphasize that commuting burdens are not merely a byproduct of spatial mismatch but arise through the interaction of housing affordability, employment geography, occupation group, and transportation accessibility.

Methodological Contribution

This dissertation develops a joint residence–work location choice model that captures the interdependence between residential and employment decisions. This approach extends traditional discrete-choice models by incorporating commuting directly into the utility function and modeling residential and workplace alternatives simultaneously.

The research further links the estimated behavioral model to a scenario-based housing-policy simulation framework. The simulations apply controlled changes to housing prices and ZIP-level housing capacity and then recalculate the complete distribution of residence–work choice probabilities. This combination provides a consistent framework for evaluating how demand-side affordability incentives and supply-side housing-capacity expansion alter the relative attractiveness of residential alternatives and the resulting probability-weighted commute outcomes.

The framework therefore provides a transparent assessment of behavioral responses to housing policy assumptions while remaining consistent with the spatial scale and explanatory variables used in the estimated choice model.

Empirical Contribution

Using detailed ZIP-code-level spatial data and individual-level travel behavior, this dissertation provides one of the most comprehensive empirical characterizations of commuting burdens in Southern

California. The findings quantify the magnitude and distribution of long-distance commuting and identify substantial heterogeneity across income groups, occupations, and geographic contexts.

The research also provides empirical evidence linking housing constraints and concentrations of employment opportunities to spatially uneven commuting burdens. The results demonstrate that housing availability near major employment centers is only one component of a more complex system involving housing costs, workplace geography, occupational matching, and transportation accessibility.

Policy Contribution

This dissertation develops a policy-relevant simulation framework that links behavioral estimation to scenario analysis, enabling the evaluation of housing interventions based on estimated residence–work location preferences.

The analysis compares two complementary policy interventions individually and in combination:

- employer-sponsored housing subsidies for eligible professional and essential workers, representing a demand-side affordability intervention; and
- office-to-residential capacity expansion in selected employment-oriented ZIP codes, representing a supply-side housing intervention.

A third simulation scenario evaluates the combined implementation of these two policies, allowing the analysis to examine whether simultaneously expanding housing capacity and improving affordability produces complementary effects. Scenario 3 is therefore not a separate policy intervention but a combined-policy simulation used to evaluate the interaction of the two policy mechanisms

The results distinguish between localized changes in residential-choice probabilities and broader changes in regional commuting outcomes. Policy 1 increases the attractiveness of qualifying residential alternatives for eligible workers, while Policy 2 increases the availability and relative attractiveness of housing within selected employment centers. The combined Scenario 3 simulations evaluate these mechanisms simultaneously. Across the simulations, aggregate commute outcomes change only modestly, demonstrating that housing affordability and capacity interventions alone do not fully overcome the broader regional constraints shaping residence–work location choices.

Together, these findings demonstrate the value of evaluating housing policies through both their localized residential-choice effects and their regional transportation consequences. They also show that policies intended to reduce commuting burdens must account for the combined influence of housing supply, affordability, employment geography, occupation group, and regional accessibility.

5.3 Limitations and Future Research

While this dissertation provides a comprehensive framework for analyzing joint residential and workplace decision-making, several limitations should be acknowledged.

First, the estimated choice model captures behavior under observed market conditions, but not all relevant decision-making factors are directly observed. Unmodeled influences, such as household preferences, moving costs, school quality considerations, and attachment to place, may limit responsiveness to changes in housing affordability or commuting costs. As a result, the estimated responses should be interpreted as reflecting revealed preferences under current constraints.

Second, the model is estimated using cross-sectional data and therefore does not explicitly capture dynamic adjustment processes. Residential relocation decisions often occur over time and may be influenced by expectations, lifecycle transitions, and housing market frictions. Future research could extend this framework using longitudinal or panel data to better capture temporal dynamics.

