UNIVERSITY OF CALIFORNIA,
IRVINE

To Commute or Not to Commute?
Impacts of Land Use, Housing Costs, and COVID-19 on Commuting

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Transportation Science

by

Md Rabiul Islam

Dissertation Committee:
Professor Jean-Daniel Saphores, Chair
Professor Michael G. McNally
Professor Douglas Houston
Assistant Professor Michael Hyland

2023

DEDICATION

To

my parents for bringing me in this beautiful world,

my 3 years old daughter and my wife.

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Acknowledgements

I am a first-generation university student from my family for which I had to face so many constraints and uncertainties throughout this way. God is always on my side during this long journey.

During this Journey, I got the opportunity of a PhD admission at the Institute of Transportation Studies, University of California, Irvine. After completing the required coursework in one year, I had the opportunity to work with Professor Jean-Daniel Saphores to start my research work. He considered me in one of his SB1 funded projects which analyzed the impact of housing costs on commuting in Los Angeles County for one-worker households. Consecutively, we worked together on two-worker households commuting followed by the impacts of COVID-19 on telecommuting. These projects have potential significance in California and the US context, in general. I would like to express my deep acknowledgements and gratitude to Professor Saphores for his continuous guidance in writing my dissertation, for developing Structural Equation Models, and for the continuous funding support throughout my PhD journey of four years nine months.

I would also like to thank other Committee members of my dissertation, especially Professor McNally, Professor Houston, and Professor Hyland for giving consent to serve on my committee. Their thoughtful comments and feedback both in my candidacy exam and dissertation exam helped me to substantially improve my dissertation.

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I would also like to express my acknowledgements to all ITS administrative staffs, especially Cam and Jared for their instant supports when required. Moreover, I am grateful to Verano Place (a UCI administered housing) for providing me the accommodation for the full duration of my PhD. In addition, Bangladeshi community at UCI helped me a lot at the beginning of my PhD to have a driver's license.

Finally, I would like to thank my 3 years old daughter who was all the way in my PhD and my wife, Naila Sharmeen (a UCI PhD graduate) for her continuous support during this journey. Last but not least, I would like to extend my gratitude to my parents for their unconditional love and sacrifices.

Vita
Md Rabiul Islam

EXECUTIVE SUMMARY

Transportation planner with 10+ years of experience spread across academia, research, traffic engineering, and transportation planning broadly in urban and regional planning. Well-experienced in collaborating with various and diverse stakeholders in academic environments.
Collaborating in a diverse range of projects such as ridership of Bus Rapid Transit in a developing country (Ahmedabad, India), commuting and housing cost in Los Angeles, telework during Covid-19 pandemic in California, and two-worker households commuting in five MSAs in the US.

EXPERIENCE (Projects-Highlights)

PhD candidate, Transportation Science, University of California Irvine (UCI) (September 2018 – June 2023)

- Worked as Graduate Student Researcher (GSR) on a PSR and Caltrans funded project titled "Impact of housing cost on two-worker households commuting in five MSAs in the US". Understanding the two-worker households commuting is important for planning future travel demands as some researchers estimate that the number of two-earner households has been growing. At least 35% of households in the US metropolitan areas are two or more worker households. For this study, I selected five metropolitan areas of the US, Los Angeles and San Francisco in California, Dallas and Houston in Texas and Atlanta in Georgia from the 2017 National Household Travel Survey (Spring 2022 to June 2023).
- Worked as GSR on a PSR and Caltrans funded project titled "Telework and the pandemic: before, during, and possibly after". Understanding the relationship between socio-economic groups and telework frequency before, during and potentially after the COVID-19 pandemic is critical to inform planners and decisionmakers about how to effectively support the affected groups such as health care, restaurant, and other retail workers where women are more involved. To investigate this context, I analyzed a unique dataset collected at the end of May 2021 by IPSOS using a random survey of Californians. This paper quantifies recent changes in telework which is important for understanding the likely contribution of telework in meeting California's GHG reduction targets (Fall 2021 to Summer 2022).
- Worked as GSR on a SB1 (Road Repair and Accountability Act of 2017) project titled "Time or Distance? Understanding the Impact of Housing Costs in California on the Length (time and distance) of Commuting". To investigate the linkage between housing affordability and commuting (key issues for many Californians), I analyzed 2012 California Household Travel Survey data for Los Angeles County – the most populous county in the US. Better understanding the determinants of commuting is critical to inform housing and transportation policy, improve the health of commuters, reduce air pollution, and achieve climate goals (Winter 2020 to Summer 2021).
- Worked as Teaching Assistant (TA) for the EngrCEE 40: Economics Analysis for Engineers at the Department of Civil and Environmental Engineering, UCI (Spring 2022 and Spring 2023).

Faculty of Urban of Regional Planning, Chittagong University of Engineering & Technology, Bangladesh (June 2012 – August 2014 and April 2016 –August 2018)

Supervised several bachelor theses. In addition, the course conducted on Traffic and Transportation Study, Transportation Policy and Planning, Introduction to GIS, Urban Planning Principles, and Environmental Planning and Management.
Also worked as a key Researcher in the research project entitled "Response of Natural Disasters through Resilience: Addressing Extreme Climatic Disasters to Annihilate the Insecurity of Food, Nutrition and Livelihood – A Study on Disaster affected Countries of Asia". This project was conducted by the Institute for Risk & Disaster Reduction of University College London in collaboration with the Department of Urban

and Regional Planning, CUET. Selected case study-Flash flood prone area in Ramu, Cox's Bazar, Bangladesh (December 2016 – September 2017).

MSc Student, ITC, University of Twente, Netherlands (September 2014 – March 2016)
Worked as Graduate Researcher on a Bus Rapid Transit Project of Ahmedabad, India. The Janmarg (people's way) Bus Rapid Transit System (BRTS) in Ahmedabad, India, achieved worldwide accolades since its introduction, however, it has not reached its expected ridership. To assess the ridership of the Janmarg BRTS, a methodology was developed based on built-form indicators (Land use) that were quantified using the "5D" approach. Land-use diversity, road connectivity, and job accessibility by BRTS were found to be poorly associated with ridership. Several policy recommendations were suggested along the BRTS corridors in line with the existing policy such as the utilization of full Floor Space Index potential, the application of Transit Oriented Development strategies and the integration with non-motorized modes to increase the accessibility to the most important job locations.

Junior Planner, BUET, Dhaka, Bangladesh (May 2011– May 2012)
Worked as a Junior Planner on a project titled "Integrated Water Supply Sanitation and Hygiene (WASH) Planning for Local Government Institution in Bangladesh" to prepare a 5-year Water and Sanitation Plan for 96 unions (lowest level of rural local government) and 5 paurashavas (urban local government) and a training manual for the trainers of National Institute of Local Government (NILG): Project funded by UNICEF and UK AID. This project enhanced about 1.5 million residents' life standard by implementing the water systems in the project area.

EDUCATION

Ph.D. candidate, Transportation Science, **University of California Irvine, California** (Fall 2018 – Spring 2023)

Dissertation: To commute or not to commute? Impacts of land use, housing costs and COVID-19 on commuting

Course-Highlight: Travel Demand Analysis I and II *Transportation Planning *Transportation Systems: Planning and Forecasting *Transportation Data Analysis I *Transportation System Analysis I and II *Transit System Planning *Smart Cities *History of Urban Planning *Geographic Information System (GIS) and Planning *Structural Equation Model I *Microeconomics and Public Policy

MSc in Geoinformation Science and Earth Observation (Specialization: Urban Planning and Management), University of Twente, Netherlands (September 2014 – March 2016)

Dissertation: Evaluation of Bus Rapid Transit System based on ridership analysis: A case study of Ahmedabad Janmarg BRTS

Bachelor of Urban & Regional Planning, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh (January 2006- February 2011)

Dissertation: Schools of Dhaka city: A study from spatial planning perspective

SELECTED PUBLICATIONS & PRESENTATIONS

- Islam, M.R., Saphores, J.-D.M., 2022. An L.A. story: The impact of housing costs on commuting. J. Transp. Geogr. 98, 103266. https://doi.org/10.1016/j.jtrangeo.2021.103266
- Ahmed, B; Kelman, I; Raja, DR; Islam, MR; Das, S; Shamsudduha, M; Fordham, M; (2019). Livelihood impacts of flash floods in Cox's Bazar District, Bangladesh. International Journal of Mass Emergencies and Disasters, 37 (3) pp. 306-326
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- Zannat K.E., Showkat S. & Islam M.R. (2014). A Methodology for Assessing the Performance of Structural Measures to Mitigate Traffic Congestion: A Case Study of Chittagong Port Flyover, Journal of Bangladesh Institute of Planners, 7, pp 1-10. (ISSN 2075-9363)
- Islam M. R. & Sharmeen N. (2011). Road accident: contemporary scenario and policy issues in Bangladesh', Journal of Bangladesh Institute of Planners, 4, pp 45-55. (ISSN 2075-9363)

SELECTED HONORS & AWARDS

- Graduate Dean's Dissertation Fellowship 2022 by Graduate Division, UCI (https://www.its.uci.edu/node/572)
- Fellowship with tuition fee waiver for one academic year 2018-19 as a full-time PhD student in Institute of Transportation Studies, UCI
- Netherland Fellowship Program (NFP) fellowship for the full duration (2014-2016) of my MSc study at ITC, University of Twente, Netherlands

SKILLS & INTERESTS

- Expert in AutoCAD, ArcGIS (ArcMap, ArcGIS Pro), TransCAD, ERDAS Imagine, Synchro, Adobe Illustrator, Python, RStudio, SPSS, Stata, R, CorelDRAW, MS Word, MS Excel, MS PowerPoint, MS Access, MS Project.
- Member of Institute of Transportation Engineers (ITE) and Bangladesh Institute of Planners (BIP)

Abstract of the Dissertation

To Commute or Not to Commute?
Impacts of Land Use, Housing Costs, and COVID-19 on Commuting

by

Md Rabiul Islam

Doctor of Philosophy in Transportation Science

University of California, Irvine, 2023

Professor Jean-Daniel Saphores, Chair

Apart from the COVID-19 pandemic, two chronic problems affecting Californians are high housing costs and road congestion. Although high housing costs and the determinants of commuting have separately received a lot of attention from academic researchers, to my knowledge very few papers have analyzed the linkage between them. In this dissertation, I present three essays that will enhance our understanding on the relationship between commuting, land use, housing costs, and the impact of COVID-19 on telecommuting. In all three essays, I use Structural Equation Model (SEM).

In my first essay, I propose a framework for understanding the impact of housing costs on commuting time and commuting distance in one worker-households in Los Angeles County, which is the most populous county in the US. After analyzing data from the 2012 California Household Travel Survey (CHTS), I find that households who can afford more expensive neighborhoods have on average a commute 3.1% shorter per additional $100k to their residence median home values.

In my second essay, I analyze the commutes of two-worker households to understand some of the trade-offs they need to make, since two-worker households have dual work constraints. My data for this essay come from 2017 National Household Travel Survey (NHTS) respondents who reside in five U.S. MSAs (San Francisco, Los Angeles, Dallas, Houston, and Atlanta). Results

show that women do not commute as far as men on average, although their commuting time is not necessarily shorter than men's, and that the commuting times of men and women are weakly positively correlated. Moreover, households have faster commutes by 14.5% for men and 22.7% for women per additional $1000 to their residence median monthly housing cost.

My third essay investigates the impact of the COVID-19 pandemic on telecommuting by analyzing a unique dataset collected at the end of May 2021 by IPSOS via a random survey of California members of KnowledgePanel®. I find that an additional 4.2% of California workers would engage in some level of telecommuting and more educated workers are expecting to telecommute more (0.383* for bachelor's degree) post-pandemic.

Teasing out the impact of high housing costs on commuting is important at a time when concerns about the environmental impacts of transportation have turned reducing vehicle-miles traveled (VMT) into a policy priority. More generally, a better understanding of the determinants of commuting is critical to inform housing and transportation policy, improve the health of commuters, reduce air pollution, and achieve climate goals.

Chapter 1. Introduction

Apart from the COVID-19 pandemic, two chronic problems affecting California are high housing costs and road congestion, especially during the morning and evening peak hours when Californians are commuting to work and driving back home. Although the determinants of commuting have received a lot of attention from academic researchers, to my knowledge very few papers have analyzed the linkage between housing costs and commuting. This linkage is especially salient in California where the high costs of housing in coastal areas have forced many lower- and middle-class households to move inland in search for more affordable housing at the cost of longer commutes (The Pew Charitable Trusts, 2017).

Better understanding the impact of high housing costs is important at a time when concerns about the environmental impacts of transportation have turned reducing vehicle-miles traveled (VMT) into a policy priority. One way to decrease VMT is to reduce the length of commuting trips, and to get commuters out of their private motor vehicles (Mitra and Saphores, 2019; Schiller et al., 2010). Unfortunately, the average one-way commute keeps getting longer in the U.S., increasing from 25.1 to 27.6 min between 2005 and 2019 (United States Census Bureau, 2019) as the percentage of work trips made by private vehicle has soared, jumping from 66.9 % in 1960 to 84.8% in 2019, although average commute distances have remained approximately the same (United States Census Bureau, 2019; Zolnik, 2011). As commuting typically occurs during peak hours, it is a major contributor to congestion and air pollution (Wang, 2001). In the long run, unchecked growth in commuting will likely cripple California's efforts to meet its Greenhouse gas (GHG) emission reduction goals (Kallerman and Weinberg, 2016).

In this context, my dissertation makes three contributions which are described in three essays. In all three essays, I use Structural Equation Model (SEM) which is a model of simultaneous equations (Kline, 2015). In my first essay (Chapter 2), I propose a framework to understand the impact of housing costs on commuting time and distance in one worker-households. My model builds on Van Acker and Witlox (2011), who did not account for housing costs. It accounts for residential self-selection, the endogeneity of car ownership and of commuting by car, as well as key land use variables around both residences and workplaces. For this work, I analyze data from the 2012 California Household Travel Survey (CHTS) because it offers a large dataset for which I have access to location data. I focus on Los Angeles County because it is the most populous county in the United States with 10.08 million residents. Census data shows that the average commute time for Los Angeles County residents was 32.8 minutes, 18.8% higher than the national average (United States Census Bureau, 2019). Although Los Angeles County houses over a quarter of California's population, it accounts for 34% of total greenhouse gas emissions.

For my second essay, presented in Chapter 3, I focus on understanding the impacts of housing costs on the commutes of two-worker households. Two-worker households face a tougher residential location decision than one-worker households because they need to deal with dual work constraints, so they are less likely to find locations that would result in short commutes for both workers. Data shows that almost 30% of households in major metropolitan areas are dual-earner households, so for this study I analyze 2017 National Household Travel Survey (NHTS) data for five U.S. MSAs (Los Angeles and San Francisco in California, Dallas and Houston in Texas, and Atlanta in Georgia) to tease out the impact of gender on commuting in heterosexual two-worker households. I selected these metropolitan areas because they are located in add-on states of the 2017 NHTS that are willing to share home and work location data with academic researchers.

My third essay (Chapter 4) examines how commuting may change as a result of the COVID-19 pandemic, and more specifically how telecommuting may decrease the need to commute, thus giving workers more freedom to select their residential location. To understand the extent to which telecommuting could increase as a result of the pandemic, I analyze a unique dataset on commuting and telecommuting that was collected during a May 2021 random survey of Californians of KnowledgePanel® conducted by IPSOS. I estimate a model to understand changes in telecommuting (comparing before, during, and possibly after the pandemic) while controlling for personal and household characteristics, land use patterns around residential areas, and changes in vehicle holdings. I pay particular attention to income, gender, race, and occupation variables to understand what groups of Californians have been disproportionately affected by the pandemic. Better understanding the determinants of commuting and especially the impact of housing costs on commuting is critical to inform housing and transportation policy, and to achieve climate goals.

Finally, Chapter 5 summarizes my conclusions and proposes suggestions for future work.

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Chapter 2. An L.A. Story: The Impact of Housing Costs on Commuting

2.1 Introduction

Concerns about the environmental impacts of transportation have turned reducing vehicle-miles traveled (VMT) into a policy priority. One way to decrease VMT is to decrease the length of commuting trips, and to get commuters out of their private motor vehicles (Mitra and Saphores, 2019; Schiller et al., 2010). Unfortunately, the average one-way commute keeps getting longer in the U.S., increasing from 25.1 to 27.6 min between 2005 and 2019 (United States Census Bureau, 2019) as the percentage of work trips made by private vehicle has soared, jumping from 66.9 % in 1960 to 84.8% in 2019, although average commute distances have remained approximately the same (United States Census Bureau, 2019; Zolnik, 2011). As commuting typically occurs during traffic peaks, it is a major contributor to congestion and air pollution (Wang, 2001).

Although many papers have investigated the determinants of commuting, few empirical studies have analyzed the linkage between housing costs and commuting. This linkage is especially salient in California given the state's perennial housing shortage and the high costs of housing, which have forced many lower- and middle-class households to move inland in search for more affordable housing at the cost of longer commutes (The Pew Charitable Trusts, 2017). In the short run, heavy commuting can affect subjective well-being (Choi et al., 2013), degrade sleep quality (Hansson et al., 2011), and even cause depression (Feng and Boyle, 2014). In the long run, unchecked growth in commuting will likely cripple California's efforts to meet its Greenhouse gas (GHG) emission reduction goals (Kallerman and Weinberg, 2016).

In this context, the main contribution of this essay is to tease out the impact of housing costs on commuting by estimating a comprehensive model that jointly explains commuting time and distance, building on Van Acker and Witlox (2011), and accounts for residential self-selection, the endogeneity of car ownership, and key land use variables around both residences and workplaces. Only a handful of studies have controlled for residential self-selection (Van Acker and Witlox, 2011; Wang and Chai, 2009), accounted for the endogeneity of car ownership and use (de Abreu e Silva et al., 2012; Jahanshahi et al., 2015; Jahanshahi and Jin, 2021, 2016; Van Acker and Witlox, 2011), or considered how housing costs may influence commuting (Blumenberg and King, 2021, 2019; Sultana, 2005, 2002; Zhao, 2015; Zhao and Cao, 2020). It is well-known that ignoring self-selection and the endogeneity of explanatory variables will result in biased estimates of model coefficients, which in this context would alter my understanding of the determinants of commuting (Cao et al., 2009; He et al., 2015).

For this study, I selected Los Angeles County – with 10.08 million residents, the most populous county in the United States – because it is emblematic of the transportation and housing conundrum facing many parts of the U.S. Census data shows that the average commute time for Los Angeles County residents pre-pandemic was 32.8 minutes, 18.8% higher than the national average (United States Census Bureau, 2019). Although Los Angeles County houses over a quarter of California's population, it accounts for 34% of greenhouse gas emissions (Kallerman and Weinberg, 2016; United States Census Bureau, 2019).

In Section 2.2, I review selected papers to inform my modeling choices. I then describe the data (Section 2.3) and present the methodology (Section 2.4), before discussing results in Section 2.5. Finally, in Section 2.6, I summarize conclusions, discuss some policy implications, and suggest alternatives for future research.

2.2 Literature Review

In the transportation literature, commuting has been characterized by travel distance, travel time, or both to capture the spatial separation of residences and workplaces as well as transportation constraints (e.g., roadway capacity) (Antipova et al., 2011). As shown in Table 2.1, recent empirical studies have examined commuting in Europe, Asia (mostly China), and the U.S. I note that most empirical papers rely on a similar modeling framework (with similar personal/household variables and land-use characteristics) to explain commuting time and/or distance, irrespective of urban geography, although a few papers explicitly account for some key features of polycentric urban areas (e.g., see Modarres, 2011; Wang, 2000).

My review of selected empirical papers indicates that only a handful of studies controlled for residential self-selection (Van Acker and Witlox, 2011; Wang and Chai, 2009) or considered how housing costs may influence commuting (Sultana, 2005, 2002; Zhao, 2015; Zhao and Cao, 2020). It is well-known that ignoring residential self-selection risks biasing the influence of land-use characteristics on travel behavior (Cao et al., 2009). According to urban economic theory, employments concentrate in the central business district or in sub-centers and residents make location decisions based on the relative costs of land and travel to their workplace to maximize their utility (Anas et al., 2000; Lowry, 1964), which depends on characteristics of their residence and of their neighborhood, given their budget and time constraints (Cervero and Wu, 1997). As a result, personal, household, and land-use characteristics enter most residential choice models (Mokhtarian and Cao, 2008; Prashker et al., 2008). I note, however, that with a few exceptions (e.g., de Abreu e Silva et al., 2012; Jahanshahi and Jin, 2021, 2016; Van Acker and Witlox, 2011), published empirical studies of commuting do not account for the endogeneity of car ownership and use. A lack of space precludes me from reviewing numerical and simulation models, such as Jin et al. (2013) (also see references therein), who developed a generic recursive spatial equilibrium model for urban activity location and travel choices in a large city region.

2.2.1 Personal and household characteristics

Most of the papers I reviewed agree that employed women tend to have shorter commuting distances than men (Axisa et al., 2012; Blumenberg and King, 2019; Ding et al., 2017; Maoh and Tang, 2012) because they are balancing an outside job with a disproportionate share of household tasks (Brenan, 2020).

Several studies report that higher-income people tend to have longer commutes because more income compensates for commuting cost (Sakanishi, 2020; Sultana, 2002) by making it possible to afford a high-quality suburban lifestyle (low-density neighborhoods) farther away from city centers (Blumenberg and King, 2019; Zolnik, 2011).

Education would seem to align with income because higher paying jobs often require more education (He et al., 2015). However, in Columbus Ohio, Wang (2001) found that more educated workers tend to have shorter commute times, a finding corroborated by Sultana (2005) for Atlanta, Georgia. In Guangzhou City, China, Dai et al. (2016) concluded that people with more education are more likely to commute by car, which results in faster commutes since commuting by car is often faster than commuting via transit. And in Ghent, Belgium, Van Acker and Witlox (2011) reported that education does not impact commuting time.