Third, the analysis relies on spatial aggregation at the ZIP code level and the use of proxy variables to represent neighborhood characteristics. While this approach is consistent with prior research, it may mask within-area heterogeneity and limit the ability to capture micro-level decision processes. Incorporating finer spatial resolution or parcel-level data could improve model precision.

Fourth, the use of a multinomial logit framework imposes the independence of irrelevant alternatives (IIA) assumption. While appropriate for the scale of the analysis, future research could explore more flexible model forms, such as mixed logit or nested logit models, to capture correlation across alternatives and unobserved preference heterogeneity.

Fifth, the policy simulations assume that behavioral parameters remain stable across scenarios. In practice, large-scale policy interventions may alter underlying market conditions and behavioral relationships. Future work could explore endogenous feedback effects, including changes in housing prices, wages, and development patterns.

Future Research Directions

Building on these limitations, several avenues for future research emerge. Future work could incorporate dynamic modeling approaches to capture relocation over time and better reflect household adjustment processes. Integrating network-based accessibility measures or gravity-based commuting models could further improve representation of spatial interactions between housing and employment. Expanding the framework to include heterogeneous preferences across demographic groups would provide deeper insight into equity impacts and differential policy responses. In addition, applying the model to multiple metropolitan regions would support comparative analysis and improve understanding of how institutional and market conditions influence jobs–housing dynamics.

Additionally, future research may evaluate whether reductions in regional commute burden and improvements in jobs-housing balance could alter interregional migration attractiveness and residential demand patterns within Southern California. Finally, extending the simulation framework to incorporate endogenous housing supply responses and land-use change would enable evaluation of longer-term policy impacts, providing a more complete representation of urban system dynamics.

The relatively limited behavioral response observed under targeted housing subsidy scenarios suggests that housing affordability interventions alone may be insufficient to substantially alter regional commuting patterns within highly concentrated metropolitan labor markets. Because the strongest behavioral responses in the estimated model are associated with workplace accessibility, occupational composition, and labor-market concentration, the findings suggest that the spatial organization of employment opportunities may play an important role in shaping long-distance commuting behavior.

Future research could therefore evaluate whether policies aimed at decentralizing high-wage employment opportunities, expanding suburban employment accessibility, or increasing remote and hybrid work flexibility may produce larger reductions in regional commute burdens than housing affordability interventions alone. Such strategies could potentially improve jobs–housing alignment by altering the spatial distribution of employment opportunities rather than only residential affordability conditions.

At the same time, strategies that encourage employment decentralization may involve important trade-offs, including reduced labor market efficiency, weaker matching between workers and employers, and lower productivity associated with more dispersed employment centers. Consequently, the findings suggest that long term reductions in commuting burdens may require balancing improved residential accessibility with the economic advantages associated with concentrated employment centers.

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Appendix A – Data Integration Workflow

Appendix A documents the data integration workflow used to construct the analysis datasets for the three studies. The workflow integrates worker-level travel survey records, ZIP-code-level housing and employment attributes, Google Maps travel-time matrices, and spatial boundary files into a unified modeling framework. The purpose of this appendix is to document the major merge structure and derived variables rather than raw cleaning steps. The workflow is designed to provide methodological transparency and reproducibility for the integrated behavioral and policy simulation framework used throughout the dissertation.

The data construction process followed four major stages. First, worker records from the California Household Travel Survey were filtered to retain valid workers with reported home and employment ZIP codes where available. Second, ZIP-level housing, employment, accessibility, and neighborhood variables were constructed from Zillow, LEHD/LODES WAC, GTFS, ACS, and TIGER/ZCTA sources. Third, ZIP-to-ZIP travel-time matrices were created using peak-period Google Maps travel times between ZIP-code centroids. Fourth, worker records were merged to origin, destination, and OD-level attributes to create the final modeling and policy simulation datasets.