Other personal and household variables have a more consistent impact on commuting. Age is one of these. While some studies suggest that distance is negatively related to the age of commuters (Manaugh et al., 2010; Sun et al., 2017), others found a non-linear relationship between age and commuting distance where people commute farther when they are younger but increasingly less in their later years (Axisa et al., 2012; Maoh and Tang, 2012).

Empirical evidence also suggests that commuting varies by ethnicity (Zolnik, 2011). Factors such as exclusionary zoning and racial discrimination have precluded some minority households from moving to the suburbs and trapped them in inner-city ghettos, as shown by Sultana in Atlanta, Georgia (Sultana, 2005, 2002).

The presence of children often has a negative effect on commuting as family members need to bring their children to daycare and to after-school activities (He et al., 2015; Sun et al., 2017). Occupation type also impacts commuting characteristics. Numerous studies categorized occupation types as “worker” vs. “other” (Wu et al., 2019), “formal” vs. “informal” (Geyer and Molayi, 2018), “public sector” vs. “private sector” (Andersson et al., 2018), and “part-time” vs. “full-time” (Blumenberg and King, 2019). When possible, detailed occupation information helps better understand commuting (Andersson et al., 2018; Mitra and Saphores, 2019).

Household size is a common explanatory variable in commuting studies (Dai et al., 2016; de Abreu e Silva et al., 2012; Ding et al., 2017; Van Acker and Witlox, 2011). In Van Acker and Witlox (2011), for example, household size indirectly impacts commuting time via the car availability equation: as household size increases, it decreases the likelihood of car availability, which indirectly increases commuting time.

In addition, a longer residence time decreases commuting time/distance because workers seek shorter commutes over time to reduce the toll of commuting on their family (Dai et al., 2016; Mitra and Saphores, 2019).

Likewise, households with more cars than drivers tend to have a shorter commuting time (Van Acker and Witlox, 2011). The same is true for workers who commute by car since taking transit, walking, or biking, typically takes more time (Van Acker and Witlox, 2011, 2010).

2.2.2 Land use characteristics excluding housing costs

The ‘5Ds’ concept, which was developed by Cervero & Kockelman (1997) and Ewing & Cervero (2001), offers a convenient way of organizing land use variables. Key variables include density, diversity, design, destination/job accessibility, and distance to transit stops.

Density usually refers to the number of homes, people, or jobs per unit of area (Islam et al., 2018). Higher densities are associated with more transit use, less car use, and an emphasis on walking and cycling (Cervero and Kockelman, 1997). Moreover, density is negatively associated with car ownership, commuting distance, and commuting time (Van Acker and Witlox, 2011).

Land-use diversity measures the degree of heterogeneity of various land uses. Its most common measure is the entropy index (Boarnet, 2011), which quantifies land use heterogeneity in an area. It ranges between 0 and 1, where 0 corresponds to a single land use, and 1 to an equal share of all the land uses considered (Frank and Pivo, 1994). In general, a higher mix of compatible land uses increases jobs, shopping, and entertainment opportunities within walking distance of housing. More land use diversity is also believed to lower car ownership and use, shorten commute distances, and cut commute times (Ma and Chen, 2013; Van Acker and Witlox, 2011).

In the 5Ds framework, design refers to road connectivity. Road Connectivity is the degree of connectivity towards destinations. It can be measured with various indices, including road density, intersection density, the proportion of four-way intersections, and the proportion of dead-end streets (Islam et al., 2018). Ewing & Cervero (2010) found that increasing intersection or road density reduces VMT while a poorly connected road network with many cul-de-sacs (dead ends) diminishes accessibility and increases commuting distances (Litman and Steele, 2012).

Table 2.1: Summary of selected papers

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
Commuting time			
Sakanishi (2020)	• 0.47 million persons from IPUMS-USA (2014) • 2SLS and OLS	• Hours worked, marital status, number of children, number of mothers, occupational median total income score, home ownership, use of cars for commuting • Residential metropolitan area	Commuting time depends on wages, marital status, presence of children, homeownership, and household automobile ownership.
Wu et al. (2019)	• 675 commuting trips in Nanjing, China (2010) • Decision tree	• Car ownership, job type, commuting mode • Job-housing co-location, bus accessibility, subway availability, distance to CBD • Departure time	Car-ownership, job type, job-housing distance, subway service, job location and departure time influence commuting time
Lin et al. (2016)	• 578 respondents in Beijing, China (2012) • OLS	• Gender, age, education, monthly income, occupation, commuting mode • Job-housing proximity	A balanced jobs-housing relationship can be achieved by adjusting the location of affordable housing
Lin et al. (2015)	• 578 respondents in Beijing, China (2012) • OLS	• Education level, housing ownership, transport mode • Job-housing proximity	Workplace jobs-housing balance has a more negative impact on worker commuting times than worker socio-economic characteristics
Silveira Neto et al. (2015)	• 549,867 workers in Sao Paulo area, Brazil (2010) • Ordinal probit	• Marital status, presence of children, inactive senior, race, education, age, occupation, economic activities, income, household size, property characteristics	Marital status has a stronger influence on commuting time of working women than men; the number of dependents has a smaller impact on commuting time
Zhao (2015)	• 742 employed persons in Beijing, China (2006) • OLS	• Gender, income, age, children (<10 yrs.) • Residential & job densities, job-housing balance, land use mix, distance to city center, housing cost, road density, distance to nearest metro station, bus service • Household residential preferences	Uncontrolled urban sprawl, insufficient affordable housing and lower levels of public transport services are major factors for low-income workers commuting time
Zhao (2013)	• 712 employed persons in Beijing, China (2001) • OLS, LR, MNL	• Gender, household income, occupation, employment type, car ownership	A better job-housing balance would reduce the probability of motorized travel, commuting time and the need for suburb-to-center commutes

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
		• Residential & employment densities, land use mix, road density, transit accessibility, distance to old city center	
McQuaid and Chen (2012)	• 53,000 households from UK Labor Force Survey (2008) • LR	• Occupation, travel mode, age, weekly pay range, younger child age, number of children under 19, home ownership, race, health status, disability, gender, full-time/ part-time job	Commuting is related with age, having children and the age of the youngest child, occupation, weekly pay, work status and mode of transport
Zhao et al. (2011)	• 712 employed persons in Beijing, China (2001) • OLS	• Occupation, employment type, household income, transport mode • Job-housing balance, population density, transport infrastructure-based accessibility, *Danwei* housing	The job-housing balance impacts commuting time. High income, high or mid-level professionals tend to commute less
Zhao (2011)	• 370 employed persons from urban fringe in Beijing, China (2006) • MNL and OLS	• Household annual income, occupation, gender, family composition • Density, job-housing balance, transport accessibility • Household preferences, commuting mode	Importance of residential self-selection
Modarres (2011)	• 5.7 million persons in Southern California (2005) • Stepwise regression	• Personal income, population density, weekly hours worked, jobs-to-population ratio, % non-Hispanic white and % minority commuters, working population, average vehicle ridership • Distance to closest major employment center, working population density	Gender, vehicle occupancy, travel-time ratio, departure time and local employment opportunities influence commuting time at the individual level
Commuting distance			
Blumenberg and King (2019)	• 230,841 workers from US NHTS (2001, 2009, 2017) • OLS	• Gender, age, race, household structure, part-time job, 0-vehicle household • Residential density, metropolitan area size	Commuting distance increases largely due to a shift in residential location towards low-density neighborhoods for all income groups.
Jain et al. (2018)	• 28 rural areas, 30 urban areas in Delhi, India (2011) • OLS	• Percentage of high-skilled workers, unemployment rate, share of socially disadvantaged groups, % women employment • Rural dummy, distance from Delhi, population size, road density, rail density	Rural location has a significant impact on commuting. Residents from areas with high unemployment tend to commute farther

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
Ding et al. (2017)	• 8,327 commuters in Washington, DC (2007-08) • Multilevel mixture hazard model	• Age, gender, race, household size, occupation, household income, car ownership • Residential density, employment density, land use mix, average block size, distance from CBD	Commuting distance is more sensitive to the effects of distance from CBD, residential density, and land use mix
Sun et al. (2017)	• 857 workers in Shanghai, China (2009) • Discrete-continuous copula-based model	• Gender, age, education, income, housing source, household size, number of workers, number of children. • Population density, job density, land-use diversity, design, destination accessibility, distance to nearest metro station.	Family income, gender, number of children, age, household size, and housing type impact commuting distance
Hjorthol and Vågane (2014)	• 9486 respondents from Norwegian Travel Survey (2009) • OLS	• Gender, age, presence of children, education, place of living, income, occupation	Women do not commute as far as men in comparable groups
de Abreu e Silva et al. (2012)	• 7277 workers in Montreal, Canada (2003) • SEM	• Gender, income, household structure, age, number of workers, car ownership • Time spent between first and last trip, distance traveled, number of trips	Land use mix and density are important determinants of commuting. Substantial land use effects are passed through commuting distance and car ownership
Axisa et al. (2012)	• 20% Toronto area, Canada Master file (2006) • OLS	• Job type, gender, age, occupation status, income, household structure, marital status, age of youngest child, long term resident, recent migrant • Geographic place of residence	Recent migrant status, employment type, gender, and age significantly influence commuting distance
Maoh and Tang (2012)	• 15,886 normal and 6,423 extreme commuters, Ontario, Canada (2006) • OLS	• Gender, mode of transportation, type of occupation, age, employment status, migration status • Land use mix, location quotient	Socioeconomic factors are more important for explaining normal commutes; land use is more important for explaining extreme commutes.
Kim et al. (2012)	• 48 groups from CTPP in Hamilton	• Race, Hispanic status, education, employment status, income, poverty, household with children	Commutes between occupation groups vary more than those between gender groups

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
	County, Ohio (2000) • OLS	• Distance from CBD, bounded community	
Li (2010)	• 1500 (2001) and 1200 (2005) households in Guangzhou, China • OLS	• Gender, income, occupation, work unit type	Men in Guangzhou have appreciably shorter commutes than women
Manaugh et al. (2010)	• 31,997 car trips in Montreal, Canada (2003) • FA, OLS, SEM	• Age, income, total number of trips per day, number of cars, gender, full-time work status	Age, income, total number of trips per day negatively impact commuting distance
Zhao et al. (2010)	• 228 respondents in Beijing, China (2001) • MNL	• Income, occupation, home ownership • Population density, job housing ratio, auto accessibility, transport accessibility	Accessibility improvements in the city fringe are likely to lead to further long-distance commuting
Commuting distance and time			
Jahanshahi and Jin (2021)	• National Travel Survey, UK (2002-2015) • LCA and SEM	• Car ownership, household size, income, gender, journey purpose, full time worker, Job type • Area type, population density, frequency of local buses, walk time to bus stop, walk time to rail station • Fuel price	Car ownership and travel choices are highly heterogeneous across settlements
Engelfriet and Koomen (2018)	• 30 cities in China (2014) • OLS	• City size (population and built-up area), urban density, land-use mix, polycentricity, spatial clustering	Both commuting distance and time decrease when high-density clusters are present
Motte et al. (2016)	• 32,000 workers in Rio de Janeiro, Brazil (2003) • SEM	• Transport mode, sector of activity, informal job, position in household, educational attainment • Distance to CBD, place of work	Ceteris paribus, commuting distances and times are shorter in the informal sector
Dai et al. (2016)	• 816 respondents from Guangzhou, China (2014)	• Gender, income, age, education, number of family houses, family cars, household size, employment, occupation, number of workers	Job-housing balance and commuting mode influence both commuting time and distance

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
	• Multilevel LR and OLS	• Housing source, transport accessibility, population density, job-housing balance	
He et al. (2015)	• 1242 households from Kunming, China (2011) • OLS	• Age, education, income, house ownership, occupation status, household structure • Residential location	Education level, gender, and occupation status significantly impact commute time and distance
Grunfelder and Nielsen (2012)	• 2483 trips (1993-94) and 2056 trips (2002-03), East Jutland, Denmark • OLS and LR	• Gender, age, household type, occupation, income, hours worked, driving license • Population and employment density, ratio of jobs to population, distance to various urban centers, and to nearest transit stop	No general change in commuting was observable in East Jutland between 1993-94 and 2002-03 for commuting time and distance
Antipova et al. (2011)	• 1,104 workers in East Baton Rouge Parish, Louisiana (1997) • FA and MR	• Race, sex, education, life cycle, job status, number of workers, income • Land use type, job to workers ratio, proximity to high performing school, neighborhood socio-economic attributes	Data in two levels (neighborhood and individual levels) better fit. Distance model is better than time model based on AIC
Van Acker and Witlox (2011)	• 2,174 trips from travel behavior survey in Ghent, Belgium (2000-01) • Multiple Group SEM	• Household size, children <6, income, age, gender, marital status, car availability, job status • Job density, built-up index, land use mix, job-housing balance, distance to bus stop, railway stop, and CBD, job accessibility • Commuting distance and time, tour complexity, car use during commuting	Land use policy can successfully influence commuting, only if it simultaneously accounts for the effects on car availability, car use, commuting distance and commuting time
Zolnik (2011)	• 2943 households from US NHTS (2001) • MR	• Occupation, gender, age, ethnicity, income, stage in life cycle, ratio of workers to vehicles • Residential density, land-use mix, degree of centering, street accessibility • Vehicle age & type, gas cost, fuel efficiency	Three measures of sprawl (residential density, degree of centering, and street accessibility) have significant but small impacts on private vehicle commuting distances and times

Notes.

1) Data abbreviation: MSA= Metropolitan Statistical Area, CTPP= Census Transportation Planning Package, NHTS= National Household Travel Survey, IPUMS= Integrated Public Use Microdata Series.

2) Model abbreviation: FA=Factor Analysis, LCA= Latent Class Analysis, OLS= Ordinary Least Square, MR=Multilevel Regression, LR=Logistic Regression, MNL= Multinomial Logit, 2SLS= Two Stage Least Square, SEM= Structural Equation Modeling

A fourth important land use characteristics is accessibility, which refers to the ability of reaching activities or locations (Geurs and van Wee, 2004). Ewing & Cervero (2010) and Kockelman (1997) concluded that good accessibility can significantly reduce commuting times.

The fifth variable in the 5Ds framework is distance to the nearest transit stop, which is usually measured using a shortest path route (Ewing & Cervero, 2010).

Apart from the 5Ds variables, I also included in my model a measure of the job-housing balance and median home value. The job-housing balance refers to the spatial relationship between the number of jobs and housing units within an area. An area is considered balanced when resident workers can obtain a job locally, and when available housing types can serve the housing needs of a variety of workers (Giuliano, 1991). In an early study, Frank & Pivo (1994) found that the average distance of work trips ending in balanced census tracts was 29% shorter than those ending in less balanced tracts, which supports the findings of Ewing's study of over 500 Florida communities (Cervero and Duncan, 2006).

2.2.3 Housing costs

The cost of housing appears to have often been overlooked in empirical work since 2000. Rare exceptions include Blumenberg and King (2021, 2019), Sultana (2002, 2005), Zhao (2015), and Zhao and Cao (2020).

After analyzing NHTS data to understand the relationship between residential location and commute distance, Blumenberg and King (2019) reported that the observed increase in commute distance among low-income workers is mostly due to a shift toward lower-density neighborhoods. Blumenberg and King (2021) focused on California and analyzed 2002 and 2015 data from the

Longitudinal Employer–Household Dynamics (LEHD) Origin–Destination Employment dataset. They showed that a shortage of affordable housing contributed to lengthening workers' commutes.

Sultana (2005, 2002) studied the Atlanta area. After analyzing data from the 1990 census, Sultana (2002) concluded that the job-housing imbalance contributes to longer commute times. Sultana (2005) examined whether dual-earner households are an obstacle to achieving job-housing but found that their commutes are on average no longer than those of single-earner households.

Zhao (2015) and Zhao and Cao (2020) worked respectively on Beijing and Shanghai, China. Zhao (2015) estimated simple linear regressions to explain commuting time from socio-economic, local transportation, and land use characteristics. They found that the lack of affordable housing, and especially the job-housing imbalance significantly affected the commute time of low-income workers. Zhao and Cao (2020) analyzed 81 million transit trips using geographically weighted regression. They reported that disadvantaged areas (with lower rents and poor job accessibility), are inhabited by a disproportionate number of workers with long commutes.

2.3 Data

In this essay, I analyzed data from the 2012 California Household Travel Survey (CHTS), which gathered travel information from 42,431 households in all of California's 58 counties. The 2012 CHTS provides detailed information about the socio-economic characteristics of its respondents and their households. I worked with this slightly older dataset because I obtained access to the location of the residence and the workplace of respondents, which enabled me to create land use characteristics that are essential to my models.

Since my goal is to analyze the time and distance of commutes reported in travel diaries, I focused on workers who traveled directly from home to work (commuters are not asked to report the typical length of their commute; I need to calculate it from their diary). I considered only commutes up to 50 miles one way, since people who commute over 50 miles are often considered super-commuters and analyzed separately (Maoh and Tang, 2012). After checking commuting times, I excluded observation associated with unusually high values (> 180 min).

Since I want to investigate the impact of housing cost on commuting while controlling for other variables, I selected the household as a basic unit of analysis because the choice of a residential location is a household decision. After linking the workers in my dataset to their households, I found that 77.9% of households have only one worker, 19.6% have exactly two, and the remaining 2.5% have 3 or more workers. Following the commuting literature (e.g., see Plaut, 2006; Sultana, 2005; Surprenant-Legault et al., 2013), I focused on households with only one worker because of the added-complexity of considering land-use characteristics from multiple workplaces and analyzing more than one commuting time and distance.

Restricting my focus to workers who live and work in Los Angeles County gave me a sample with 1,952 households, after excluding the three respondents who reside and work in Santa Catalina Island, which is separate from the mainland.

2.3.1 Explanatory variables

2.3.1.1 Personal and household characteristics

I considered a wide range of personal and household variables that characterize households and commuters.

For simplicity, I reclassified the ten income groups of the 2012 CHTS into four groups. To reflect the presence of children in the household, I defined three binary variables: children aged under 6, children aged 6 to 14, and children aged 15 to 18 years. In line with other studies, I included household size as a count variable (de Abreu e Silva et al., 2012; Ding et al., 2017; Van Acker and Witlox, 2011).

To capture generational effects, I defined binary variables for the age of the household worker based on definitions from the Pew Research Center (2018). I started with Millennials (18-31 years) since workers from Generation Z (<18 years) were too young in 2012 to commute to work. I combined the Greatest Generation (>84 years) with the Silent Generation (68-84 years) because the number of commuters from the former was small.

For simplicity, I reclassified the 23 categories of occupations into 13 groups from the North American Industry Classification System. Only 7 (0.55%) observations were found for ‘Primary industry’ and none for ‘Military’, so these two categories were merged with ‘Other’.

For ethnicity, apart from Caucasian, African American and Asian, I lumped other ethnicities into “Other” because of their relatively small number. I did not change the education variable, that tracks the education level of a commuter.

Finally, I considered three cases for the length of residence: less than five years, five to ten years, and more than ten years.

I lost 551 observations because of missing variables (the most important were age (42), occupation (82), income (154), and workplace home value (198)). Since I could not find transit stop data for Lancaster, Santa Clarita, and Montebello city, I excluded 73 and 18 observations that respectively to residences and workplaces in these locations.

To capture car availability, I used the ratio of the number of household vehicles to the number of household members with a driver’s license and defined a binary variable that equals 1 if this ratio is over one. Another 43 observations were lost because some households had no driver. My final sample size was 1,267.

2.3.1.2 Land use characteristics

Most empirical commuting studies describe land use characteristics around residential areas only since commuting trips originate from residences (Manaugh et al., 2010; Sun et al., 2017). However, Van Acker & Witlox (2011) confirmed that land-use around workplaces significantly influences car availability, commuting by car, commuting distance, and commuting time. A few other studies also included land use characteristics of work-trip destinations (de Abreu e Silva et al., 2012; Grunfelder and Nielsen, 2012). I characterized land use patterns around residences and workplaces with the following variables: job density, land use diversity, intersection density, distance to the nearest transit stop, to the nearest employment center, to downtown Los Angeles (LA's CBD), plus a measure of the job-housing balance, and median home values.

For density, I considered job density but not population density since the former is more influential on commuting behavior (Van Acker and Witlox, 2011). I obtained job density at the census-tract level from the 2012 Longitudinal Employer-Household Dynamics (LEHD).