Data Integration Workflow			
Step	**Dataset / Operation**	**Key Join Field**	**Output**
1	CHTS worker records (2016)	Sample Number, Person Number (Worker)	Worker-level base file
2	Home ZIP attributes	Worker Home ZIP code	Residential covariates
3	Work ZIP attributes	Worker Work ZIP code	Employment covariates
4	ZIP-to-ZIP Google travel matrix	Worker Home ZIP code, Worker Work ZIP code	Commute-time impedance
5	LODES/WAC employment totals	Employment ZIP codes / Worker Work ZIP code	Job accessibility variables
6	Final modeling dataset	Worker + ZIP + OD fields	Joint residence–work choice dataset
7	Scenario simulations	Alternative-specific ZIP pairs	Policy outputs

Table 55 - Data Integration Workflow for Joint-Residence-Work Location Modeling

Notes: ZIP-level “joins” were standardized using 5-digit ZIP/ZCTA identifiers. Google travel times were generated using peak-period automobile travel estimates between ZIP centroid pairs. Accessibility measures were subsequently computed from ZIP-to-ZIP impedance matrices and employment opportunity datasets.

Appendix B – Variable Definitions

Appendix B defines the principal variables used in the empirical analysis, model estimation, and policy simulations. Variables include observed worker attributes, ZIP-level housing and employment measures, travel impedance measures, accessibility indicators, and transformed variables used in the multinomial logit model.

Principal Variables Used in Modeling and Simulation				
	Variable	**Description**	**Source**	**Units / Transformation**
1	$tt_{h,w}$	Average peak-period automobile commute time between home and work ZIP centroids	Google Maps Distance Matrix API	Minutes
2	$\ln(tt_{h,w})$	Natural log of peak-period commute time	Derived from Google Maps API	ln(minutes)
3	zip_h	Residential ZIP code / ZCTA associated with worker home location	CHTS	ZIP
4	zip_w	Employment ZIP code / ZCTA associated with workplace location	CHTS	ZIP
5	$price_h$	Median residential listing price per square foot	Zillow listings	USD per square foot
6	$\ln(price_h)$	Standardized log housing price measure	Derived from Zillow	z-score
7	$capacity_h$	Estimated housing capacity based on ACS total housing units	ACS B25001	Housing units
8	$\ln(capacity_h)$	Standardized log housing capacity	Derived from ACS B25001	z-score
9	$jobs_w$	Total workplace employment in ZIP code	LEHD/LODES WAC	Jobs
10	$\ln(jobs_w)$	Natural log of total workplace employment	Derived from LODES/WAC	ln(jobs + 1)
11	$prof_i$	Professional employment opportunities in ZIP code	LODES/WAC CNS grouping	Jobs
12	ess_i	Essential employment opportunities in ZIP code	LODES/WAC CNS grouping	Jobs
13	$access_{jobs}$	Gravity-weighted accessible jobs from residential ZIP	Derived from LODES/WAC + Google travel times	Weighted jobs
14	$access_{prof}$	Gravity-weighted accessible professional jobs from residential ZIP	Derived from ZIP-level travel impedance & employment matrices	Weighted jobs

15	$access_{ess}$	Gravity-weighted accessible essential jobs from residential ZIP	Derived from ZIP-level travel impedance & employment matrices	Weighted jobs
16	$transit_h$	ZIP-level transit-stop-density / accessibility measure	GTFS	z-score
17	β_{time}	Estimated coefficient on log commute time	Model output	Utility coefficient
18	β_{price}	Estimated coefficient on housing price	Model output	Utility coefficient
19	$\beta_{capacity}$	Estimated coefficient on housing capacity	Model output	Utility coefficient
20	β_{earn}	Estimated coefficient on workplace earnings	Model output	Utility coefficient
21	β_{prof}	Estimated coefficient on professional occupational match	Model output	Utility coefficient
22	β_{ess}	Estimated coefficient on essential occupational match	Model output	Utility coefficient

Table 56 - Principal Variables Used in Accessibility Analysis, Residential Choice Modeling, and Policy Simulation

Note: Accessibility measures were computed using gravity-based formulations incorporating ZIP-level travel impedance and employment opportunity distributions.