I relied on SCAG's (Southern California Association of Government, the metropolitan planning organization that includes Los Angeles County) 2012 General Land Use Plan to measure land-use diversity. I considered seven land use categories - commercial, industrial, residential, education, open space and recreation, mixed use, and others (public facilities, special use facilities, transportation and communication, and utility facility) - for computing the entropy index EI_i for census tract *i*:

$$EI_i = -\sum_{j=1}^{7} p_{ij} \cdot \ln(p_{ij}) / \ln(7), \tag{1}$$

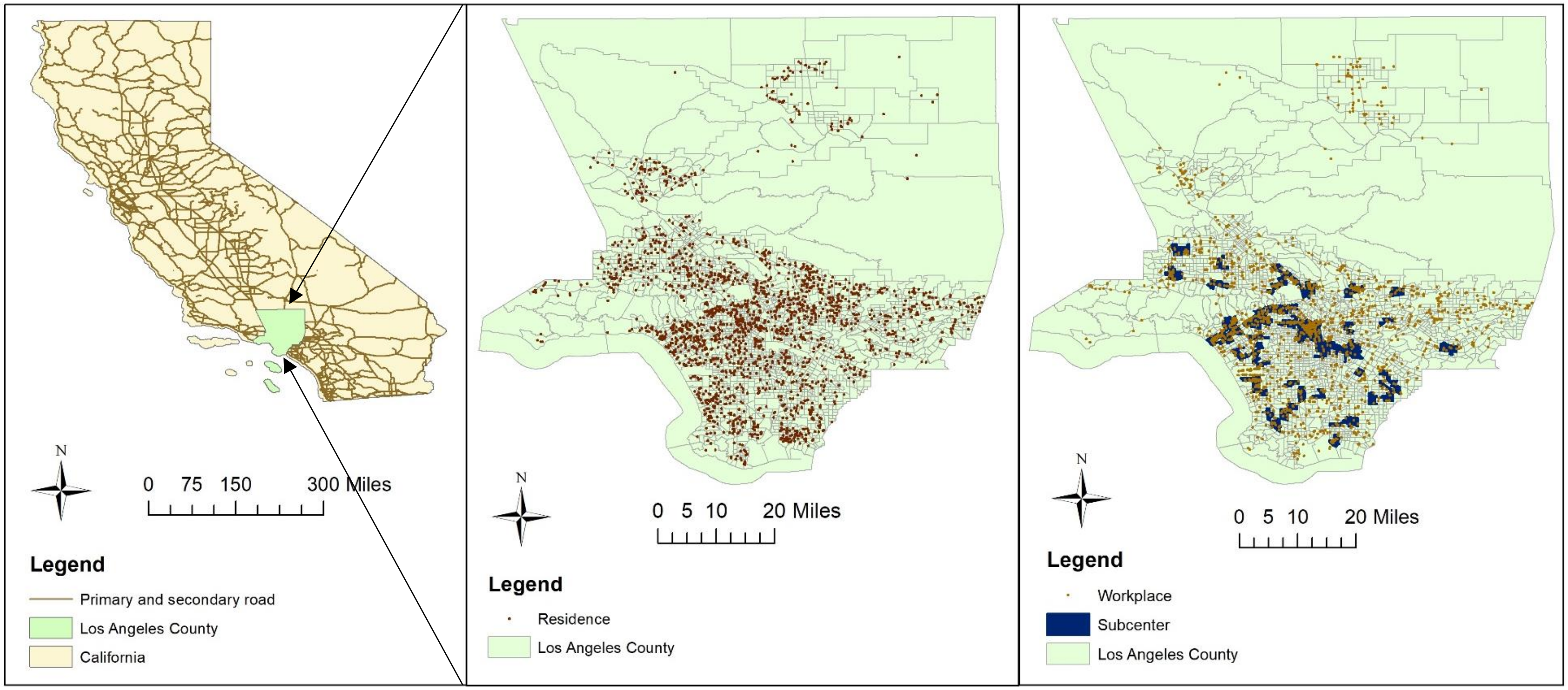
where p_{ij} is the proportion of land-use category *j* in census tract *i*.

The intersection density variable, which is a measure of road connectivity, was calculated from by taking into account intersections with three or more links in each census tract (Cervero et al., 2010). Before computing the network distance to the nearest transit stop for each residence and workplace in the sample, I obtained road network data from the 2012 TIGER/Line shapefiles from the Census. As of 2012, there were 25,801 transit stops in Los Angeles County according to the 2012 General Transit Feed Specification (GTFS) dataset (https://gtfs.org).

To capture job accessibility, I followed Sun et al. (2017) and created two variables: 1) distance to the CBD (here, downtown LA); and 2) distance to the nearest employment center. Both are commonly used for analyzing commuting patterns in polycentric cities (Modarres, 2011; Wang, 2000). LA's CBD is a diverse residential neighborhood that covers 5.84 sq mi and was home to over 500,000 jobs in 2013 (Downtown Center Business Improvement District, 2013).

Two approaches are popular for identifying subcenters: clustering (Giuliano et al., 2007; Giuliano and Small, 1991) and nonparametric models (McMillen, 2001; Redfearn, 2007). Clustering models rely on local knowledge for density cutoffs while nonparametric models make strong assumptions about physical symmetry (Giuliano et al., 2007).

Giuliano & Small (1991) introduced a clustering model that detects subcenters based on employment density given some thresholds. They defined two types of subcenters: '10-10' and '20-20'. The first is an agglomeration of contiguous tracts with a minimum employment density of 10 jobs per acre and over 10,000 jobs; the second has 20 jobs per acre and at least 20,000 jobs. Building on Giuliano & Small (1991), Giuliano et al. (2007) found 48 '10-10' subcenters and 10 '20-20' subcenters in the LA Metropolitan Area. Alternatively, Boarnet & Wang (2019) identified 46 subcenters in the LA Combined Statistical Area using a '95%-10k' approach, where 95% is the job-density percentile and 10k is the minimum total subcenter employment.



Panel A: Location of LA County **Panel B**: Home locations of respondents **Panel C** Work locations and job centers

Figure 2.1: Location maps

Table 2.2: Descriptive statistics for binary model variables (N=1,267)

Category	Mean		Mean
Endogenous commuter characteristic		**Endogenous household characteristics**	
Commute by car	0.892	Car availability	0.829
Exogenous commuter characteristics		**Exogenous household characteristics**	
Generation		***Annual income***	
Millennial	0.137	<$35 k	0.204
Generation X	0.318	$ 35k to $ 75k	0.315
Baby Boomers	0.500	$ 75k to $ 150k	0.342
Silent and GI	0.043	>$150k	0.140
Gender (Male=1)	0.552	***Length of residence***	
Hispanic	0.299	<5 years	0.204
Ethnicity		5 to 10 years	0.218
Caucasian	0.624	More than 10 years	0.579
African American	0.070	***Presence of children***	
Asian	0.085	Child <6 years	0.119
Other	0.221	Child 6-14 years	0.227
Education		Child 15-18 years	0.139
High school or less	0.216		
Some college credit	0.154		
Associate or technical degree	0.098		
Bachelor’s degree	0.304		
Graduate degree	0.228		
Occupation			
Management	0.138		
Business/Finance/Admin.	0.170		
Natural and Applied Sciences	0.026		
Health	0.075		
Social and Government Service	0.031		
Educational	0.115		
Art/Culture/Religion/ Sport	0.034		
Trades/Transport & equipment	0.125		
Sales and Service	0.148		
Engineer/Architect/Lawyer	0.103		
Other	0.035		

Table 2.3: Descriptive statistics for count and continuous model variables (N=1,267)

Variable	Mean	Std. Dev.	Min	Max
Endogenous commuting variables				
Commuting distance (km)	17	14	0.001	78.5
Ln (Commuting distance (km))	2.393	1.123	-6.984	4.364
Commuting time (minutes)	29.4	19.7	1	155
Ln (Commuting time (minutes))	3.159	0.710	0	5.043
Exogenous household variable				
Household size	2.798	1.454	1	8
Land use variables (exogenous except for median home value around residence)				
Land use around residence				
Jobs-housing ratio	1.254	3.726	0.039	49.894
Median home value ($100k)	4.796	3.339	1.232	54.116
Job density (# jobs per sq. km)	1,625.9	4,646.6	0.086	91,417.9
Ln (Job density (# jobs per sq. km))	6.487	1.389	-2.452	11.423
Land-use diversity	0.363	0.169	0	0.889
Distance to CBD (km)	24.926	14.877	0.811	99.711
Distance to nearest subcenter (km)	7.603	10.811	0.117	85.428
Intersection density (# per sq. km)	6.053	6.190	0	41.850
Distance to nearest transit stop (km)	0.751	2.240	0	34.434
Land use around workplace				
Jobs-housing ratio	5.823	10.583	0.042	49.894
Median home value ($100k)	4.849	3.844	1.216	58.923
Job density jobs (# per sq. km)	6,295.24	12,743.29	1.270	91,417.87
Ln (Job density (# jobs per sq. km))	7.625	1.601	0.239	11.423
Land-use diversity	0.446	0.187	0	0.889
Distance to CBD (km)	22.860	14.611	0.274	110.053
Distance to nearest subcenter (km)	6.334	10.406	0.008	97.002
Intersection density (# per sq. km)	7.093	6.665	0	39.975
Distance to nearest transit stop (km)	0.466	2.145	0	37.560

I found 33 subcenters (see Panel C of Figure 2.1) in LA County using the '10–10' approach applied to 2012 LEHD data. These 33 subcenters offer a total of 1,897,009 jobs over 77,240.01 acres in 262 census tracts, which account for 45.9% of all jobs and 2.54% of the land in LA County.

The simplest and most common measure of the job-housing balance in a census tract, which I used, is the ratio of the number of jobs to the number of resident workers (Cervero, 1989).

Finally, I purchased year 2012 median home values at the census tract level from

CoreLogic (CoreLogic, 2012).

Summary statistics for the variables are provided in Table 2.2 and Table 2.3. Variance Inflation Factors (VIF) for the variables have a mean of 2.44 and a maximum of 7.25, which is on the high side, but further investigations (estimating our preferred model without the offending variable) suggest that multicollinearity is not an issue here.

2.4 Methodology

2.4.1 Conceptual model

Most of the commuting studies I reviewed (see Table 2.1) developed separate models for commuting distance and commuting time (Antipova et al., 2011; Dai et al., 2016; Grunfelder and Nielsen, 2012; He et al., 2015; Motte et al., 2016). One exception is Van Acker & Witlox (2011), who argued convincingly that commuting time depends on both commuting distance and mode, which led them to model commuting time as a function of commuting distance and car ownership.

My conceptual model is shown in Figure 2.2. I assume that the socio-economic characteristics of a commuter and her/his household characteristics leads her/him to select a dwelling, whose characteristics (structural, locational, environmental) are reflected in its price, in accordance with microeconomics theory. This is a long-term decision which, combined with the choice of a job (determined outside of the model), determines commuting distance. For simplicity, I assume that the other residential land use variables are exogenous. The choice of driving (instead of using another mode) to work depends both on the availability of a car (as in Van Acker and Witlox, 2011 and 2010), and on commuting distance (as in de Abreu e Silva et al., 2006, 2012, and Van Acker and Witlox, 2011). Like de Abreu e Silva et al. (2012) and Van Acker and Witlox (2011), I assume that commuting time is influenced by both commuting distance and by whether a worker is driving to work, since in the U.S., a longer commuting distance tends to favor driving (Cervero and Kockelman, 1997). In addition, land use characteristics around residences and workplaces determine driving distance, whether a worker drives (because land use determines the presence and the characteristics of other modes), and driving time. My model also allows other relationships (shown by dashed lines), but they are not statistically significant.

To control for residential self-selection (namely the fact that households tend to choose their residential location based on their abilities, needs, and preferences for travel; see Mokhtarian and Cao, 2008), personal and household characteristics explain median home value around the residence, which implies that personal and household characteristics can indirectly affect commuting behavior via residential median home values.

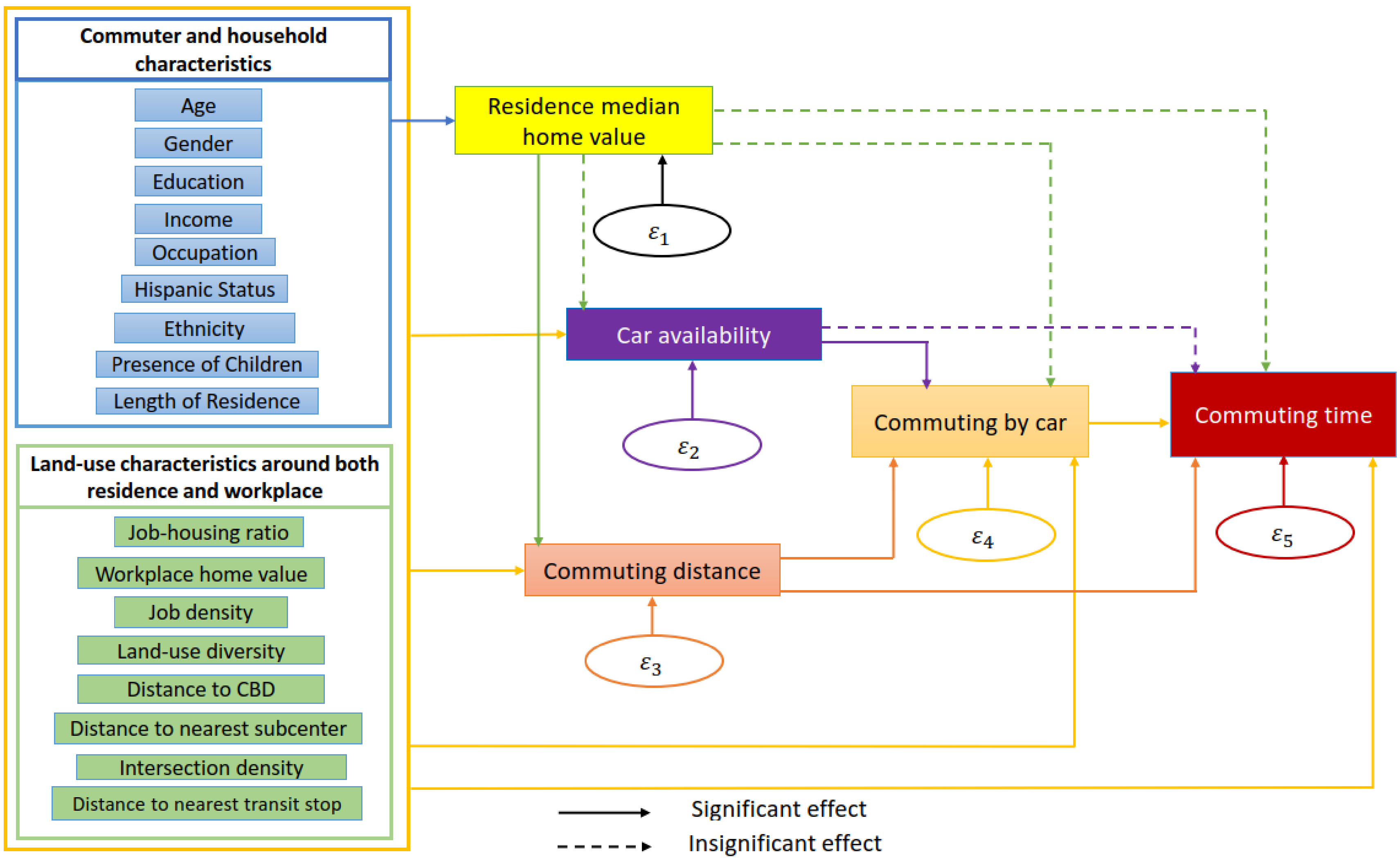


Figure 2.2: Conceptual model

2.4.2 Model

My model is a system of five simultaneous equations (2A-2E) that reflect the causal paths shown in Figure 2.2:

Regression model for residential home value:

$$\mathbf{L} = \mathbf{X}_1\mathbf{\Gamma}_1 + \boldsymbol{\varepsilon}_1, \tag{2A}$$

Logit model for car availability:

$$\mathbf{V}_i = \begin{cases} 1 \text{ if } \mathbf{V}_i^* > 0, \\ 0 \text{ if } \mathbf{V}_i^* \leq 0, \end{cases} \quad \mathbf{V}^* = \beta_{21}\mathbf{L} + \mathbf{X}_2\mathbf{\Gamma}_2 + \boldsymbol{\varepsilon}_2, \tag{2B}$$

Regression model for commuting distance:

$$\ln(\mathbf{D}) = \beta_{31}\mathbf{L} + \mathbf{X}_3\mathbf{\Gamma}_3 + \boldsymbol{\varepsilon}_3, \tag{2C}$$

Logit model for commuting by car:

$$\mathbf{C}_i = \begin{cases} 1 \text{ if } \mathbf{C}_i^* > 0, \\ 0 \text{ if } \mathbf{C}_i^* \leq 0, \end{cases} \quad \mathbf{C}^* = \beta_{41}\mathbf{L} + \beta_{42}\mathbf{D} + \beta_{43}\mathbf{V} + \mathbf{X}_4\mathbf{\Gamma}_4 + \boldsymbol{\varepsilon}_4, \tag{2D}$$

Regression model for commuting time:

$$\ln(\mathbf{T}) = \beta_{51}\mathbf{L} + \beta_{52}\mathbf{D} + \beta_{53}\mathbf{V} + \beta_{54}\mathbf{C} + \mathbf{X}_5\mathbf{\Gamma}_5 + \boldsymbol{\varepsilon}_5, \tag{2E}$$

In the above:

- **L** is an n × 1 vector of median home values (in \$100,000) in the census tracts where commuters in the sample reside;
- **V** is an n × 1 vector of 0s and 1s; $\mathbf{V}_i$=1 if there is at least one car per driver in household "*i*" and it equals 0 otherwise;
- **D** is an n × 1 vector of commuting distances (km);
- **C** is an n × 1 vector of 0s and 1s; $\mathbf{C}i$=1 if commuter "*i*" drives to work and 0 otherwise;

- $\mathbf{T}$ is an n × 1 vector of commuting times (minutes);
- $\mathbf{X}_k$ ($k \in \{1, \ldots, 5\}$) is an $n \times p_k$ matrix of personal and household characteristics and land use characteristics around places of residence and work; it is assumed to be exogenous;
- β_{21}, β_{31}, β_{41}, β_{42}.......... β_{53}, and β_{54} are unknown model parameters to estimate jointly with the $p_k \times 1$ vectors $\mathbf{\Gamma}_1$ to $\mathbf{\Gamma}_5$; and
- ε_1, ε_2, ε_3, ε_4 and ε_5 are n × 1 error vectors.

L, **V**, **D**, **C**, and **T** are endogenous. Since the model is recursive, it is identified (Kline, 2015). Unknown model parameters were estimated by minimizing the difference between the sample covariance and the covariance predicted by the model (Bollen, 1989).

SEM decomposes the impacts of exogenous and endogenous variables on the dependent variable into direct, indirect, and total effects. Direct effects quantify the impact of one variable on another without mediation. Indirect effects are mediated by at least one other variable. Finally, total effects are the sum of direct and indirect effects (Bollen, 1989). For conciseness, I report only direct and total effects. They are discussed in the next section.

2.5 Results

Results for my best model, obtained using Stata 15.1, are presented in Table 2.4. Only significant results are shown for conciseness. I estimated a GSEM model using quasi-maximum likelihood with the Huber-White sandwich estimator to relax the assumption that errors are identically and normally distributed (Rabe-Hesketh et al., 2004), since many of the explanatory variables are binary.

I explored several model specifications, including different correlation structure between error terms of commuting distance and time, of car availability and commuting by car, and some simple transformations (e.g., log transform) of the continuous explanatory variables. Comparing different plausible models using AIC and BIC (models with lower values are preferred) gave me the preferred model, which is presented below. Unfortunately, common fit statistics developed for SEM are not available for GSEM, so I simply examined each individual equation, performed common diagnostic checks, and looked for influential observations.

Equation 2A is a plain linear regression model, so its interpretation is straightforward. Its dependent variable (median home value in the census tract of residence) is in hundreds of thousands of dollars so to obtain the impact of changing one explanatory variable by 1 unit, I multiply its coefficient by 100 to get results in thousands of dollars ($1k).

Since Equations (2B) and (2D) describe logit models, I report their results as odds ratios. The odds ratio for explanatory variable x_i is the ratio of the odds after changing x_i to x_i+1 (while keeping other variables constant) divided by the odds for the original explanatory variables; the odds is the probability that the dependent variable equals 1 divided by the probability that it equals 0. If x_i is binary, its value in the odds in the numerator is 1 and its value in the odds in the denominator is 0. To better link my discussion below with Table 2.4, I refer to the value of statistically significant odds by writing "OR=" before its value shown in Table 2.4.

As indicated in the Methodology section, I log-transformed commuting distance (km) (explained by Equation 2C), commuting time (min) (modeled by Equation 2E), and job density because the resulting models have lower AIC and BIC values. In my discussion of the results for Equations 2C and 2E, I therefore report exp(β_j)-1 in parentheses for quantifying the percentage change in the expected value of the dependent variable for a unit change in explanatory variable "j" if that variable was not itself log-transformed; otherwise, β_j is an elasticity, and I simply report its value preceded by "elasticity=".

2.5.1 Direct effects

2.5.1.1 Residence home value (Equation 2A; Column I)

Starting with commuter characteristics, I see that residential home values are higher when the commuter is male ($35.4k), which possibly points to the persisting pay gap between women and men. Conversely, Hispanic workers (-$110.7k) live in less valuable neighborhoods compared to non-Hispanics workers, and the same holds for African American (−$159.7k) and to a smaller degree Asian (-$63.0k) workers compared to Caucasians. This reflects differences in wealth partly stemming from past discrimination (especially against African Americans) (e.g., see Galster and Carr, 1991; Taeuber, 1988; or Yinger, 1995) and immigration history.

As expected, workers with a college education (+$83.9k for bachelor's degree) or higher (+$115.3) also tend to live in neighborhoods with higher median home values, especially if they are in business (+$66.5k) or sales and services (+$52.7k). Income is especially important here ($253.8k for incomes >$150k), but length of residence ($48.4k for >10 years) also plays a role likely because housing values in California have been steadily increasing over time.

2.5.1.2 Car availability (Equation 2B; Column II)

As shown in Column II of Table 2.4, the generation of a commuter is not statistically significant, but her/his ethnicity is, as African American households (OR=0.462†) tend to own fewer cars than Caucasians, possibly because they tend to be less wealthy, and they are more likely to reside in city centers where higher parking and insurance costs make owing a motor vehicle more expensive.

Education is not significant, but occupation matters. As expected, as income increases, so does car ownership (OR=1.509*, 2.312‡, and 2.999‡ for annual household income categories ($35k, $75k), ($75k, $150k) and >$150k respectively).

Likewise, residence time matters as longer-term residents tend to own more motor vehicles than families who have lived in the same location for under 5 years.

Household size and family structure are also statistically significant, but their impacts are opposite. Indeed, I see that household size (OR=0.438‡) is negatively associated with car availability because car availability does not increase at the same rate as household size. Households with children are more likely to own a car, likely because of the flexibility motorization brings to transporting children to and from school, daycare, or after-school activities. This impact is larger for households with younger children (OR=6.989‡ and 4.521‡ respectively for children <6 years and 6-14 years), a finding that agrees with recent lifecycle/life-course studies (Oakil et al., 2014).