Appendix C – Occupational Classification

Appendix C documents the occupational and industry classification rules used to define professional, essential, and other worker categories. In the worker-level CHTS analysis, categories are based on reported occupation codes. In the accessibility and policy simulation analysis, employment opportunities are classified using LEHD/LODES WAC Census Industry Sector variables. These classifications are designed to distinguish workers and jobs most relevant to workforce housing, essential-worker accessibility, and occupational sorting.

These classification systems were developed to distinguish worker categories expected to exhibit different residential-location constraints, wage structures, and commuting burdens within high-cost metropolitan labor markets. The classifications support the policy simulation framework evaluated in Study 3 by operationalizing workforce-priority targeting mechanisms.

CHTS Worker Classification		
Worker Group	**SOC Major Groups Included**	**Description**
Professional	11, 13, 15, 17, 19, 21, 23, 25, 27, 29	Management, business, STEM, legal, education, arts, healthcare professional occupations
Essential	31, 33, 35, 37, 39, 43, 47, 49, 51, 53	Healthcare support, protective service, food service, maintenance, office support, construction, transportation, production occupations
Other	Remaining occupation groups	Occupations not classified as professional or essential

Table 57 - Professional and Essential Worker Occupational Classification Using SOC Major Groups

Note: SOC major groups follow Standard Occupational Classification aggregation categories adapted for workforce accessibility analysis.

WAC Industry Classification		
Worker Group	**WAC CNS Sectors Included**	**Industry Description**
Professional	CNS09, CNS10, CNS11, CNS12	Information; Finance & Insurance; Real Estate; Professional, Scientific, and Technical Services
Essential	CNS03, CNS04, CNS05, CNS08, CNS15, CNS16, CNS19	Utilities; Construction; Manufacturing; Transportation/Warehousing; Education; Healthcare/Social Assistance; Public Administration
Other	Remaining CNS sectors	Remaining industries not classified as professional or essential

Table 58 - Professional and Essential Industry Classification Using LEHD/LODES WAC CNS Sectors

Note: CNS sector classifications follow LEHD/LODES Workplace Area Characteristics industry grouping conventions.

Appendix D – Choice Set Construction Justification

D.1 Objective

There were several different alternatives considered in creating the choice set including: 1) expanding the alternative universe using all home ZIPs x observed work ZIPs, then filtering by distance/time, 2) sampling alternatives separately, for home and for work then form combinations, 3) use centroid distance as pre-screen, then only google-query sampled pairs, generating plausible pairs first by filtering to maybe within 90–120 miles or same/nearby counties, then query only those. The current strategy of using the empirically observed residence-work ZIP network was ultimately selected for several reasons. See the table below for additional details on the choice set alternatives that were considered.

The purpose of the empirical residence-work network is not to restrict the behavioral model to currently observed commuting patterns, but rather to define a realistic estimation universe composed of feasible residential-employment opportunities. The sampling procedure then draws alternatives from this empirically observed opportunity space using established sampling-of-alternatives methods.

D.2 Alternative Strategies Considered

Strategy	Advantages	Limitations
Full Cartesian Product	Complete universe	Hundreds of thousands of impossible pairs
Home ZIP × Work ZIP Independent Uniform Random Sampling	Simple to explain	Generates many behaviorally infeasible alternatives
Distance Threshold	Removes outlying long trips	Arbitrary cutoff that may not apply to many of the workers
County-Based Candidate Restriction (Same County / Adjacent County / Counties w/in a fixed Distance)	Simple to explain	Administrative boundaries do not determine labor markets
Observed OD Pairs (*Chosen*)	Behaviorally realistic	Rare/unrealistic combinations omitted

Table 59 - Choice-Set Construction Alternatives Considered

D.3 Why the Empirical Network was Selected

The current Empirical Network choice set strategy was ultimately selected for several reasons:

1. First, every alternative is guaranteed to be behaviorally feasible. This is important because the model would spend an enormous amount of time and effort learning and filtering out the alternatives that are realistic (such as home ZIP in Beverly Hills and work ZIP in Victorville).
2. Every alternative has an observed travel impedance since the Google Maps API Matrix was run on observed OD pairs. This gives every alternative an AM and PM congestion commute time and realistic routing without having to be concerned with synthetic travel times or Euclidean approximations.

3. This strategy preserves land-use realism. In other words, some ZIP codes are almost entirely industrial while others are almost entirely residential, or military, or airfields, or universities; therefore, if randomly selected ZIPs were chosen and combined into residence-work pairs the risk is higher that these combinations never function as actual residence-work systems. Using observed pair automatically removes this risk.
4. A full Cartesian product would have generated approximately 250,000 residence workplace pairs, resulting in substantial computational costs while adding many behaviorally unrealistic alternatives.

After the analysis of all alternatives mentioned above, it was determined that, although the current choice set strategy has some setbacks such as possible missing pairs, many of these omitted alternative pairs would be impossible, extremely uncommon, prohibitively expensive, or outside of commuting norms. Therefore, the strength of this current choice set strategy is that it shows, given realistic opportunities such as the empirically observed residence-work pairs, what are the configurations of those that are most attractive.

Appendix E – Robustness Check

This appendix presents supplementary robustness and diagnostic analyses conducted to evaluate the stability, reliability, and behavioral consistency of the joint residence–workplace location choice model. The analyses include robustness testing of chooser-specific heterogeneity effects, pairwise correlation diagnostics, and Variance Inflation Factor (VIF) assessment for multicollinearity. Together, these diagnostics support the validity and stability of the final model specification.

Robustness Results

Robustness analyses evaluate whether the primary behavioral findings remain stable under an alternative utility specification incorporating additional worker related heterogeneity. Table 48 compares selected coefficients from the preferred specification with their corresponding estimates from the robustness specification.

The principal coefficient signs remain unchanged across specifications. Commute time and housing price retain negative coefficients, while workplace earnings, housing capacity, employment opportunity, and occupational matching retain positive coefficients. The commute time and occupational matching estimates remain especially stable in magnitude. The housing capacity and employment opportunity coefficients become slightly smaller in the robustness specification but retain their expected positive directions.

These results indicate that the primary behavioral conclusions do not depend on a single model specification. Workers consistently prefer shorter commutes, lower housing costs, higher workplace earnings, and employment locations that align with their occupational group. The stability of these relationships supports the behavioral consistency of the preferred specification.

Strong Robustness Terms			
Variable	**Baseline**	**Robustness**	**Interpretation**
β_{time}	-0.16	-0.161	Direction and magnitude remain highly stable
$\beta_{affordability}$	-0.098	-0.104	Negative housing price effect remains stable
β_{earn}	0.809	0.758	Positive workplace earnings effect remains stable
β_{prof_match}	7.78	7.76	Professional occupational matching effect remains highly stable
β_{ess_match}	6.81	6.84	Essential occupational matching effect remains highly stable
$\beta_{capacity}$	0.103	0.088	Positive effect remains, with a modest reduction in magnitude
β_{jobs}	0.031	0.027	Positive effect remains, with a modest reduction in magnitude