2.5.1.3 Commuting distance (Equation 2C; Column III)

Starting with commuter characteristics, I see that Gen X members and Baby Boomers have longer (+22.4% and +27.6% respectively) commutes than Millennials, possibly because many in these age groups have financial commitments (Mitra and Saphores, 2019). By contrast, Silent and GI generation workers have shorter commutes (-37.4%) possibly to limit the strain of commuting.

Gender and ethnicity do not impact commuting distance here, although I will see that the latter matters for total effects. Moreover, only one education variable (some college credit, +34.6% compared to workers with only a high school educations) positively influences commuting distance. Conversely, commuting distance increases with annual household income, from 25.2% for annual household incomes in [$35k, $75k] to 36.1% for annual household incomes over $150k.

Length of residence, household size, and the presence of younger children do not impact commuting distance, but households with children aged 15 to 18 years have shorter commutes (-23.7%) compared to childless households.

Let me now consider land-use variables. In agreement with urban economic theory (for which households select their residential locations after considering trade-offs between commuting and housing costs), median home values around the residence and around the workplace are both significant. Households who can afford more expensive neighborhoods have on average a commute 3.1% shorter per additional $100k to the median house value of their residence census tract. Conversely, a $100k increase in the median home value of a workplace census tract raise the average of commuting distance by 2.3%.

Job density around people's residence also matters (elasticity=-0.099) but its impact on commuting distance is small partly because jobs and housing are still typically zoned separately in LA County.

As expected, households who reside farther away from downtown Los Angeles, a large regional employment center, tend to have slightly longer commutes (+0.7% for each km farther from downtown LA). Conversely, people whose work location is farther from downtown LA have on average slightly shorter commutes (it decreases by 1% for each km farther from downtown LA).

Finally, a higher workplace job-housing ratio tends to increase commuting distance (each unit increase augments commuting distance by 0.6%) because job centers already have more jobs than residences and additional jobs are taken by workers who reside farther away.

2.5.1.4 Commute by car (Equation 2D; Column IV)

As expected, a longer commuting distance (OR=1.884‡) is associated with commuting by car because driving is faster than transit, especially for trips that do not start and end very close to a transit node.

The need for flexibility may explain why female workers rely more than male workers on motor vehicles for commuting (OR=0.477‡ for male commuters). As explained in Axisa et al. (2012), Ding et al. (2017), or Maoh and Tang (2012), working women with children need to balance work, domestic responsibilities, and childcare. Private motor vehicles are available any time (unlike transit), and they are more convenient for transporting shopping and small children.

Everything else being equal, several occupations (Business/Finance/Administration, Nature and Applied Science, Education, and Sales/Services) impact (all negatively) the choice of driving for commuting.

Car availability is paramount for commuting by car (OR=3.898‡). I also note that households with longer residence times (> 10 years) (OR=1.797†) and households with children aged 6-14 years (OR=1.956*) are more likely to commute by car.

Several land use variables are statistically significant, but only one (intersection density) is connected to residential land use, and it has a relatively small impact on commuting by car (OR=0.973*).

By contrast, four workplace land use variables are statistically significant. As workplace job density increases, the likelihood of commuting by car drops (OR=0.736‡) possibly because larger LA job centers are better served by transit, and a higher concentration of jobs entails more road congestion. I also note that employers that have 250 or more employees at a worksite are subject to Rule 2202, which mandates employers to implement various strategies to reduce mobile source emissions from employee commutes, including providing high-occupancy travel options (South Coast AQMD, 2021). Conversely, as workplace land use diversity increases, so does the likelihood of commuting by car (OR=5.610‡). The commuting literature is divided on the impacts of land use diversity on commuting. Some studies (Ewing and Cervero, 2010; Spears et al., 2010) report that an increase in land use diversity decreases commuting by car, but Van Acker & Witlox (2010) find (like me) the reverse. As they explained, more diversity is associated with higher real estate prices, which attract households with higher incomes and more cars. The practical impact of the other two workplace land use variables (distance to the CBD and to the nearest subcenter) is small because their odds ratios are close to 1.

2.5.1.5 Commuting time (Equation 2E; Column V)

As expected, longer commutes take more time (elasticity=0.482) while commuting by car reduces commuting time by 29.5% because other modes (e.g., transit) are typically slower.

Interestingly, no socio-economic characteristic is statistically significant here, except for one generation variable: older commuters take 28.3% more time to commute than Millennials, even though they do not travel as far (see results for Equation 2C). In addition, a longer residence time (> 10 years) decreases commuting time by 6.8%, possibly because workers seek shorter commutes over time to reduce the toll of commuting on their family.

However, five land use characteristics are statistically significant. First, higher job densities - both around the residence and the workplace – entail more time-consuming commutes (elasticity=0.024 for both), likely because roads to denser employment centers are more congested or more employees arrive via transit, which increases commuting time (Antipova et al., 2011).

Table 2.4: Generalized SEM results (N=1,267)

	Direct effects					Total effects				
Variables	**Residence home value** Eq. 2A	**Car availability** Eq. 2B	**Ln of commuting distance** Eq. 2C	**Commute by car** Eq. 2D	**Ln of commuting time** Eq. 2E	**Residence home value** Eq. 2A	**Car availability** Eq. 2B	**Ln of commuting distance** Eq. 2C	**Commute by car** Eq. 2D	**Ln of commuting time** Eq. 2E
Column number and estimate type	I. Coef.	II. OR	III. Coef.	IV. OR	V. Coef.	VI. Coef.	VII. OR	VIII. Coef.	IX. OR	X. Coef.
Ln(Commuting distance)	NA	NA	NA	1.884‡	0.482‡	NA	NA	NA	1.884‡	0.261‡
Generation (baseline: Millennial)										
Generation X	-	-	0.202*	-	-	-	-	0.202*	-	-
Baby Boomers	-	-	0.244‡	-	-	-	-	0.244‡	-	-
Silent and GI	-	-	-0.469†	-	0.249‡	-	-	-0.469†	-	0.249‡
Gender: Male	0.354*	-	-	0.477‡	-	0.354*	-	-	0.477‡	0.345‡
Hispanic status: Hispanic	-1.107‡	-	-	-	-	-1.107‡	-	0.034†	-	-
Ethnicity (baseline: Caucasian)										
African American	-1.597‡	0.462†	-	-	-	-1.597‡	0.462†	0.050‡	0.393*	0.579†
Asian	-0.630†	-	-	-	-	-0.630†	-	0.020*	-	-
Other	-	-	-	-	-	-	-	-	-	-
Education (baseline: high school or less)										
Some college credit	-	-	0.297‡	-	-	-	-	0.297‡	-	-
Associate or technical degree	-	-	-	-	-	-	-	-	-	-
Bachelor's degree	0.839‡	-	-	-	-	0.839‡	-	-0.026†	-	-
Graduate degree	1.153‡	-	-	-	-	1.153‡	-	-0.036†	-	-
Occupation (baseline: other)										
Management	-	-	-	-	-	-	-		-	-
Business /Finance / Administration	0.665*	0.340*	-	0.135*	-	0.665*	0.340*	-	0.030†	1.196†
Natural and Applied Sciences	-	0.240*	-	0.103*	-	-	0.240*		0.103*	1.516†
Health	-	-	-	-	-	-	-		-	0.995*

Variables	Direct effects: Residence home value Eq. 2A	Direct effects: Car availability Eq. 2B	Direct effects: Ln of commuting distance Eq. 2C	Direct effects: Commute by car Eq. 2D	Direct effects: Ln of commuting time Eq. 2E	Total effects: Residence home value Eq. 2A	Total effects: Car availability Eq. 2B	Total effects: Ln of commuting distance Eq. 2C	Total effects: Commute by car Eq. 2D	Total effects: Ln of commuting time Eq. 2E
Column number and estimate type	I. Coef.	II. OR	III. Coef.	IV. OR	V. Coef.	VI. Coef.	VII. OR	VIII. Coef.	IX. OR	X. Coef.
Social and Government Service	-	-	-	-	-	-	-			
Education	-	0.368*	-0.343*	0.133*	-	-	0.368*	-0.343*	0.028†	1.087†
Art/Culture/Religion/ Sport	-	-	-	-	-	-	-	-		
Trades/Transport & equipment operators	-	0.390*	-	-	-	-	0.390*	-		0.946*
Sales and Service	0.527*	0.379*	-	0.147*	-	0.527*	0.379*	-	0.038†	1.116†
Engineer / Architect / Lawyer	-	-	-	-	-	-	-	-	-	0.918*
Vehicle status										
Car availability	NA	NA	NA	3.898‡	-	NA	NA	NA	3.898‡	-0.474‡
Commute by car	NA	NA	NA	NA	-0.349‡	NA	NA	NA	NA	-0.349‡
Annual household income; baseline: <$35k										
$ 35k to $ 75k	-	1.509*	0.225†	-	-	-	1.509*	0.225†	2.024†	-
$ 75k to $ 150k	-	2.312‡	0.291‡	-	-	-	2.312‡	0.291‡	3.738‡	-0.505†
>$150k	2.538‡	2.999‡	0.308†	-	-	2.538‡	2.999‡	-	5.151‡	-0.680†
Length of residence (baseline: <5 years)										
5 to 10 years	-	2.303‡	-	-	-	-	2.303‡	-	3.268‡	-0.474†
More than 10 years	0.484†	1.962‡	-	1.797†	-0.070*	0.484†	1.962‡	-0.015†	4.406‡	-0.602‡
Household Size	-	0.438‡	-	-	-	-	0.438‡	-	0.331‡	0.414‡
Presence of children by age (baseline: no child)										
Child <6 years	-	6.989‡	-	-	-	-	6.989‡	-	14.124‡	-0.875‡
Child 6-14 years	-	4.521‡	-	1.956*	-	-	4.521‡	-	14.245‡	-0.978‡
Child 15-18 years	-	1.672†	-0.270‡	-	-	-	1.672†	-0.270‡	-	-
Land use (Residence)										

Variables	Direct effects: Residence home value Eq. 2A	Direct effects: Car availability Eq. 2B	Direct effects: Ln of commuting distance Eq. 2C	Direct effects: Commute by car Eq. 2D	Direct effects: Ln of commuting time Eq. 2E	Total effects: Residence home value Eq. 2A	Total effects: Car availability Eq. 2B	Total effects: Ln of commuting distance Eq. 2C	Total effects: Commute by car Eq. 2D	Total effects: Ln of commuting time Eq. 2E
Column number and estimate type	I. Coef.	II. OR	III. Coef.	IV. OR	V. Coef.	VI. Coef.	VII. OR	VIII. Coef.	IX. OR	X. Coef.
Job-housing ratio	NA	-	-	-	-	NA	-	-	-	-
Median home value	NA	-	-0.031‡	-	-	NA	-	-0.031‡	0.981‡	-8.1E-3†
Ln(Job density)	NA	-	-0.099‡	-	0.024*	NA	-	-0.099‡	-	0.024*
Land-use diversity	NA	-	-	-	-	NA	-	-	-	-
Distance to CBD	NA	-	7.3E-3†	-	-	NA	-	7.3E-3†	-	-
Distance to nearest subcenter	NA	-	-	-	-	NA	-	-	-	-
Intersection density	NA	-	-	0.973*	-	NA	-	-	0.973*	-
Distance to nearest transit stop	NA	-	-	-	-	NA	-	-	-	-
Land use (Workplace)										
Job-housing ratio	NA	-	6.4E-3*	-	-	NA	-	6.4E-3*	-	-
Median home value	NA	-	0.023‡	-	0.011‡	NA	-	0.023‡	-	0.011‡
Ln(Job density)	NA	-	-	0.736‡	0.024*	NA	-	-	0.736‡	0.175‡
Land-use diversity	NA	-	-	5.610‡	-0.166†	NA	-	-	5.610‡	-1.023‡
Distance to CBD	NA	-	-0.010‡	1.073‡	-4.8E-3‡	NA	-	-0.010‡	1.073‡	-0.035‡
Distance to nearest subcenter	NA	-	-	0.926†	-	NA	-	-	0.926†	0.033†
Intersection density	NA	-	-	-	-	NA	-	-	-	-
Distance to nearest transit stop	NA	-	-	-	-	NA	-	-	-	-
Constant	3.328‡	3.624‡	2.468‡	2.767*	2.196‡					

Notes: 1) ∗, †, & ‡: significance at 10%, 5%, & 1% respectively. 2) Coef.=coefficient; OR=odds ratio; "-" (dash)= statistically non-significant coefficient; NA= Not applicable for that model. 3) Median home values are in $100,000, distances are in km, densities are in persons per square km. 4) Shaded cells indicate statistically significant indirect effects (so total effects – shown in Columns VI to X – differ from direct effects – shown in Columns I to V). 5) Log-likelihood = -6648.6; AIC = 13,761.2; BIC = 14,954.7.

Second, for each $100k increase in housing costs around the workplace, the average commute takes 1.1% longer as some workers are forced farther away (see Equation 2C).

Third, more workplace land use diversity reduces commuting times (-1.53% for each 0.1 unit increase in diversity) by providing opportunities for workers to move closer to their jobs.

Finally, just as for the commuting distance (Equation 2C), households who work farther from downtown LA (LA's CBD) tend to have slightly faster commutes (-0.5% per km) possibly because they commute to other job centers and avoid the brunt of peak hour congestion.

2.5.2 Indirect and total effects

The last five columns of Table 2.4 report total effects. For conciseness, indirect effects are not shown separately since they can be calculated as the difference between total and direct effects. In this sub-section, I discuss total effects for variables with significant indirect effects, which were shaded in Table 2.4 to make them stand out.

Given the structure of my model (see Figure 2.2), there are no indirect effects for Equations 2A ("Residence median home value") and 2B ("Car availability") since no explanatory variable is endogenous in the former and the residence median home value variable is not statistically significant in the latter.

However, indirect effects (via the residence median home value variable) play an important role in the "Commuting distance" equation (Column VIII of Table 2.4). First, I see that Hispanic (+3.5%) compared to non-Hispanic workers, but also African American (+5.1%) and Asian (+2.0%) workers compared to Caucasian workers all have slightly longer commutes. Conversely, more educated workers (-2.6% for bachelor and -3.6% for graduate degrees) have slightly shorter commutes, although income effects also come into play. Results indicate that workers with an annual household income over $150,000 do not commute farther than baseline workers. Moreover, longer term residents (households who have not moved for at least a decade) tend to have a shorter commute (-1.5%).

Indirect effects for the “Commute by car” equation (Column IX of Table 2.4) come from both the “Commuting distance” and the “Car availability” variables. I see that African American workers are substantially less likely to commute by car (OR=0.393*), and even more so workers in the business/finance/administration (OR=0.030†), education (OR=0.028†), and sales and service (OR=0.038†). The same is true for commuters employed in natural and applied sciences but there are no indirect effects in this case. Conversely, as household income increases, so does the likelihood of commuting by car (OR=2.024†, 3.738‡, and 5.151‡ for income brackets ($ 35k to $ 75k), ($ 75k to $ 150k), and >$150k respectively), a tendency reinforced by length of residence (OR=3.268‡ and 4.406‡ for 5 to 10 years, and over 10 years respectively). While a larger household size reduces the likelihood of commuting by car (OR=0.331‡), the presence of younger children has a strong, opposite effect (OR=14.124‡ and 14.245‡ for children under 6 and children between 6 and 14 respectively). Finally, residing in a more expensive neighborhood very sightly decreases (OR=0.981‡) the likelihood of commuting by car, but this is a small correction compared to the strong income and length of residence effects described above. There are no indirect effects for the other land use variables in this equation.

In the “Commuting time” equation (Column X in Table 2.4), indirect effects come from the “Commuting by car” and “Commuting distance” variables. I see that indirect effects impact the commuting time of a few occupations (mostly the ones less likely to commute by car). Interestingly, car availability substantially reduces commuting time (-37.7%). Moreover, commuters in the top two income brackets tend to have shorter commutes compared to commuters with lower incomes (-39.6% and -49.3% for ($75k to $150k) and >$150k respectively), and to longer-term residents compared to newcomers (-37.7% and -45.2% for length of residence of 5 to 10 years and over 10 years, respectively). As for commuting by car, larger households tend to have longer commutes (+51.3%) but younger children substantially decrease commute duration (-58.3% and -62.4% for a child <6 years and between 6 and 14 years respectively) compared to childless households.

One residence and four workplace land use variables have significant indirect effects. For the former, more expensive home values are associated with shorter commuting time (-0.8% for each additional $100k). For the latter, the elasticity of commuting time with respect to workplace job density increases to 0.175 (so a 1% increase in workplace job density increases commuting time by 0.175%, likely because of congestion as all 33 of LA County's job centers are served by major roads). Land-use diversity around the workplace is also important: a 0.1-unit increase (recall that land use diversity varies between 0 – no diversity – and 1 – all land uses have the same share) decreases commuting time by 6.4%. Finally, households who work farther from downtown LA (LA's CBD) tend to have slightly faster commutes (-3.4% per km) and their commute duration rises with the distance from their workplace to the nearest job center (also +3.4% per km).

2.6 Conclusions

In this essay, I estimated a generalized structural equation model on 2012 CHTS data for Los Angeles County – the most populous county in the U.S. – to tease out the impacts of housing costs on commuting. My model, which jointly explains commuting distance and time, accounts for residential self-selection and the endogeneity of car use, while controlling for household characteristics and land use around residences and workplaces. My results confirm the presence of residential self-selection since residential home values are partly explained by personal and household socio-economic variables.

Results show that households who can afford more expensive neighborhoods have on average a commute that is 3.1% shorter per additional $100k to median home values in their residence census tract. Likewise, a $100k increase in the median home value of their workplace census tract raises the average commuting distance by 2.3%. Commuting time was also affected although the impact of home values was relatively small. This suggests that longer commutes are to some extent a consequence of California's high housing costs.

Like de Abreu e Silva et al. (2012), Grunfelder and Nielsen (2012), and Van Acker and Witlox (2011), I quantified the impact of land use characteristics of both residences and workplace on commuting. However, unlike other papers in this literature, I found that job density, distance to the CBD, and land-use diversity measured in workplace census tracts have a relatively greater impact on commuting than the same variables measured around the residences of the commuters in my sample.

Although more land-use diversity around workplaces increases the likelihood of commuting by car in LA County, higher job densities are associated with lower car use. Somewhat surprisingly, the job-housing ratio is hardly significant in our study, possibly because the dwellings near employment centers tend to be unaffordable.

While the relationship between jobs and housing used to be a popular subject of inquiry two or three decades ago (e.g., see Cervero, 1996, 1989; Levine, 1998; Peng, 1997; Sultana, 2002; Wachs et al., 1993), after a relatively quiet period it is coming back to the forefront in the affordable housing literature (Blumenberg and King, 2021). Indeed, after analyzing 2002 and 2015 data from the LEHD Origin–Destination Employment Statistics for cities in California, Blumenberg and

King (2021) showed that a shortage of affordable housing is another factor that contributes to lengthening California workers' commutes.

California's high housing costs are partly due to Proposition 13 (http://www.californiataxdata.com/pdf/Prop13.pdf), which has been limiting since 1978 the ability of municipalities to raise property taxes. This has encouraged local governments to zone land on fiscal grounds (Fulton, 1991), restricting housing production and driving up the price of the existing housing stock. In addition, nimbyism by long-time residents (Pendall, 1999) and other exclusionary practices adopted in the wake of Proposition 13 have displaced some low- and middle-income workers to residential communities far from their jobs.

Short of repealing Proposition 13, one possibility for reducing exclusionary zoning is tax-base sharing, where job-rich cities share their tax receipts with job-poor cities to house their workers (for details, see Downs, 1994; Reschovsky & Knaff, 1977). Tax relief (Cervero and Wu, 1997) and cash grants (Cervero and Duncan, 2006), in addition to zoning for affordable housing are others way of balancing job and housing growth. For example, in Palo Alto, California, rezoning from commercial to residential uses was conducted to attract low- and moderate-income households (inclusionary zoning) (Cervero and Duncan, 2006). In Los Angeles, LA Metro (2018) has a Joint Development Affordable Housing Policy, which requires 35% of housing units built on its properties to be affordable for households earning up to 60% of the area's median income.

My results also showed that race, Hispanic status, gender, and income are determinants of commuting. Compared to non-Hispanics, Hispanic workers commute longer distances (+3.5%), and so do African American (+5.1%) and Asian (+2.0%) workers compared to Caucasians. These findings reflects differences in wealth partly stemming from past discrimination (e.g., see Galster and Carr, 1991; Taeuber, 1988; or Yinger, 1995) and the history of immigration in the U.S.

I also found that commuters in the top two income brackets tend to have faster commutes than lower income workers as they have more choices when selecting the location of their residence in relation to their workplace.

My results confirm that women have commutes that are 41.2% (=(1-*exp*(0.345)) 100%) faster than men, possibly because they are often balancing an outside job with childcare and household tasks (Axisa et al., 2012; Ding et al., 2017).

Finally, my result on the commute characteristics of households with children are in line with other commuting studies (McQuaid and Chen, 2012; Sakanishi, 2020; Sun et al., 2017; Van Acker and Witlox, 2011), who reported that households with younger children are more likely to own a car and have faster commutes, likely to have time to transport children to and from school, daycare, or after-school activities.

There are multiple avenues for future research. First, my results apply only to single worker households, so it would be of interest to explore the impact of housing costs on households with two or more workers. Second, although Lin et al. (2015) and Zhao et al. (2010) argued that employment decentralization would decrease individual commuting times and change commuting mode choices, other studies concluded the opposite (Cervero and Wu, 1997; McMillen, 2001). To explore this question, a panel dataset with commuting data is needed to understand changes in commuting. It could also help explore feedback effects between commuting by car and commute distance, as suggested by a reviewer. Third, it would be of interest to examine changes in residence and employment location over time (Blumenberg and King, 2019). Fourth, it would be of interest to examine the impact of attitudes and lifestyle on commuting. Finally, it will be very much of interest to investigate the long-term impacts of the Covid-19 pandemic on commuting, which caused workers in entire sectors of the economy to stop commuting and work from home.