Table 60 - Strong Robustness Terms

Multicollinearity Results

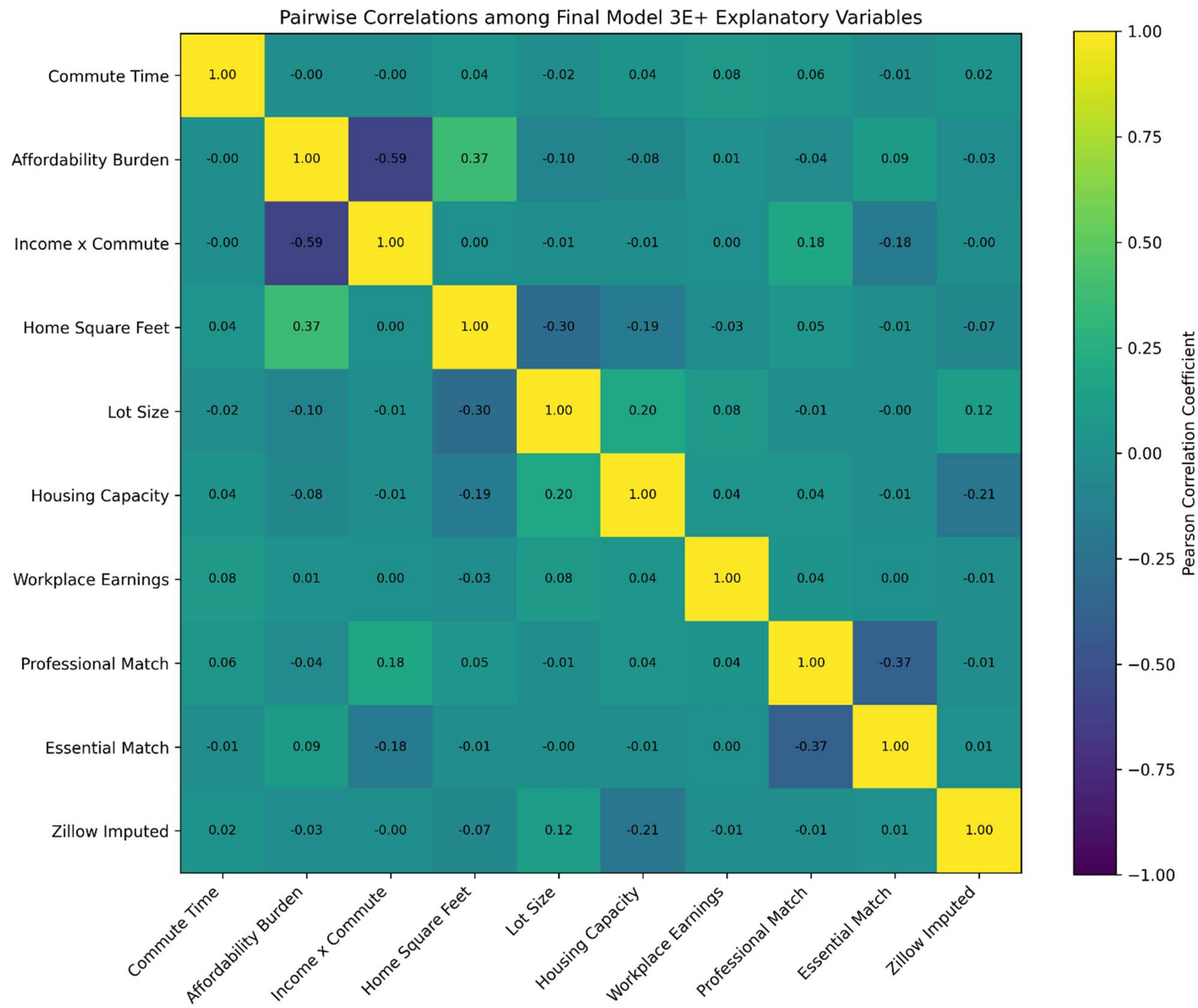

Figure 26 - Correlation Matrix of Independent Variables

Figure 26 presents the correlation matrix for the explanatory variables in the final joint residence-work location choice model. Correlations are generally low to moderate, and no pairwise absolute correlation exceeds 0.70. The largest observed relationship is between affordability burden and the income–commute-time interaction (r ≈ −0.59). Because household income contributes to the construction of affordability burden and also enters the commute-time interaction, some relationship between these variables is expected. However, the variables capture different behavioral mechanisms and the observed correlation does not reach conventional levels generally associated with severe pairwise collinearity.