Although I focus on LA County in this essay, this methodology is widely applicable so it could be used to investigate how housing costs impact commuting in other parts of the world.

2.7 References

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Chapter 3. Two Rode, but not Together: Gender Commuting Trade-offs in Two-worker Households

3.1 Introduction

Although commuting trips make up only 17.4% of all trips (U.S. Department of Transportation, 2018), they are major contributors to congestion and air pollution since commuting typically occurs during traffic peaks (Wang, 2001). My review of the transportation literature shows that most commuting studies analyzed one-worker households, which represent approximately two thirds of commuters (U.S. Census Bureau, 2022), and that researchers paid relatively little attention to commuting by two-worker households, although they make up at least 30% of households in metropolitan areas. Two-worker households face additional constraints when selecting their residence as they need to consider the burden of commuting to two workplace locations, so it is important to understand the trade-offs they are willing to make in length of their commutes. To plan appropriately for the future, their travel behavior should be considered in the context of urban land-use and transportation policies (Akbari and Habib, 2018).

The rise of two-worker households in the US since the second world war has been driven primarily by an increase in the labor force participation rate for women, as the service sector has expanded, and the education gap has narrowed. In 2023, the US Department of Labor was projecting that although both men and women are likely to experience a fall in their labor force participation, the decline for women would be smaller than for men, increasing the relative importance of two-worker households (Machovec, 2023).

To the best of my knowledge, no published empirical studies of two-worker households commuting simultaneously explains commuting time and distance, and account for the endogeneity of commuting by car. It is well-known that ignoring the endogeneity of explanatory variables will result in biased estimates of model coefficients, which would alter our understanding of the determinants of commuting for two-worker households (Cao et al., 2009). Moreover, only a handful of studies has considered how housing costs may influence commuting (Plaut, 2006; Singell and Lillydahl, 1986; Sultana, 2005).

In this context, the main contribution of this study is to tease out the impact of gender on both commuting time and distance in two-worker households, while accounting for the endogeneity of commuting by car, housing costs, and land use around residences and workplaces. My starting hypothesis is that the commute duration for women is significantly shorter than for men, and that there can be substantial heterogeneity between metropolitan areas. Although many papers in the transportation literature conclude that women's commutes are on average significantly shorter than men's (Frändberg and Vilhelmson, 2011; Hjorthol and Vågane, 2014; Jun and Kwon, 2015; Plaut, 2006; Surprenant-Legault et al., 2013; Wheatley, 2014), some studies have concluded the reverse (Chidambaram and Scheiner, 2020; Iwata and Tamada, 2014; Kim, 2022) so this debate is not fully settled.

I estimated our comprehensive SEM model using data from the 2017 National Household Travel Survey (NHTS) from five metropolitan areas in three US states: Los Angeles and San Francisco in California, Dallas and Houston in Texas, and Atlanta in Georgia. I selected these metropolitan areas for their relative importance and because of the availability of detailed residential and workplace location data, which enabled me to include detailed land use characteristics in my models.

Understanding the determinants of commuting in two-worker households is important for planning for future travel demand as the number of two-earner households is expected to grow

(Akbari and Habib, 2018, 2015). Moreover, my study contributes to the debate of whether there is any trade-off or complementary effect of commuting between men and women in two-worker households (Akbari and Habib, 2018; Plaut, 2006; Surprenant-Legault et al., 2013).

In Section 3.2, I review selected papers to inform my modeling choices. I then describe my data (Section 3.3) and present my methodology (Section 3.4), before discussing my results in Section 3.5. In Section 3.6, I summarize my main findings, discuss some policy implications, mention some limitations, and suggest alternatives for future research.

3.2 Literature review

To inform my modeling effort, I first review selected papers on commuting for two-worker households, before motivating my choice of explanatory variables.

3.2.1 Commuting in two-worker households

One major strand of the literature on commuting for two-worker households examined the difference in commuting distances and times between men and women. Empirical evidence suggests that the commute length and duration are significantly shorter for women than for men (Dargay and Clark, 2012; Frändberg and Vilhelmson, 2011; Hjorthol and Vågane, 2014; Johnston-Anumonwo, 1992; McQuaid and Chen, 2012; Plaut, 2006; Surprenant-Legault et al., 2013; Wheatley, 2014). In Korea, Jun and Kwon (2015) showed that dual-earner households in the Seoul Metropolitan Area (SMA) live closer to the wife's workplace than the husband's, which reflect cultural constraints.

The prevalent explanation for women's shorter commutes is that they carry a larger share of household work (housework, children and family care) than men (Johnston-Anumonwo, 1992; Turner and Niemeier, 1997). Spain and Bianchi (1996) argued that employed wives effectively tend to be secondary earners owing to their household responsibilities, and they are more likely to have shorter work hours and lower wages than their husbands, as they seek convenient jobs closer to home. Benson (2014) and MacDonald (1999) reported that women are over-represented in occupations that require less skill and pay relatively low wages. These jobs tend to be closer to residential locations than typically male-dominated occupations. Nevertheless, Roberts et al. (2011) and Wheatley (2013) concluded that even in dual-worker households where both husband and wife are employed full-time in highly skilled managerial or professional occupations, it is often the wife who has a shorter commute so she can take care of household tasks.

On the other hand, Chidambaram and Scheiner (2020) analyzed the gender gap using 2012/13 German Time Use Survey (GTUS) on 1,596 heterosexual couples. They found that a relative dominance of car access by women and an increase in time spent on unpaid work (e.g., household maintenance and childcare) by the male partner reduce the gender gap in commuting distances. Moreover, Iwata and Tamada (2014) and Singell and Lillydahl (1986) found that in dual-earner households where both spouses work full-time, the work trip length of the wife increases more than her husband's when her income is higher. In short, if a wife who contributes more to the household income than her husband, he is now more likely to reduce his commuting time to allow for a greater share of household responsibilities (Iwata and Tamada, 2014; Kim, 2022; Lee and McDonald, 2003).

A second major strand of the literature on commuting examines commuting differences between one-worker and two-worker households, and whether there is any trade-off or complementary commuting effect between the members of a two-worker household (Akbari and Habib, 2018; Kim, 1995; Plaut, 2006; Sultana, 2005; Surprenant-Legault et al., 2013).

Since two-worker households typically face more constraints for choosing their residential and employment locations, it may be challenging for them to find locations that result in short commutes for both workers. However, Sultana (2005) found the opposite. After examining the average commute times between single and dual-earner households in the Atlanta MSA, she concluded that the average commuting time of married dual-earner couples is no longer than for single-earner households. Similarly, Kim (1995) found that average commutes are shorter in two-worker than in one-worker households in the Los Angeles MSA.

After analyzing two-worker households in the 2001 American Housing Survey where both are car commuters, Plaut (2006) concluded that commuting distances and times for spouses appear to be strongly complementary which means commute trips for both are adjusted together (both trips are made longer or both shorter) as part of a household selection of preferred housing and neighborhood characteristics. She concluded that spouses do not appear to be trading off commuting distance/time.

However, Akbari and Habib (2018) found that members of two-worker households are trading off commuting distances (as one commute increases, the other decreases) for the 2014 Greater Toronto Area. Similarly, after analyzing travel data from the Montreal Metropolitan Community (CMM), Surprenant-Legault et al. (2013) found that a 1% increase in the commuting distance of one worker results in total commuting distance growing by less than 1%, so they concluded that two-worker households are trading off commuting distance. They also reported that members of two-worker households travel the same or less than one-worker households.

3.2.2 Variables that impact commuting

Empirical studies show that a broad range of factors influence commuting. They include commuter and household characteristics, as well as land use characteristics around the residence and the workplace (Chidambaram and Scheiner, 2020; Jun and Kwon, 2015; Kim, 2022; Surprenant-Legault et al., 2013). I examine them in turn.

3.2.2.1 Commuter and household characteristics

Most of the papers I reviewed agree that age is negatively associated with commuting as people commute farther when they are younger but increasingly less in their later years (Sultana, 2005; Surprenant-Legault et al., 2013).

Several studies concluded that a higher income is associated with a longer commuting distance as a higher income compensates for commuting cost (Chidambaram and Scheiner, 2020; Dargay and Clark, 2012; Jun and Kwon, 2015; Surprenant-Legault et al., 2013). A higher household income is often associated with longer commutes for women, which reduces the gender gap in commuting (Chidambaram and Scheiner, 2020). However, this result seems to depend on urban form as Sultana (2005, 2002) reported that wealthier households tend to reside closer to the city center of Atlanta, GA, where their jobs are located while middle income households trade longer commutes for more affordable and spacious housing in suburban neighborhoods.

Education can be expected to align with income because higher paying jobs often require more education (Groot et al., 2012; He et al., 2015). Chidambaram and Scheiner (2020) and Shearmur (2006) reported that women with less education and a lower income commute shorter distances than their male counterparts.

Occupation type also impacts commuting. When both spouses of dual-earner households are working in more locationally constrained careers such as managerial/professional occupations (mostly high skilled jobs), they may have longer average commuting times (Jun and Kwon, 2015;

Sultana, 2005). In contrast, Brun and Fagnani (1994) found that professional workers prefer to live closer to their workplace to reduce the burden of long commutes.

Working hours were found to be negatively associated with commuting time since longer working hours are assumed to be compensated for by shorter commuting hours (Kim, 2022). Although, a large proportion of part-time workers are women (Hjorthol and Vågane, 2014), the work trip length of a full-time working wife increases more than her husband's when she earns more than her husband (Iwata and Tamada, 2014; Singell and Lillydahl, 1986).

Empirical evidence also suggests that commuting varies by ethnicity (Wheatley, 2013). African American married couples have slightly longer commutes than White married couples (Sultana, 2005). Some African American and Hispanic women commute as long as African American and Hispanic men, but much longer than White men (McLafferty, 1997).

The presence of children in a household also matters. Singell and Lillydahl (1986) observed a reduction in commuting times for both genders when children are present but since women are more likely to bring their children to daycare and to after-school activities, their commutes tend to be longer (Chidambaram and Scheiner, 2020; Hjorthol and Vågane, 2014; McQuaid and Chen, 2012; Surprenant-Legault et al., 2013). Moreover, Sultana (2005) argued that the presence of both school-age and younger children adds extra commuting time for those families compared to families without children.

Household size is a common explanatory variable in commuting studies which can be used as a proxy for family responsibility. A commuter in a dual-worker household with a larger household size is likely to have a shorter commuting time (Jun and Kwon, 2015).

3.2.2.2 Land use characteristics

Most published papers on commuting in two-worker households I reviewed include variables characterizing land use around the residence and the workplace of commuters (Chidambaram and Scheiner, 2020; Hjorthol and Vågane, 2014; Iwata and Tamada, 2014; Kim, 2022; Plaut, 2006; Singell and Lillydahl, 1986; Sultana, 2005; Wheatley, 2013). Some also used employment and population density (de Meester and van Ham, 2009; Jun and Kwon, 2015), accessibility to jobs (e.g., the distance to the nearest subcenter) (de Meester and van Ham, 2009; Jun and Kwon, 2015; Surprenant-Legault et al., 2013), and distance to the nearest freeway or subway station (Jun and Kwon, 2015).

I relied here on the following variables to organize my discussion below: density, design, destination/job accessibility, and distance to transit stops (Cervero and Kockelman, 1997; Ewing and Cervero, 2010).

Density (the number of people or jobs per unit of area) has been found to be negatively associated with commuting by car, commuting distance, and time (Van Acker and Witlox, 2011). Working spouses from low-density regions commute longer than those who reside in larger, denser cities in Germany (Chidambaram and Scheiner, 2020). However, de Meester and van Ham (2009) found for the Netherlands that living in very urbanized areas increases the commutes of both partners.

Design reflects the degree of road connectivity towards destinations. A common measure of road connectivity is intersection density (Cervero et al., 2010; Islam and Saphores, 2022). Ewing and Cervero (2010) found that increasing intersection density reduces commuting distances while a poorly connected road network with many cul-de-sacs (dead-ends) does the opposite (Litman and Steele, 2012).

Accessibility refers to the ability of reaching activities or locations (Geurs and van Wee, 2004). Improved accessibility to jobs from home is expected to decrease commuting distance, while accessibility to jobs from the workplace has the opposite effect (Surprenant-Legault et al., 2013). However, Jun and Kwon (2015) found that distance from home or workplace to the nearest subcenter is negatively related to commuting time, which implies that suburban residents or workers are likely to have shorter commuting times.

Access to transit favors commuting via transit. Jun and Kwon (2015) found that a commuter living near a subway station is likely to have a shorter commuting time because more jobs are available near subway stations, in particular within the city center.

I also included in my model a measure of the job-housing balance and median monthly housing cost. The job-housing balance refers to the spatial relationship between the number of jobs and the number of housing units. An area is considered balanced if resident workers can get a job locally, and if available housing units can serve the needs of a variety of workers (Giuliano, 1991).

I also expect the cost of housing to play a role in the decision to commute because unaffordable housing increases local commutes (Plaut, 2006). However, two-earner households tend to have higher incomes, so they are more likely to be able to afford living closer to higher cost neighborhoods and to better schools, which results in a shorter commute (Iwata and Tamada, 2014; Sultana, 2005).

3.3 Data

In this study, I analyzed the commuting patterns of two-worker households from the 2017 National Household Travel Survey (NHTS), which gathered travel information from 129,112 households in all 50 States, the District of Columbia, and Puerto Rico from April 19, 2016, through April 25, 2017. The 2017 NHTS is comprised of a national sample of 26,000 households and 103,112 add-on partner households from thirteen States or MPOs. It provides detailed information about the socio-economic characteristics of its respondents and their households (U.S. Department of Transportation, 2018).

I focus in this study on five metropolitan areas (MSA) because they are in add-on states willing to share home and work location information with researchers: Los Angeles and San Francisco in California, Dallas and Houston in Texas, and Atlanta in Georgia (see Figure 3.1). An MSA is a region with a relatively high population density at its core and less dense surrounding areas that are economically and socially linked (Yao and Kim, 2019). Almost 30% of households in the NHTS data for these metropolitan areas are dual earners, which resulted in a sample of 4,271 households. Moreover, I obtained access to the location of the residence and the workplace of respondents, which enabled me to include more detailed land use characteristics in my models.

Since I want to investigate trade-offs between commuting time and housing costs within two-worker households, I selected the household as my basic unit of analysis. As the 2017 NHTS does not provide data on the income of each worker, I used gender to differentiate household workers, which means that I lost some observations from same gender couples.

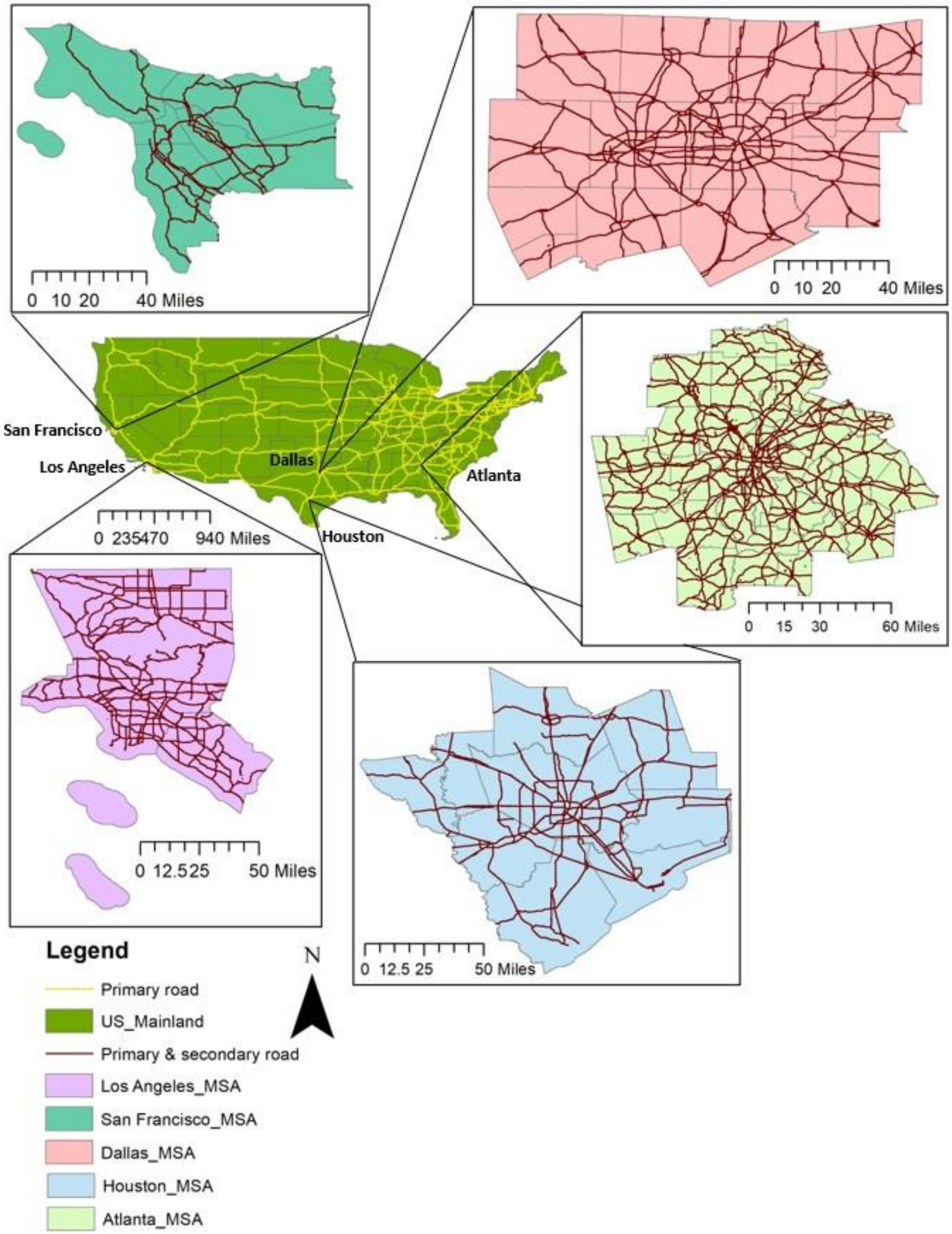

Figure 3.1: Location of five MSAs in the US

Table 3.1: Descriptive statistics for non-binary explanatory variables in five pooled MSAs (N=3,224)

Variables	**Mean**		**Std. Dev.**		**Min**		**Max**	
	Men	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*
Commute time (minute)	30.83	28.30	18.96	18.49	1.00	1.00	120.00	120.00
Ln (Commute time (minute))	3.22	3.11	0.70	0.73	0	0	4.79	4.79
Commute distance (km)	24.04	20.42	17.33	15.74	0.02	0.02	80.06	79.58
Ln (Commute distance (km))	2.81	2.63	1.05	1.03	-4.13	-4.13	4.38	4.38
Household size	2.86		1.09		2.00		10.00	
Land use variables around residence								
Median monthly housing cost ($1000)	1.63		0.58		0.42		4.00	
Job density (#1000/sq. km)	1.03		3.70		0		75.71	
Job-housing ratio	1.03		2.32		0.01		31.75	
Intersection density (#/sq. km)	3.77		5.40		0		67.51	
Distance to nearest transit stop (km)	5.81		8.89		0		126.90	
Distance to nearest subcenter (km)	13.65		12.59		0.17		159.66	
Land use variables around workplace								
Median monthly housing cost ($1000)	1.51	1.56	0.59	0.59	0.29	0.29	4.00	4.00
Job density (#1000/sq. km)	6.48	5.88	17.16	15.30	0	0	169.68	169.68
Job-housing ratio	7.76	6.40	14.96	11.10	0.01	0.01	257.10	116.40
Intersection density (#/sq. km)	5.36	5.30	6.22	6.22	0	0	67.51	67.51
Distance to nearest transit stop (km)	3.23	3.50	7.20	7.39	0	0	63.22	72.64
Distance to nearest subcenter (km)	9.09	9.42	11.75	11.75	0.03	0.02	87.00	86.00

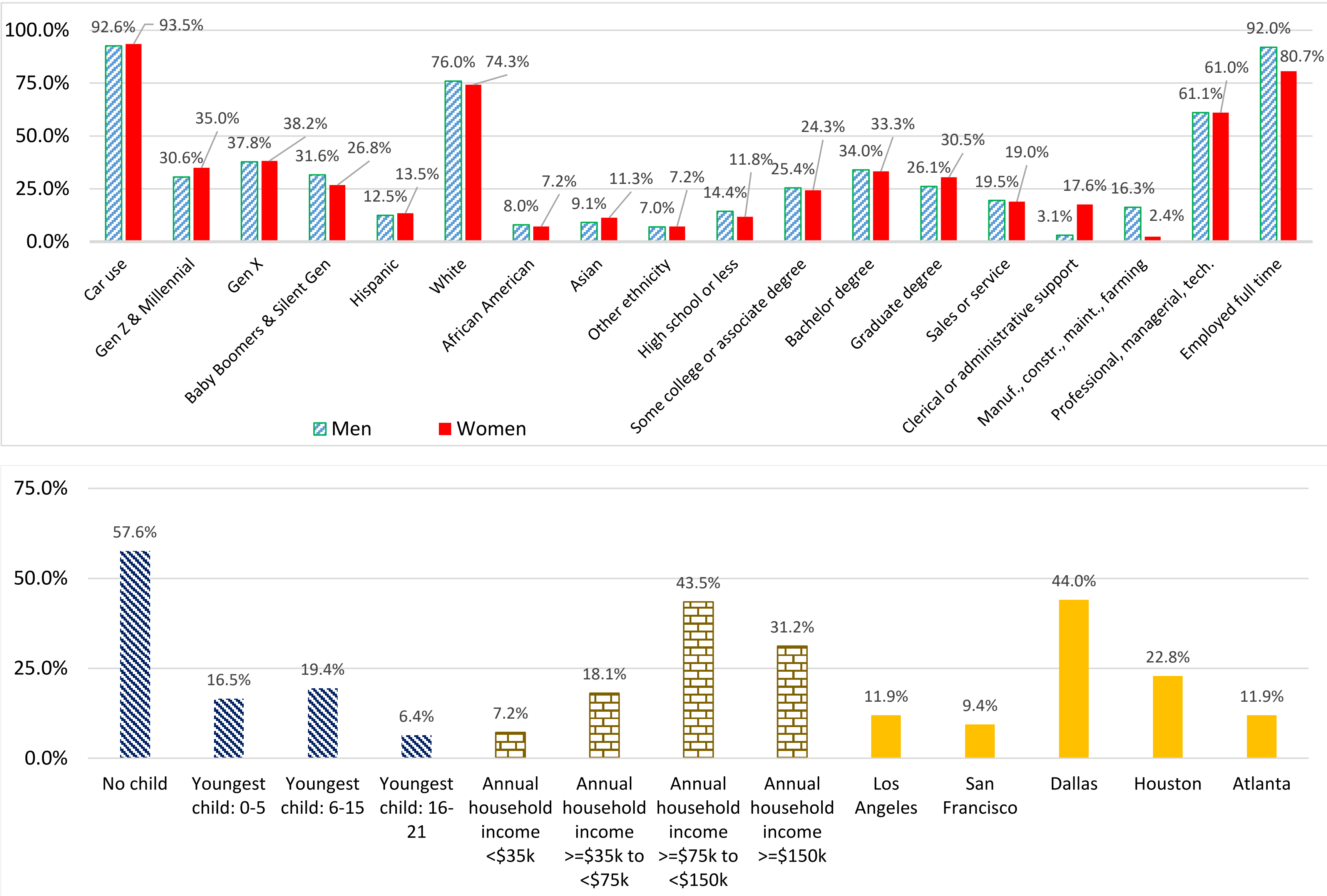

Figure 3.2: Descriptive statistics for binary explanatory variables (commuter and household variables) (N=3,224)

3.3.1 Dependent variables

My dependent variable is the duration of a usual one-way home to work trip (in minutes). It comes from the following 2017 NHTS question: "Thinking about daily commute to work last week, how many minutes did it usually take to get from home to job/work". From Table 3.1, I see that the average commuting time of men (30.8 minutes) is higher than for women (28.3 minutes) for the pooled data of my five MSAs. However, these averages vary widely by MSA, from 35.7 and 31.1 minutes for men and women respectively in San Francisco at the higher end, to 29.1 and 27.0 for Dallas at the lower end (details not shown for conciseness).