Other moderate relationships include affordability burden and residential square footage (r ≈ 0.37), professional and essential occupational matching (r ≈ −0.37), and residential square footage and lot size (r ≈ −0.30). Remaining pairwise relationships are comparatively small. These results indicate that the final explanatory variables primarily contribute complementary rather than redundant information to the joint residence–work location choice model.

Variance Inflation Factor

Variance Inflation Factor (VIF) diagnostics further confirm the absence of problematic multicollinearity. All VIF values remain close to 1.0 and substantially below conventional concern thresholds (e.g., VIF > 5), indicating highly independent explanatory variables and stable coefficient estimation. These diagnostics provide additional support for the validity and interpretability of the final model specification. All reported VIF values, shown in Table 61, remained substantially below conventional multicollinearity concern thresholds.

VIF diagnostics	
Variable	**VIF**
Affordability Burden	1.990
Housing Capacity	1.139
Home Square Feet	1.407
Professional Job Match	1.197
Essential Job Match	1.180
Property Lot Size	1.153
Income x Commute Time	1.775
Workplace Earnings	1.016
Zillow Imputed Price Data	1.086
Commute Time	1.016

Table 61 - VIF Diagnostics

Choice-Set Size Sensitivity Analysis

A sensitivity analysis was conducted to evaluate whether the estimated parameters of the final model specification were materially affected by the number of sampled nonchosen alternatives included in each worker's choice set. The primary model uses $K = 150$sampled nonchosen alternatives, while the sensitivity analysis re-estimates the identical model specification using $K = 10$, $K = 30$, and $K = 50$. The same 1,041-worker estimation sample, variable definitions, utility specification, and estimation procedure were maintained across sensitivity runs; only the number of sampled nonchosen alternatives was varied.

The results demonstrate substantial stability in the behavioral parameters across alternative choice-set sizes. The coefficients for affordability burden and peak commute time remain negative across all specifications, while the income–commute-time interaction and the professional- and essential-worker employment-match coefficients remain positive. The magnitudes of these coefficients also remain relatively stable as Kincreases toward the primary $K = 150$specification. Parameters that are statistically weak in the primary specification, including housing capacity, lot size, housing square footage, and the Zillow-imputation indicator, remain comparatively small and generally statistically insignificant across the sensitivity models. The work-earnings coefficient exhibits greater variation in statistical significance, although its estimated effect remains positive in each specification.

Overall, the sensitivity analysis indicates that the principal behavioral findings of the final model specification are not materially dependent on the selected number of sampled alternatives. The $K = 150$specification is therefore retained as the primary model, while the alternative specifications provide evidence that the substantive interpretation of the model is robust to smaller sampled choice sets.