3.3.2 Explanatory variables

I organize my explanatory variables in two groups: commuter and household characteristics, and land use variables.

3.3.2.1 Commuter and household characteristics

I considered a broad range of commuter and household variables that characterize households and commuters based on data available in the 2017 NHTS dataset.

For simplicity, I reclassified the eleven income groups into four groups (Chidambaram and Scheiner, 2020; Jun and Kwon, 2015), which are shown in Figure 3.2. I also reclassified the categories for education into four groups: high school or less, some college or associate degree, bachelor's degree, and graduate professional.

To reflect the presence of children in the household, I defined four binary variables: no child, youngest child aged under 5, youngest child aged 6 to 15, and youngest child aged 16 to 21 years (de Meester and van Ham, 2009; Hjorthol and Vågane, 2014; Iwata and Tamada, 2014;

Wheatley, 2013). In line with other studies, I included household size as a count variable (Jun and Kwon, 2015).

To capture generational effects (Hjorthol and Vågane, 2014; Kim, 2022; Wheatley, 2014), I defined binary variables for the age of employed respondents based on definitions from the Pew Research Center (2018). I combined members from Generation Z (18-20 years) with Millennials (21-36 years), and members from the Silent Generation (72-89 years) with Baby Boomers (53-71 years) because the numbers of workers from Generation Z and Silent Generation respondents are small. Like Van Acker and Witlox (2011), I considered only workers 18 and older, as younger workers are likely to depend on their parents for where they reside and work.

For ethnicity, apart from Caucasian, African American and Asian, I lumped other ethnicities into "Other" because of their relatively small number. I did not change the education and occupation variables. Moreover, I included in our models the Hispanic status of the respondent, and full-time/part-time work status (Kim, 2022).

3.3.2.2 Land use characteristics

Most of the commuting studies I reviewed consider land use characteristics around residential areas only since commuting trips originate from residences (Chidambaram and Scheiner, 2020; de Meester and van Ham, 2009; Kim, 2022; Surprenant-Legault et al., 2013). Van Acker and Witlox (2011) showed that land-use around workplaces also significantly influences commuting by car, commuting distance, and commuting time. A few other studies also include land use characteristics around workplaces (Jun and Kwon, 2015; Sultana, 2005). I characterized land use around residences and workplaces using job density, intersection density, median monthly housing cost, distance to the nearest transit stop and to the nearest employment center. I also added a measure of the job-housing balance.

For density, I considered job density since it is more influential on commuting behavior (Van Acker and Witlox, 2011). I obtained job density at the census-tract level from the 2017 Longitudinal Employer-Household Dynamics (LEHD).

The intersection density variable was calculated by taking into account intersections with three or more links in each census tract (Cervero et al., 2010). For each residence and workplace in my sample, I computed the network distance to the nearest transit stop after obtaining road network data from the 2017 TIGER/Line shapefiles of the Census. I obtained transit stop data from the 2017 General Transit Feed Specification (GTFS) dataset (https://gtfs.org).

To capture job accessibility for each residence and workplace in my sample, I created distance to the nearest employment center. This measure is often used to examine commuting patterns in polycentric MSAs such as Atlanta, Dallas, and Houston (Schleith et al., 2019).

Like Hajrasouliha and Hamidi (2017) and Kim and Choi (2019), I used a '90%–10k' approach (90% refers to the job-density percentile and 10k is the minimum total subcenter employment) to detect subcenters from an analysis of 2017 LEHD data. In California, I found 41 subcenters in the Los Angeles MSA and 14 in the San Francisco MSA. These 55 subcenters offer a total of 3,419,086 jobs over 321 census tracts. In Texas, I found 20 subcenters in the Dallas MSA and 22 in the Houston MSA using the same approach. In these 42 subcenters, there are 2,659,346 jobs over 206 census tracts. For Atlanta, I found 19 subcenters, which offer a total of 1,040,829 jobs over 90 census tracts.

I used the most common measure of the job-housing balance in a census tract which is the ratio of the number of jobs to the number of resident workers (Cervero, 1989).

Finally, I obtained median monthly housing cost at the census tract level from the 2015-2019 American Community Survey.

3.3.3 Sample size

First, my commuting model for two-worker households was estimated with 3,224 households from the five pooled MSAs. I lost 921 observations, including 594 observations from same gender households, and 217 from missing median monthly housing cost around the workplace. In addition, I excluded 67 super-commuter households in which at least one worker commutes more than 50 mile one way (48) or whose commute time is over 120 min. Finally, I excluded 59 observations that had commuting times and distances reported as zero since I want to investigate trade-offs between commuting time and housing costs within two-worker households. Summary statistics are provided in Figure 3.2 and Table 3.1.

3.4 Methodology

3.4.1 Conceptual model

Most of the two-worker commuting studies I reviewed developed separate models for commuting distance, and time (Akbari and Habib, 2018; Hjorthol and Vågane, 2014; Jun and Kwon, 2015; Kim, 2022; Sultana, 2005; Surprenant-Legault et al., 2013; Wheatley, 2014). However, like de Abreu e Silva et al. (2012) and Van Acker and Witlox (2011), I assumed that commuting time depends on both commuting distance and mode, which led me to model commuting time as a function of commuting distance and commuting by car.

My conceptual model is shown in Figure 3.3. Since, I analyzed the impact of gender on commuting, I grouped individual socio-economic characteristics separately for men and women commuters in the same household, although they share common household characteristics. I assumed that the socio-economic characteristics of a commuter and their household characteristics impact their dwelling choice, whose characteristics (structural, locational, and environmental) are reflected in its price, in accordance with microeconomics theory. This is a long-term decision which, combined with the choice of a job (set outside of our model), determines commuting time and distance. For simplicity, I also assumed that the other land use variables (i.e., other than housing cost) are exogenous.

The choice of driving (instead of using another mode) to work depends on commuting distance since in the US, a longer commuting distance tends to favor driving (Cervero and Kockelman, 1997). Moreover, commuting distance, the decision to drive to work (as land use conditions the presence and the characteristics of other modes), and most importantly the commuting time are determined by land use characteristics around residences and workplaces. In line with Akbari and Habib (2018), Plaut (2006), and Surprenant-Legault et al. (2013), to explain the interactions between the commute characteristics of two-workers in the same household, I considered a two-way relationship between their commuting times.

To control for residential self-selection (namely the fact that households tend to choose their residential location based on their abilities, needs, and preferences for travel, as explained in Mokhtarian and Cao, 2008), commuter and household characteristics influence median monthly housing cost around the residence, which implies that these characteristics can indirectly affect commuting behavior via residential housing prices.

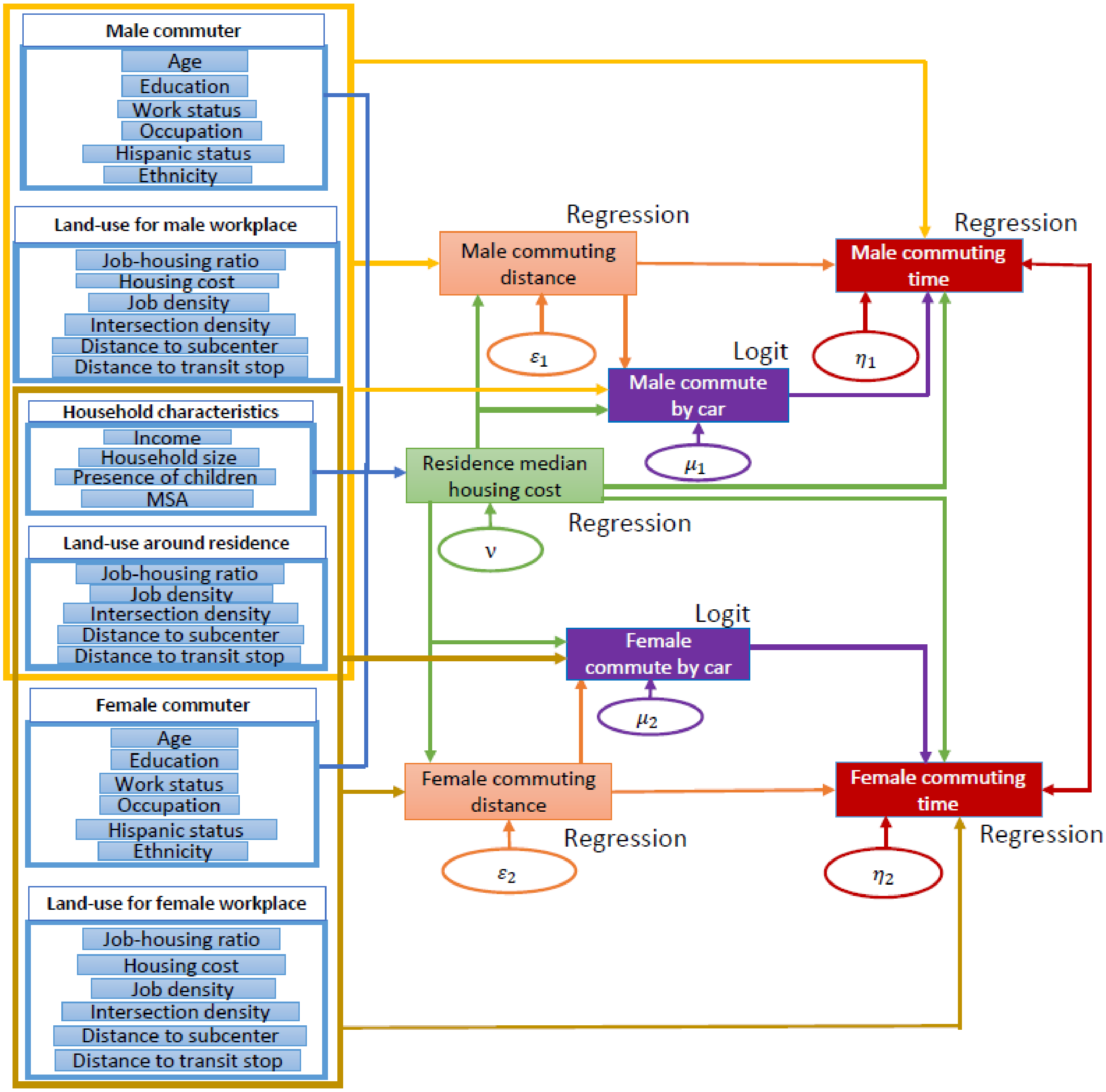

Figure 3.3: Conceptual model

3.4.2 Model

Structural Equation Models (SEM) can estimate the statistical relationships among a set of observed and unobserved variables (represented as latent factors) based on a theoretical model that reflects the influence of exogenous variables on endogenous variables, and the influence of endogenous variables on each other (Kline, 2015). My model is a system of seven simultaneous equations that reflect the causal paths shown in Figure 3.3:

Regression model for median housing cost around residence:

$$\boldsymbol{H} = \boldsymbol{X_{H1}}\boldsymbol{\Gamma_{H1}} + \boldsymbol{\nu}. \tag{1}$$

Regression models for commuting distance (k=1 for men, k=2 for women):

$$\boldsymbol{Ln}(\boldsymbol{D_k}) = \beta_{k1}\boldsymbol{H} + \boldsymbol{X_{Dk}}\boldsymbol{\Gamma_{Dk}} + \boldsymbol{\varepsilon_k}, \tag{2}$$

Logit models for commuting by car (k=1 for mean, k=2 for women; $i \in (1, \ldots, n\})$:

$$\boldsymbol{C_{ki}} = \begin{cases} \mathbf{1 \text{ if } C_{ki}^* > 0}, \\ \mathbf{0 \text{ if } C_{ki}^* \leq 0}, \end{cases} \quad \boldsymbol{C_k^*} = \gamma_{k1}\boldsymbol{H} + \gamma_{k2}\boldsymbol{D_k} + \boldsymbol{X_{Ck}}\boldsymbol{\Gamma_{Ck}} + \boldsymbol{\mu_k}, \tag{3}$$

Regression models for commuting time (k=1 for men, k=2 for women):

$$\boldsymbol{Ln}(\boldsymbol{T_k}) = \theta_{k1}\boldsymbol{H} + \theta_{k2}\boldsymbol{D_k} + \theta_{k3}\boldsymbol{C_k} + \theta_{k4}\boldsymbol{Ln}(\boldsymbol{T_{k-(-1)^k}}) + \boldsymbol{X_{Tk}}\boldsymbol{\Gamma_{Tk}} + \boldsymbol{\eta_k}, \tag{4}$$

In the above:

- n is the number of households in my sample;
- $\boldsymbol{H}$ is an $n \times 1$ vector of median monthly housing cost (in \$1,000) in the census tracts where commuters in my sample reside;
- $\boldsymbol{D_1}$ and $\boldsymbol{D_2}$ are n×1 vectors of commuting distances (km);
- $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ are n×1 vectors of 0s and 1s, with $\boldsymbol{C}_i$=1 if commuter "i" drives to work and 0 otherwise; $\boldsymbol{C_1^*}$ and $\boldsymbol{C_2^*}$ are the associated latent variables;
- $\boldsymbol{T_1}$ and $\boldsymbol{T_2}$ are n×1 vectors of commuting times (minutes);
- $\boldsymbol{X_{H1}}$, $\boldsymbol{X_{D1}}$, $\boldsymbol{X_{D2}}$, $\boldsymbol{X_{C1}}$, $\boldsymbol{X_{C2}}$, $\boldsymbol{X_{T1}}$, and $\boldsymbol{X_{T2}}$ are $n \times p_j$ matrices (where $j \in \{H, D, C, T\}$ matches the first index of $\boldsymbol{X_{jk}}$, k=1 or 2 where appropriate) of personal, household, land use around residence and workplaces, and MSA binary variables; they are assumed to be exogenous;
- β_{11}, β_{21}, γ_{11}, γ_{12}, γ_{21}, γ_{22}, θ_{11}, θ_{12}, θ_{13}, θ_{14}, θ_{21}, θ_{22}, θ_{23}, and θ_{24} are unknown model parameters to estimate jointly with the $p_j \times 1$ vectors $\boldsymbol{\Gamma}_{jk}$ (where $j \in \{H, D, C, T\}$ and k=1 or 2 where

appropriate); and

- $\boldsymbol{\nu}$, $\boldsymbol{\varepsilon_k}$, $\boldsymbol{\mu_k}$, and $\boldsymbol{\eta_k}$ are n × 1 error vectors.

H, ***D₁***, ***D₂***, ***C₁***, ***C₂***, ***T₁*** and ***T₂*** are endogenous. Since, there is no feedback loop in my conceptual model (see Figure 3.3), it is recursive. It is therefore identified and expected to converge (Kline, 2015). Unknown model parameters are estimated by minimizing the difference between the sample covariance and the covariance predicted by the model (Bollen, 1989).

SEM decomposes the impacts of exogenous and endogenous variables on the dependent variable into direct, indirect, and total effects. Direct effects quantify the impact of one variable on another without mediation. Indirect effects are mediated by at least one other variable. Finally, total effects are obtained by summing direct and indirect effects (Bollen, 1989).

3.5 Results

3.5.1 Univariate results

First, I used paired t-tests to detect statistically significant differences in the length of commutes (distance and time) of men and women in two-worker households within each MSA (Table 3.2). Second, I compare their values between MSAs using one-way analysis of variance (Table 3.3). For the latter, to find what pairs of means are significantly different, I used Tukey-Kramer post hoc tests (Ramsey, 2010) for pairwise testing of means in a one-way analysis of variance with unequal sample sizes as in Mitra and Saphores (2017).

From Table 3.2, I see that mean commuting distances (km) significantly differ between men and women in two-worker households for all MSAs, whereas mean commuting time (minutes) significantly differ between men and women only in San Francisco, Dallas, and Houston MSAs (they are shorter in all cases).

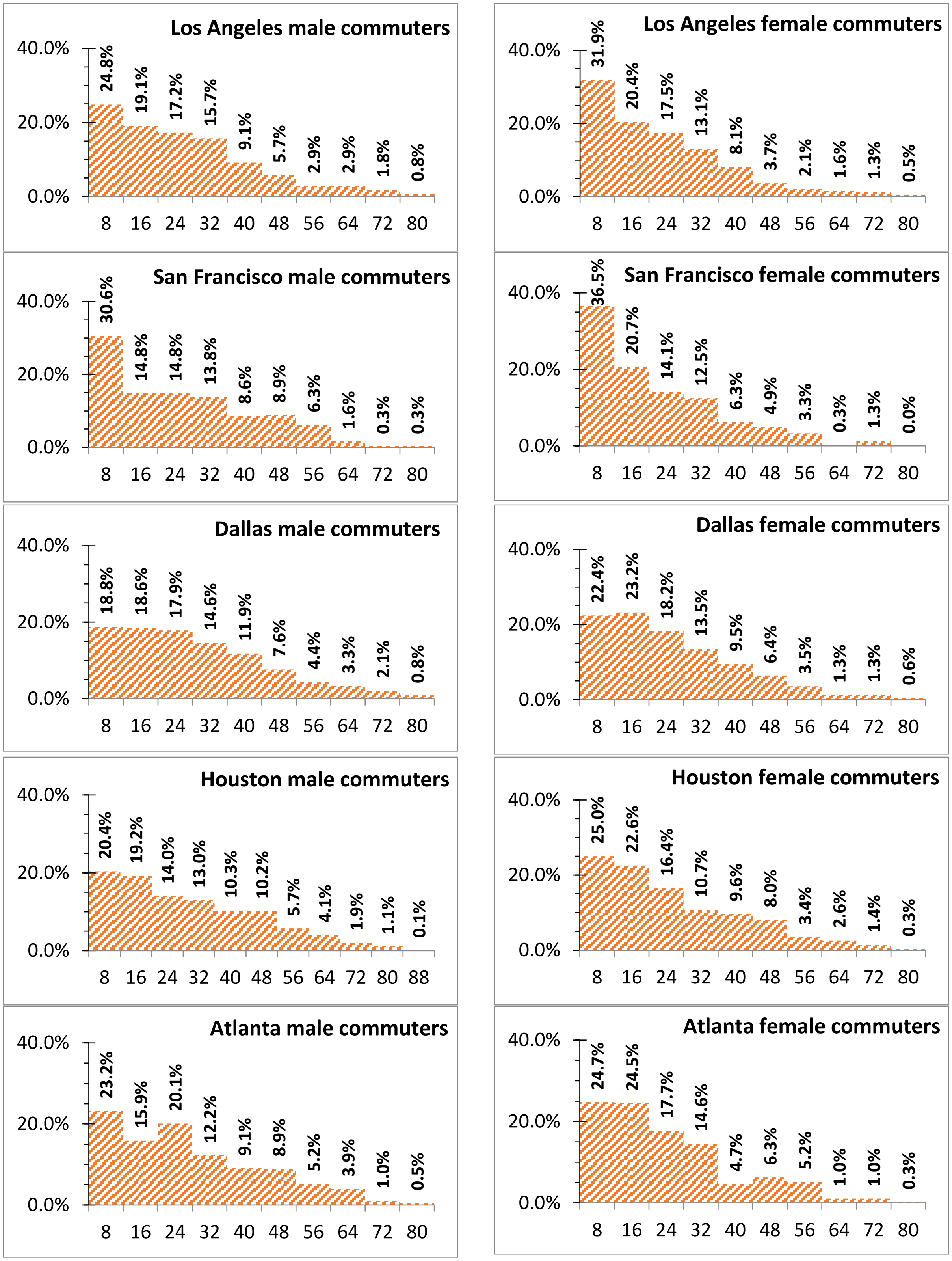

Figure 3.4: Distribution of commuting distance (km) by gender within each MSA

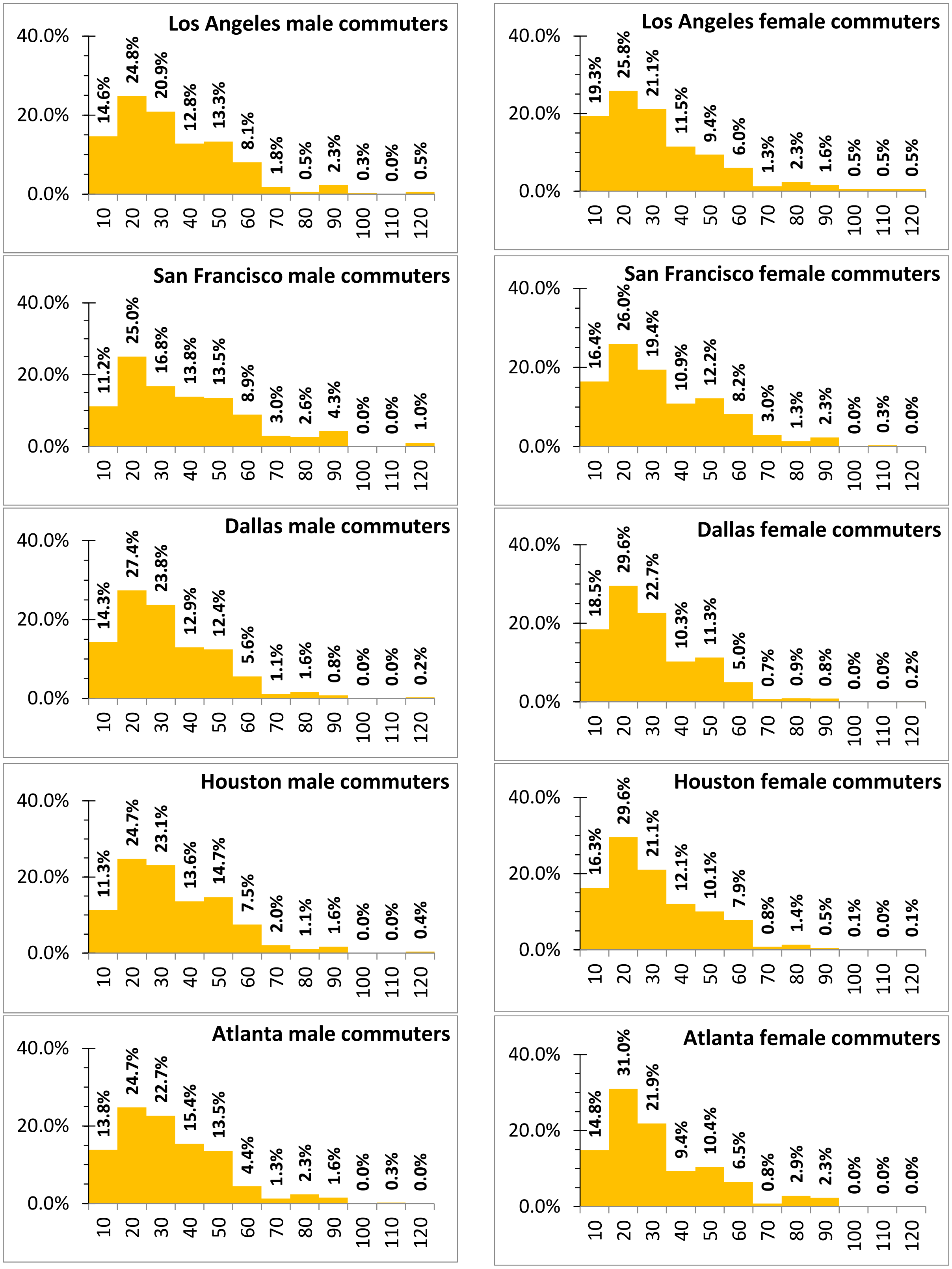

Figure 3.5: Distribution of commuting time (minutes) by gender within each MSA

Table 3.2: Paired t-tests of gender differences in commuting within each MSA

MSA	**Category**	**Mean commuting distance (km)**	**Statistical test (degrees of freedom) and significance**	**Mean commuting time (min)**	**Statistical test (degrees of freedom) and significance**
Los Angeles	Men	21.8	t(382) = 3.10‡	31.7	t(382) = 1.32
	Women	18.5		29.8	
San Francisco	Men	21.6	t(303) = 4.30‡	35.7	t(303) = 2.96‡
	Women	17.2		31.1	
Dallas	Men	24.6	t(1,416) = 6.48‡	29.1	t(1,416) = 3.60‡
	Women	21.2		27.0	
Houston	Men	25.5	t(735) = 5.28‡	32.0	t(735) = 4.42‡
	Women	21.4		28.2	
Atlanta	Men	23.4	t(383) = 3.19‡	30.5	t(383) = 0.76
	Women	20.2		29.6	

*, †, and ‡ indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 3.3: ANOVA tests of commuting differences by gender between MSAs (N=3,224)

MSA	**Mean commuting distance (km)**	**Statistical test (degrees of freedom) and significance**	**Mean commuting time (min)**	**Statistical test (degrees of freedom) and significance**
Men				
Los Angeles	21.8^{cd}		31.7^{b}	
San Francisco	21.6^{cd}		35.7^{acde}	
Dallas	24.6^{ab}	F(4, 3223) = 4.81‡	29.1^{bd}	F(4, 3223) = 9.08‡
Houston	25.5^{ab}		32.0^{bc}	
Atlanta	23.4		30.5^{b}	
Women				
Los Angeles	18.5^{cd}		29.8^{c}	
San Francisco	17.2^{cde}		31.1^{c}	
Dallas	21.2^{ab}	F(4, 3223) = 6.05‡	27.0^{ab}	F(4, 3223) = 4.68‡
Houston	21.4^{ab}		28.2	
Atlanta	20.2^{b}		29.6	

Notes: Superscripts ^{abcde} indicate values that are statistically significantly different using a Tukey-Kramer post-hoc test: ^{a} = different from the Los Angeles MSA; ^{b} = different from the San Francisco MSA; ^{c} = different from the Dallas MSA; ^{d} = different from the Houston MSA; ^{e} = different from the Atlanta MSA.
*, †, and ‡ indicate statistical significance at 10%, 5%, and 1%, respectively.

From Table 3.3, I see that mean commuting distances and times within genders differ between MSAs. Post-hoc tests show that mean commuting distances for male workers in the Los Angeles and San Francisco MSAs differ significantly from those of the Dallas and Houston MSAs (commute distances are shorter in California). The same is true for mean commuting distances of women, with the addition that the mean commuting distances in the San Francisco and Atlanta MSAs also differ significantly (it is shorter in San Francisco).

Mean commuting times tell a slightly different story. For men in the San Francisco MSA, it is significantly different (longer) than in the other four MSAs, whereas the mean commuting time of women in the Dallas MSA is significantly different (shorter) than in the Los Angeles and San Francisco MSAs.

3.5.2 SEM results

3.5.2.1 Overview

After preparing my dataset with Stata 17.0, I estimated my model with Mplus 8.9 because it offers more tools for SEM. Results are presented in Table 3.4 and Table 3.5. For conciseness, only significant results are reported. To obtain my results, I relied on the robust maximum likelihood (MLR) estimator (Muthén and Muthén, 2017), because many of my explanatory variables are binary and my commuting by car variables are categorical, so they are not normally distributed. As common fit statistics are not available for MLR estimation, I examined each individual equation, performed common diagnostic checks, and looked for influential observations.

Equation 1 is a linear regression model, so its interpretation is straightforward. Its dependent variable (median housing cost around the residence) is in thousands of dollars so to obtain the impact of changing an explanatory variable by one unit, its coefficient needs to be multiplied by 1,000 to get results in dollars.

Equations 2 and 4 are also linear regressions, but as indicated in the Methodology section, I log-transformed commuting distances (km) (Equation 2), and commuting times (min) (Equation 4), because the resulting models have lower AIC and BIC values. In my discussion of the results for Equations 2 and 4, I report exp(β_j)-1 in parentheses for quantifying the percentage change in the expected value of the dependent variable for a unit change in explanatory variable "*j*" if that variable was not itself log-transformed; otherwise, β_j is an elasticity, and I simply report its value preceded by "e=".

Equation 3 is a logit model, so I report results as odds ratios. The odds ratio for explanatory variable x_i is the ratio of the odds after changing x_i to x_i+1 (while keeping other variables constant) divided by the odds for the original explanatory variables; the odds is the probability that the dependent variable equals 1 divided by the probability that it equals 0. If x_i is binary, its value in the odds in the numerator is 1 and its value in the odds in the denominator is 0. To better link my discussion, I refer to the value of statistically significant odds by writing "OR=" before its value.

3.5.2.2 Robustness checks

To assess the robustness of my results, I explored several model specifications, including correlation structures between error terms of both commuting distances and between error terms of both commuting by cars, and some simple transformations (e.g., log transform) of my commuting variables. I also explored separate models for the California (Los Angeles and San Francisco), Texas (Dallas and Houston), and Georgia (Atlanta) MSAs but models for California and Georgia didn't converge because my sample size was not large enough. I used AIC and BIC (lower values are better) to obtain my preferred models, which are discussed below.

Table 3.4: SEM direct effects for pooled MSAs (N=3,224)

Variables	**Housing cost** (Coefficient)		**Ln(Commute distance)** (Coefficient)		**Commute by car** (Odds Ratios)		**Ln(Commute time)** (Coefficient)	
	I. Men	II. Women	III. Men	IV. Women	V. Men	VI. Women	VII. Men	VIII. Women
Ln(Commute time)	- -	- -	- -	- -	- -	- -	- -	- -
Ln(Partner Commute time)	- -	- -	- -	- -	- -	- -	0.068‡	0.041‡
Ln(Commute distance)	- -	- -	- -	- -	1.215‡	1.563‡	0.466‡	0.560‡
Generation (baseline: Gen Z & Millennial)								
Generation X	•	0.052†	•	-0.092†	•	•	•	•
Baby Boomers & Silent Generation	•	•	•	-0.117†	•	•	•	•
Hispanic status (1 if Hispanic)	-0.063†	-0.062†	•	•	1.628*	•	•	•
Ethnicity (baseline: Caucasian)								
African American	•	-0.135†	0.233‡	0.256‡	•	0.528*	•	•
Asian	•	•	•	•	•	0.631*	•	-0.056†
Other	•	•	•	•	•	•	•	•
Education (baseline: high school or less)								
Some college or associate degree	0.048†	0.053†	0.139†	0.110*	1.787*	•	-0.054*	•
Bachelor's degree	0.149‡	0.104‡	0.180‡	0.130†	•	•	•	•
Graduate degree	0.176‡	0.113‡	•	•	•	•	-0.060*	•
Occupation (baseline: Professional, managerial, or technical)								
Sales or service	•	•	-0.141‡	-0.194‡	0.678*	0.636†	•	•
Clerical & administrative support	•	•	•	•	•	•	•	•
Manufacturing, construction, maintenance, or farming	-0.072‡	•	•	0.301†	1.893*	•	•	•
Employment status: full time	•	-0.067‡	0.442‡	0.302‡	•	•	•	•
Commute by car	- -	- -	- -	- -	- -	- -	-0.304‡	-0.413‡
Annual household income (baseline: <$35k)								
$ 35k to $ 75k	0.070†		0.180*	0.194†	1.873*	•	•	-0.075†
$ 75k to $ 150k	0.217‡		0.250‡	0.243‡	1.893†	2.180†	•	-0.123‡
>$150k	0.392‡		0.179*	0.271‡	2.201†	2.229†	•	-0.129‡
Household size	•		•	•	•	•	•	•
Presence of children by age (baseline: no child)								
Youngest child 0-5 years	•		•	•	•	•	•	•
Youngest child 6-15 years	0.072†		0.103*	-0.160†	•	•	•	•
Youngest child 16-21 years	0.115‡		•	•	•	•	•	•

Variables	Housing cost (Coefficient)		Ln(Commute distance) (Coefficient)		Commute by car (Odds Ratios)		Ln(Commute time) (Coefficient)	
	I. Men	II. Women	III. Men	IV. Women	V. Men	VI. Women	VII. Men	VIII. Women
Land use (Residence)								
Median monthly housing cost	- -		0.070*	•	1.738‡	1.754‡	•	-0.035†
Job density	- -		-0.032‡	-0.037‡	0.928‡	0.938‡	0.007‡	0.010‡
Job-housing ratio	- -		•	•	•	•	•	-0.008†
Intersection density	- -		-0.013‡	•	0.975†	•	•	•
Distance to nearest transit stop	- -		0.008‡	0.009†	•	0.966*	•	•
Distance to nearest subcenter	- -		0.017‡	0.022‡	•	•	•	•
Land use (Workplace)								
Median monthly housing cost	- -	- -	•	•	•	•	•	•
Job density	- -	- -	•	•	0.957‡	0.960‡	0.002‡	•
Job-housing ratio	- -	- -	0.006‡	0.006‡	1.013†	0.986†	•	•
Intersection density	- -	- -	•	•	•	•	0.004‡	0.006‡
Distance to nearest transit stop	- -	- -	-0.009†	-0.012‡	•	•	-0.003†	-0.002*
Distance to nearest subcenter	- -	- -	-0.015‡	-0.020‡	1.042†	1.052†	-0.006‡	-0.007‡
MSA (baseline: San Francisco)								
LA	-0.275‡		•	0.161*	6.457‡	7.085‡	•	•
Dallas	-0.765‡		•	0.272‡	8.934‡	16.313‡	-0.084†	-0.167‡
Houston	-0.823‡		•	0.268‡	5.541‡	12.397‡	•	-0.141‡
Atlanta	-0.882‡		•	0.217†	4.846‡	8.114‡	•	•
Constant	1.811‡		1.835‡	1.790‡	-1.201	-0.944	2.064‡	2.192‡

1) *, †, and ‡ indicate statistical significance at 10%, 5%, and 1%, respectively.
2) "•": statistically non-significant coefficient; "- -": Not applicable for that model.
3) Median housing costs are in 1000$, times are in minute, distances are in km, job densities are in 1,000 per square km.
4) Maximum VIF is 6.59, so there is no issue with multicollinearity.
5) Log-likelihood = -15,766.7; AIC = 32,079.4; BIC = 33,738.8.

Table 3.5: SEM total effects for pooled MSAs (N=3,224)

Variables	**Housing cost** (Coefficient)		**Ln(Commute distance)** (Coefficient)		**Commute by car** (Odds Ratios)		**Ln(Commute time)** (Coefficient)	
	I. Men	II. Women	III. Men	IV. Women	V. Men	VI. Women	VII. Men	VIII. Women
Ln (Commute time)	- -	- -	- -	- -	- -	- -	- -	- -
Ln (Partner Commute time)	- -	- -	- -	- -	- -	- -	0.068‡	0.041‡
Ln (Commute distance)	- -	- -	- -	- -	1.215‡	1.563‡	0.407‡	0.377‡
Generation (baseline: Generation Z & Millennial)								
Generation X	•	0.052†	•	-0.092†	•	•	•	-0.175*
Baby Boomers & Silent Generation	•	•	•	-0.117†	•	•	•	•
Hispanic status (1 if Hispanic)	-0.063†	-0.062†	•		1.628*	0.937*	•	•
Ethnicity (baseline: Caucasian)								
African American	•	-0.135†	0.233‡	0.256‡	•	0.528*	•	0.396‡
Asian	•	•	•	•	•	0.631*	•	•
Other	•	•	•	•	•	•	•	•
Education (baseline: high school or less)								
Some college or associate degree	0.048†	0.053†	0.139†	0.110*	1.887†	1.082†	-0.054*	•
Bachelor's degree	0.149‡	0.104‡	0.190‡	0.130†	1.127‡	1.125‡	•	•
Graduate degree	0.176‡	0.113‡	0.012*		1.098†	1.088*	-0.060*	•
Occupation (baseline: Professional, managerial, or technical)								
Sales or service	•	•	-0.141‡	-0.194‡	0.678*	0.584†	•	•
Clerical & administrative support	•	•	•	•	•	•	•	•
Manufacturing, construction, maintenance, or farming	-0.072‡	•	•	0.301†	1.893*	1.132*	•	0.460*
Employment status: full time	•	-0.067‡	0.442‡	0.302‡	1.116‡	1.102†	0.164*	•
Commute by car	- -	- -	- -	- -	- -	- -	-0.304‡	-0.413‡
Annual household income (baseline: <$35k)								
$ 35k to $ 75k	0.070†		0.180*	0.194†	2.018†	1.134‡	•	-0.075†
$ 75k to $ 150k	0.217‡		0.266‡	0.243‡	2.248‡	2.757‡	•	-0.414‡
>$150k	0.392‡		0.206†	0.271‡	2.845‡	3.158‡	-0.251†	-0.468‡
Household size	•		•	•	•	•	•	•
Presence of children by age (baseline: no child)								
Youngest child 0-5 years	•		•	•	•	•	•	•
Youngest child 6-15 years	0.072†		0.103*	-0.160†	1.062†	•	•	•
Youngest child 16-21 years	0.115‡		•	•	1.075†	•	•	•

Variables	Housing cost (Coefficient)		Ln(Commute distance) (Coefficient)		Commute by car (Odds Ratios)		Ln(Commute time) (Coefficient)	
	I. Men	II. Women	III. Men	IV. Women	V. Men	VI. Women	VII. Men	VIII. Women
Land use (Residence)								
Median monthly housing cost	- -		0.070*	•	1.738‡	1.754‡	-0.157†	-0.257‡
Job density	- -		-0.032‡	-0.037‡	0.922‡	0.923‡	0.007‡	0.010‡
Job-housing ratio	- -		•	•	•	•	-0.032*	-0.008†
Intersection density	- -		-0.013‡	•	0.972†	•	•	•
Distance to nearest transit stop	- -		0.008‡	0.009†	1.002*	•	•	0.018†
Distance to nearest subcenter	- -		0.017‡	0.022‡	1.003†	1.010‡	0.007*	0.010*
Land use (Workplace)								
Median monthly housing cost	- -	- -	•	•	•	•	•	•
Job density	- -	- -	•	•	0.957‡	0.960‡	0.015‡	0.017‡
Job-housing ratio	- -	- -	0.006‡	0.006‡	1.014†	0.989*	•	0.008‡
Intersection density	- -	- -	•	•	•	•	0.004‡	0.006‡
Distance to nearest transit stop	- -	- -	-0.009†	-0.012‡	•	0.995†	-0.003†	-0.002*
Distance to nearest subcenter	- -	- -	-0.015‡	-0.020‡	1.039†	1.042†	-0.025‡	-0.035‡
MSA (baseline: San Francisco)								
LA	-0.275‡		-0.019*	0.161*	5.528‡	7.085‡	-0.580‡	-0.702‡
Dallas	-0.765‡		-0.053*	0.272‡	5.851‡	11.811‡	-0.698‡	-1.053‡
Houston	-0.823‡		-0.057*	0.268‡	3.526‡	8.662‡	-0.442‡	-0.890‡
Atlanta	-0.882‡		-0.062*	0.217†	2.930‡	5.355‡	-0.412‡	-0.578‡

1) *, †, and ‡ indicate statistical significance at 10%, 5%, and 1%, respectively.
2) "•": statistically non-significant coefficient; "- -": Not applicable for that model.
3) Median housing costs are in 1000$, times are in minute, distances are in km, job densities are in 1,000 per square km.

3.5.2.3 Direct effects

Housing cost (Equation 1; Columns I and II)

Only one age variable is statistically significant in the housing cost equation, and its impact is small: women workers who belong to Generation X live in neighborhoods where monthly housing costs are just $52 more than their Gen Z and Millennial counterparts. No generation variable is significant for commuting men workers.

Conversely, African American women commuters live in less valuable neighborhoods where monthly housing costs are on average $135 lower than White women workers. Likewise, Hispanic commuters tend to live in lower cost neighborhoods (-$63 for men, and -$62 for women).

Education matters as workers with more education tend to reside in higher cost neighborhoods. For men, monthly housing costs increase by $48 for those with some college or an associate degree, by $149 for those with a BA or a BS, and by $176 for workers with a graduate or professional degree. For women, the education premium grows more slowly: $53 for some college or an associate degree, $104 for a college degree, and $113 for a graduate or professional degree.

Conversely, men who work in manufacturing, construction, maintenance, or farming are less likely to live in higher cost neighborhoods (-$72) compared to their professional, managerial, or technical counterparts. I find similar results for full time employed women (-$67).

As expected, higher income households tend to live in more expensive neighborhoods. Compared to households who earn under $35,000 per year, monthly housing costs increase on average by $70 for households with incomes between $35,000 and $75,000, to $392 for those with an annual income over $150,000. Similarly, households with children live in slightly more expensive areas, which may reflect the value of better schools ($72 if the youngest child is between

6 to 15, and $115 if they are 16 to 21).

Finally, compared to the San Francisco MSA, median monthly housing costs are lower in other MSAs (-$275 for Los Angeles, -$765 for Dallas, -$823 for Houston, and -$882 for Atlanta.)

Commuting distance (Equation 2; Columns III and IV)

Starting with commuter characteristics, I see that no generation variable is significant from male commuters (column III). However, female Gen X, and Baby Boomers/Silent Generation workers have shorter (-8.8% and -11.0% respectively) commutes than Generation Z and Millennials workers (column IV), possibly because people commute increasingly less in their later years (Sun et al., 2017; Surprenant-Legault et al., 2013).