Choice-Set Size Sensitivity Statistics					
Index	Value	Rob. Std err	Rob. t-test	Rob. p-value	K
$\beta_{affordability}$	-0.1331	0.0492	-2.7081	0.0068	10
$\beta_{capacity}$	0.0286	0.1194	0.2397	0.8105	10
β_{ess_match}	0.8754	0.3659	2.3922	0.0167	10
$\beta_{time\ x\ commute}$	0.1078	0.0260	4.1432	0.0000	10
β_{lot}	0.0286	0.0352	0.8130	0.4162	10
β_{prof_match}	0.9643	0.2796	3.4493	0.0006	10
$\beta_{HouseSF}$	0.0373	0.0426	0.8776	0.3802	10
β_{time}	-0.0971	0.0278	-3.4992	0.0005	10
β_{earn}	0.3462	0.2989	1.1582	0.2468	10
β_{Zillow_Impute}	-0.0110	0.1489	-0.0736	0.9414	10
β_{Zillow_Impute}	-0.1378	0.0454	-3.0369	0.0024	30
$\beta_{capacity}$	-0.0077	0.1110	-0.0696	0.9445	30
β_{ess_match}	0.8129	0.3652	2.2258	0.0260	30
$\beta_{time\ x\ commute}$	0.1121	0.0238	4.7176	0.0000	30
β_{lot}	0.0226	0.0352	0.6432	0.5201	30
β_{prof_match}	0.9276	0.2731	3.3970	0.0007	30
$\beta_{HouseSF}$	0.0269	0.0416	0.6466	0.5179	30
β_{time}	-0.0934	0.0266	-3.5082	0.0005	30
β_{earn}	0.5680	0.2793	2.0339	0.0420	30
β_{Zillow_Impute}	-0.0189	0.1413	-0.1335	0.8938	30
$\beta_{affordability}$	-0.1419	0.0481	-2.9474	0.0032	50
$\beta_{capacity}$	-0.0040	0.1117	-0.0361	0.9712	50
β_{ess_match}	0.8717	0.3682	2.3675	0.0179	50
$\beta_{time\ x\ commute}$	0.1093	0.0237	4.6010	0.0000	50
β_{lot}	0.0275	0.0352	0.7816	0.4345	50
β_{prof_match}	0.9524	0.2655	3.5866	0.0003	50
$\beta_{HouseSF}$	0.0357	0.0422	0.8457	0.3977	50
β_{time}	-0.1031	0.0267	-3.8567	0.0001	50
β_{earn}	0.5083	0.2809	1.8095	0.0704	50
β_{Zillow_Impute}	-0.0429	0.1415	-0.3029	0.7620	50

Table 62 - Choice-Set Size Sensitivity Analysis

Appendix F – Model Specification Development

Model Specification Evolution

During model development, several alternative specifications were estimated to evaluate variable significance, behavioral plausibility, and overall model performance. Variables considered during the iterative specification process included school quality, crime rates, transit accessibility, residential employment density, workplace earnings, workplace employment, and housing capacity.

Variables that consistently demonstrated weak statistical significance, unstable coefficients, or limited behavioral interpretability were removed from the preferred specification. Workplace earnings and workplace employment variables improved explanatory power and were retained during later model development, while occupational interaction terms consistently exhibited strong statistical significance across specifications.

The preferred specification was selected because it provided the best overall balance between statistical performance, behavioral interpretation, and model parsimony.

Model Specification Evolution Table		
Specification	**Added/Removed**	**Result**
Baseline	Variables: - Commute time - Professional worker occupation match - Essential worker occupation match - Monthly workplace earnings - Transit - Monthly workplace earnings - Essential worker occupation match - Total employment in workplace ZIP - School quality index - Housing capacity - Crime rate - Coastal proximity	Highly Significant: - Commute time - Professional worker occupation match - Essential worker occupation match - Monthly workplace earnings - Transit - Monthly workplace earnings - Essential worker occupation match Insignificant: - Total employment in workplace ZIP - School quality index - Housing capacity - Crime rate - Coastal proximity
Specification 2	Removed: - School quality index - Crime rate - Coastal proximity - Residential employment density - Total employment in workplace ZIP Added: - Income x Commute Interaction Term - Affordability Burden	Highly Significant: - Income x Commute Interaction Term - Commute time - Professional worker occupation match - Housing Price per SF - Monthly workplace earnings - Essential worker occupation match Insignificant: - Housing capacity - Transit
Specification 3	Removed: - Housing capacity - Transit	Top Highly Significant: - Income x Commute Interaction Term - Commute time - Professional worker occupation match - Housing Price per SF - Monthly workplace earnings - Essential worker occupation match
Specification 4	Added: - Housing capacity (for policy simulations)	Stable + parsimonious

Table 63 - Model Specification Evolution Table