Ethnicity and education matter for men and women. African American workers tend to have longer commutes (26.2% for men, and 29.2% for women) than White workers. Likewise, commuters with some college education or associate degree (14.9% and 11.6% respectively), and a bachelor’s degree (19.7% and 13.9% respectively) commute further than commuters with only a high school education. Full time status further increases commuting distances for both men (+55.6%) and women (+35.3%) compared to part time status.

Conversely, workers in sales or service tend to commute less (-13.2% for men and -17.6% for women) compared to workers in the professional, managerial or technical category, because people in more locationally constrained careers have longer average commutes (Jun and Kwon, 2015; Sultana, 2005).

Household income has a prominent role on commuting distance, although its impact is not linear for men: it increases by 19.7% for incomes in [$35k, $75k], 28.4% for incomes in [$75k, $150k], but then decreases by 19.6% for incomes over $150k. For women, however, it increases monotonically with income, by 21.4% for incomes in [$35k, $75k] to 31.1% for incomes over

$150k. Since household income is associated with longer commutes for women, it helps reduce the gender gap in commuting (Chidambaram and Scheiner, 2020).

The presence of children in a household influences women's commuting distance more than men's. Women in households whose youngest child is between 6 and 15 have shorter commutes (-14.8%) compared to childless households, possibly because women balance work with childcare.

Let me now consider land-use variables. Residence monthly housing cost is positively associated with a longer commuting distance for men (7.3%), possibly because men commute longer to afford better housing. An increase of 1,000 jobs per sq. km around residences tend to reduce commuting distances (-3.1% for men, and -3.6% for women) possibly because a higher job density offers more job opportunities nearby. However, a higher workplace job-housing ratio tends to slightly increase both commuting distances (0.6% for both men and women).

A higher residence intersection density tends to reduce male commuting distance (-1.3%). Conversely, a higher residence distance to the nearest transit stop tends to slightly increase commuting distances (0.8% for men, and 0.9% for women) whereas workplace distance to the nearest transit stop shows the oppossite results (-0.9% and -1.2% respectively).

As expected, households who reside farther away from employment centers tend to have longer commutes (1.7% for men, and 2.2% for women). Conversely, people whose work location is farther from employment centers have shorter commutes (-1.5% for men, and -2.0% for women), which agrees with the findings of Surprenant-Legault et al. (2013).

Finally, MSA dummy variables are significant only for women. Compared to San Francisco, women workers in Los Angeles (17.5%), Dallas (31.3%), Houston (30.7%), and Atlanta (24.2%) tend to have longer commutes.

Commute by car (Equation 3; Columns V and VI)

First, I see that longer commutes increase the likelihood of commuting by car for both (OR= 1.215‡ for men, and 1.563‡ for women) since in the US, long distance favors driving as it is faster than transit. I note that Hispanic men tend to commute by car (OR=1.628*).

Ethnicity is significant only for female commuters. Both African American and Asian women tend to commute less by car (OR=0.528* and 0.631* respectively) than White women. Conversely, male commuters with some college education or an associate degree tend to commute more by car (OR=1.787*) compared to men with only a high school education.

Occupation matters for both men and women. Workers in sales and service tend to commute less by car (OR=0.678* for men, and 0.636† for women) than the baseline. As household income increases, so does the likelihood of commuting by car. For men, I found that the odds ratio increases from OR=1.873* for incomes in [$35k, $75k] to OR=2.201† for incomes over $150k. Similarly, for women it increases from OR=2.180† for incomes in [$75k, $150k] to OR=2.229† for incomes over $150k.

Several land use variables are statistically significant, but only median monthly housing cost has an odds ratio substantially different from one (it equals 1.738‡ for men and 1.754‡ for women). Other land use variables have a relatively small impact on commuting by car because their odds ratios are close to 1.

Finally, MSA dummies show significant results for both. Compared to San Francisco, commuters in Los Angeles (OR=6.457‡ for men, and 7.085‡ for women), Dallas (OR=8.934‡ for men, and 16.313‡ for women), Houston (OR=5.541‡ for men, and 12.397‡ for women), and Atlanta (OR=4.846‡ for men, and 8.114‡ for women) are more likely to commute by car, possibly because of local governments in the Bay Area have invested in transit, carpool, active modes, and priced parking to discourage driving into denser areas.

Commuting time (Equation 4; Columns VII and VIII)

First, I see that the cross elasticities of commuting times are positive, which means that the durations of commuting trips both increase or decrease together, but these cross-elasticities are quite small (0.068‡ for men and 0.041‡ for women).

As expected, longer commutes take more time for both (e=0.466‡ for men, and e=0.560‡ for women) while driving reduces commuting time by 26.2% and 33.8% respectively because other modes (e.g., transit) are typically slower.

Interestingly, there are no generational or occupational effects, but ethnicity and education have influence. Asian women (-5.4%) tend to have faster commutes compared to similar White women, and so do men with some college or an associate degree (-5.3%) or a graduate degree (-5.8%) compared to otherwise similar men with only a high school education.

Household income plays a significant role in commuting time only for women. Their commuting time decreases with household income, from 7.2% for incomes in [$35k, $75k] to 12.1% for incomes over $150k although when their income increases, they tend to commute farther (see Column IV of Table 3.4). Household size and the presence of children are not significant here.

Several variables characterizing land use around residences are statistically significant. First, I see that for households who can afford more expensive neighborhoods, the commuting time of women workers is on average 3.4% faster per additional $1,000 in median monthly housing costs. This finding is consistent with the standard urban economic theory framework, where households make trade-offs between commuting and housing costs. Second, job density is positively associated with commuting times (0.7% for men, and 1.0% for women) as a higher concentration of jobs typically results in more congestion. Third, a higher job-housing ratio around residences reduces the commuting time (-0.8%), but only for women.

Some workplace land use variables are also statistically significant, but their magnitude is smaller than for residential land use variables, and with the exception of job density, their sign and magnitude is not gender dependent. A higher intersection density around commuter workplaces entails more time-consuming commutes (0.4% for men, 0.6% for women). In addition, just as for commuting distance (see Columns III and IV), commuting time decreases with the workplace distance to the nearest transit stop (-0.3% for men, -0.2% for women), and to the nearest employment center (-0.6% for men, -0.7% for women), possibly because they can avoid the brunt of peak hour congestion at job centers.

There are also some MSA-wide effects. Dallas workers tend to have faster commutes (-8.1% for men, and -15.4% for women) than similar San Francisco workers, and so do women in Houston (-13.2%).

3.5.2.4 Indirect and total effects

Table 3.5 reports total effects. For conciseness, indirect effects are not shown separately since they can be calculated as the difference between total and direct effects. In this sub-section, I discuss total effects for variables with significant indirect effects, which are shaded in grey in Table 3.5.

Given the structure of my model (see Figure 3.3), there are no indirect effects for Equations 1 (“Residence median monthly housing cost”) and 2 (“commuting distance”) for women since no explanatory variable is endogenous in the former and the median monthly housing cost variable is not statistically significant in the latter.

However, indirect effects (via the monthly housing cost) matter in the "commuting distance" equation for men (Column III of Table 3.5). First, I see that male workers with specific education levels (20.9% for bachelor and 1.2% for graduate degrees) have longer commutes, although income effects also come into play. Indeed, male workers with a higher income (30.5% and 22.9% for household incomes in [$75k, $150k] and over $150k, respectively) tend to commute farther than baseline workers. Moreover, compared to San Francisco, male workers in Los Angeles (-1.9%), Dallas (-5.2%), Houston (-5.5%), and Atlanta (-6.0%) have slightly shorter commutes.

Indirect effects for the "Commute by car" equation (Columns V and VI) come from both the "Commuting distance" and the "monthly housing cost" variables. I see that education has substantial indirect and positive effects (OR>1) on commuting by car for both commuters. Moreover, women in sales or services are less likely to commute by car than baseline workers (OR=0.584†). Full-time status impacts commuting by car only indirectly for men (OR=1.116‡) and women (OR=1.102†). Indirect effects also reinforce the impact of income variables on commuting by car for both men and women. Finally, MSA variables are still positively associated (OR>1) with both men and women for commuting by car after negative indirect effects.

In the "Commuting time" equation (Columns VII and VIII), indirect effects come from the "Commute by car," "Commute distance" and "Median monthly housing cost" variables. I see that commuting distances are still positively associated for men (e=0.407‡) and women (e=0.377‡) with commuting times despite negative indirect effects. Indirect effects from generation and race variables substantially impact women's commuting time. Compared to Generation Z and Millennial commuters, female Generation X workers (-16.1%) have faster commutes while African American women have substantially longer commutes (+48.6%). Employment in manufacturing, construction, maintenance, or farming lengthens (+58.4%) the commute time of women. Interestingly, full-time employment increases the commuting time (+17.8%) of men. Moreover, indirect effects reinforce the impact on women's commuting time for two income variables (-33.9% for [$75k, $150k], and -37.4% for >$150k) and on men's commuting time in the upper income range (-22.2% for >$150k).

Several land use variables have significant indirect effects. Higher median monthly housing costs around the residence are associated with faster commutes for men (-14.5%) and women (-22.7%) for each additional $1000, but workplace median monthly housing costs do not matter. A higher job density around both workplaces tend to increase the commute time slightly (1.5% and 1.7% respectively). However, a higher residence job housing ratio tends to reduce men's commuting time (-3.1%) while distance from home to the nearest subcenter shows the opposite effect (0.7%). Moreover, women's commuting time rises mildly with an increase of the workplace job-housing ratio (0.8%), with a higher residence distance to the nearest transit stop (1.8%) and to the nearest subcenter (1%). Moreover, workers of either gender who work farther from a nearest subcenter tend to have faster commutes (-2.5% for men, and -3.4% for women). Finally, compared to San Francisco, workers in other MSAs have faster commutes on average.

3.6 Conclusions

In this study, I estimated a structural equation model on 2017 NHTS data for five metropolitan areas in three US states - Los Angeles and San Francisco in California, Dallas and Houston in Texas, and Atlanta in Georgia - to tease out the impact of gender on commuting in two-worker households. My model jointly explains commuting distance and time, accounts for residential self-selection and the endogeneity of commuting by car, while controlling for commuter and household characteristics, and land use around residences and workplaces.

My results show that households who can afford more expensive neighborhoods have a faster commute (-14.5% for men, and -22.7% for women) per additional $1000 to median monthly housing cost in the census tract of their residence. Housing costs around workplaces do not impact commuting time in my model. This suggests that longer commutes are to some extent a consequence of high housing costs in MSAs. The job-housing ratio has a significant but small impact on commutes, possibly because housing near employment centers tends to be expensive.

Moreover, my study contributes to the debate on whether there is a trade-off or complementary effect between male and female commutes in two-worker households (Plaut, 2006; Surprenant-Legault et al., 2013). My results show that their commuting times are slightly complementary (e=0.041‡ and 0.068‡ respectively), which means that commute trip durations are adjusted together. This complementary effect may reduce the commuting gender gap in two-worker households.

My results also show that age, ethnicity, and income explain the commuting time of women more than for men. Compared to Generation Z and Millennial, female Generation X workers tend to have faster commutes (-16.1%), while African American women (48.6%) tend to have more time-consuming commutes than White women. Moreover, women in the top income brackets tend to have faster commutes than their lower income counterparts as they have more choices when selecting the location of their residence in relation to their workplace.

The presence of children in a household is more influential on the commuting distance of women than of men. In households whose youngest child is between 6 and 15, women have shorter commutes (-14.8%) than those in childless households, which implies that female commuters have to balance work with child-care.

Finally, MSA binary variables indicate substantial heterogeneity between MSAs for both men and women commuters. Compared to San Francisco, commuters in Los Angeles, Dallas, Houston, and Atlanta are more likely to commute by car. Although delay per US auto commuter was highest in Los Angeles (119 hours) in 2017 (Texas A&M Transportation Institute, 2017), higher gasoline and parking costs (Shaheen et al., 2016), and high bridge tolls (on July 1, 2010, the Bay Area Toll Authority raised the tolls on the seven state-owned bridges in the Bay Area) made it more expensive to drive in San Francisco (Cervero, 2012). My results show that commuters in Los Angeles, Dallas, Houston, and Atlanta tend to have faster commutes than San Francisco workers, possibly because transit is typically slower than driving.

This study is not without limitation. The number of respondents in the 2017 NHTS in the Los Angeles, San Francisco, and Atlanta MSAs prevented us from estimating a separate model for each MSA. Moreover, individual income for each worker is not available in the 2017 NHTS, although it would really be useful to explain the gender gap in commuting (Kim, 2022).

There are multiple avenues for future research. First, it would be of interest to analyze changes in commuting in two-worker households over time (a panel dataset with commuting data would be useful). Second, to shed some light on commuting dynamics, it would be of interest to examine changes in residence and employment location over time (Blumenberg and King, 2019). Third, it is important to examine the impact of attitudes and lifestyle (e.g., pro-transit or pro-active mode behavior) on commuting. Finally, instead of gender, it would be of interest to explore the variations in commuting with respect to education and occupation potentials of both men and women (Hjorthol and Vågane, 2014).

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Chapter 4. Will COVID-19 Jump-start Telecommuting? Evidence from California

4.1 Introduction

Health concerns and government restrictions have caused many people around the world to work from home during the COVID-19 pandemic, resulting in a sharp increase in telecommuting (i.e., doing paid work facilitated by information and communication technologies (ICT) from a location that is not the regular workplace, mostly home and possibly an alternate worksite). The term "telecommuting" is attributed to Jack Nilles, who proposed it in the 1970s as a way to reduce energy consumption and alleviate traffic congestion (Allen et al. 2015).

In addition to reducing vehicle miles traveled (VMT), decreasing energy use, and lowering emissions of air pollutants and greenhouse gases (GHG), proponents of telecommuting argue that it offers numerous co-benefits, including increasing the worker pool, generating transportation time and money savings, providing more time flexibility, improving work-life balance, and decreasing stress (Gajendran and Harrison 2007). It may also stimulate non-motorized and active modes (e.g., see Haddad et al. 2009; Lachapelle et al. 2018).

However, telecommuting may also affect promotion opportunities and ties with colleagues (Baert et al. 2020), physical health (Kubo et al. 2021), mental health (Escudero-Castillo et al. 2021), work-life balance for families with children (since child-care and school facility did not operate normally during the pandemic) (Sousa-Uva et al. 2021; Tavares et al. 2021), and even work productivity (Farooq and Sultana 2021). Moreover, the work travel savings from telecommuting may stimulate additional non-work travel (Elldér 2020). Telecommuting may also increase commuting duration and length (Elldér 2020; Melo and de Abreu e Silva 2017;

Mokhtarian et al. 2004) because telecommuters tend to live in more suburban areas, usually associated with lower levels of transit supply and a higher likelihood of car use.

Although, a large body of literature has analyzed telecommuting before COVID-19 (e.g., see Allen et al. 2015, Elldér 2020, or Mokhtarian et al. 1998, and the references herein), to the best of my knowledge, a quantitative assessment of how COVID-19 impacted telecommuting in California and how telecommuting frequency may evolve after the pandemic are still missing from the literature. The purpose of this essay is to start filling this gap.

California, which ranks as the fifth largest economy in the world, is an important state to study telecommuting because it is at the forefront of environmental and social issues in the US, and telecommuting can help address congestion, air pollution, and global climate change. California is also home to some of the largest and most innovative technology companies in the World (e.g., Google, Apple, Facebook.) These companies, and others such as Zoom, have played a significant role in driving the growth of telecommuting and remote work, and have also been leaders in implementing and refining the technologies that make telecommuting possible.

In this study, I analyzed how the frequency of telecommuting changed in California during the pandemic compared to before, and how it may evolve after COVID-19. Whereas most papers on telecommuting during the pandemic relied on non-random samples, my dataset was collected at the end of May 2021 by Ipsos, which randomly sampled Californian members of KnowledgePanel© (KP), the oldest and largest probability-based online panel in the US, so my results can be generalized to the California population. Moreover, my analysis covers a longer stretch of the pandemic (March 2020 to May 2021) than many other studies published until the end of 2022, and my structural equation models jointly explain car ownership, housing costs (thus accounting for residential self-selection), and telecommuting frequency.

Quantifying changes in telecommuting is important for updating sustainable community strategies and gauging telecommuting's likely contribution to meeting California's GHG reduction targets (Kallerman and Weinberg 2016). Moreover, my analysis of telecommuting frequency for different socio-economic groups and occupations should help policymakers concerned about the impacts of the pandemic on different segments of the labor market (Albanesi and Kim 2021).

In the next section 4.2, I review selected papers to inform my modeling choices. I then describe my data (section 4.3) and present my methodology (section 4.4), before discussing the results (section 4.5). In the last section 4.6, I summarize my conclusions, discuss some policy implications, and suggest alternatives for future research.

4.2 Literature review

4.2.1 Background on Telecommuting

As noted by Allen et al. (2015), although researchers have been studying telecommuting for decades, they have used various terminologies (e.g., distance work, flexplace, remote work, telework, or virtual work) and conceptualizations when reporting their results, which has hindered our understanding of telecommuting by making results difficult to compare across studies.

Telecommuting has been of interest to transport researchers since Nilles (1973) proposed it to reduce traffic congestion, sprawl, and the use of scarce non-renewable resources. Although telecommuting emerged during the 1973 OPEC crisis, it started developing in earnest in the US in the 1990s, first with the 1992 Interagency Telecommuting Pilot Project, which aimed to popularize external telecenters for government agencies in Washington D.C., and then with the 1996 National Telecommuting Initiative, which attempted to reenergize telecommuting among federal workers (Joice 2000) . It also received a boost in the US from the 1990 Clean Air Act Amendments, which motivated large businesses to offer telecommuting to their employees. In the last two decades, telecommuting has been proposed as a possible travel demand management strategy thanks to developments in ICT. In 2019, almost a quarter of American workers did some of their work at home (Coate 2021). Globally, the percentage of employed persons who telecommute varied widely pre-pandemic. The corresponding percentages in the EU-27 and in Japan were only 9% and 10% in 2019, respectively, possibly because car commuting, which is one of the main reasons for promoting telecommuting in the US, is less prevalent in the EU and in Japan than in the US (European Union 2020; OECD 2021). Moreover, I note that jobs that can be performed with a computer and an internet connection are much more likely to lead to remote work arrangements.

Unfortunately, past efforts to increase telecommuting to deal with urban congestion have often yielded disappointing results (Noonan and Glass 2012). One reason might be that work trips are only 17.4% of all trips, which rises to 37.5% during morning and evening peaks (US Department of Transportation 2018). Another reason could be the low adoption rate of telecommuting (Coate 2021). Telecommuting may also be ineffective for reducing VMT because it often stimulates additional non-work travel (Elldér 2020).

Empirical findings show that various factors influence telecommuting. In addition to worker preferences, they include personal and household characteristics, and land use characteristics around home (Sener and Bhat 2011; Singh et al. 2013; Zhang et al. 2020). I examine them in turn below.

Only a handful of empirical studies have controlled for residential self-selection (namely the fact that households tend to choose their residential location based on their abilities, needs, and preferences for travel; see Mokhtarian and Cao 2008) and accounted for the endogeneity of car ownership (de Abreu e Silva and Melo 2018b; de Abreu e Silva and Melo 2018a). It is well-known that ignoring self-selection and the endogeneity of explanatory variables may bias estimates of model coefficients, which in this context would alter my understanding of the determinants of telecommuting (He et al. 2015).

4.2.2 Personal and household characteristics

The telecommuting literature suggests that socio-economic characteristics are important to characterize telecommuters, but their impact is not always clear. For example, Mokhtarian et al. (1998) found that women tend to telecommute more than men because of their extra family duties, but Bonacini et al. (2021); Fu et al. (2012); Pouri and Bhat (2003) found the opposite.

Age is another factor associated with telecommuting. Generally, middle-aged people (i.e., 36-50 years old) tend to telecommute less than workers under 35 because they are more likely to have managerial responsibilities that require their presence in the workplace (Sener and Reeder 2012; Singh et al. 2013). Conversely, employees with more experience working independently are more likely to telecommute (Peters et al. 2004; Sener and Bhat 2011; Zhang et al. 2020). In fact, some studies argue that workers over 50 years tend to prefer telecommuting (Bonacini et al. 2021; Fu et al. 2012).

Workers with higher education levels may be more likely to telecommute because they are in a better position to negotiate with their employers (Singh et al. 2013; Zhang et al. 2020), whereas less-educated workers tend to have jobs where telecommuting is not possible (Dey et al. 2020). Likewise, workers with a higher income may have greater access to the tools necessary for telecommuting, and thus may be more inclined to do so (Bonacini et al. 2021; Loo and Wang 2018; Sener and Reeder 2012; Zhang et al. 2020). Conversely, many low-income workers have manual and blue-collar jobs in sectors where telecommuting is unfeasible (He and Hu 2015; Sener and Bhat 2011; Singh et al. 2013).

Occupation thus matters for telecommuting. People in services are more likely to telecommute than those working in sales, manufacturing, trade, transport and communication (Sener and Bhat 2011; Singh et al. 2013; Zhang et al. 2020). Moreover, part time jobs may be more flexible so they may be more conducive to telecommuting (Felstead and Henseke 2017), although Abendroth and Reimann (2018) found the opposite.

Married people tend to favor telecommuting (Fu et al. 2012), and so do households with children (Bhuiyan et al. 2020; Fu et al. 2012; Singh et al. 2013) because of the added time flexibility it provides. Likewise, household size matters for telecommuting because workers in larger households tend to have more responsibilities which require them to spend more time at home (Fu et al. 2012; Yen 2000). However, it may be more challenging (e.g., finding a quiet place) for workers in larger households to work from home (Bhuiyan et al. 2020; Zhang et al. 2020).

Finally, African American and Hispanic workers tend to telecommute less since they are more likely to be in jobs for which telecommuting is not feasible (Dey et al. 2020).

4.2.3 Land use characteristics

Specific land uses may be more conducive to telecommuting because telecommuters tend to be located in suburban areas (Kim et al. 2012). As a result, they often have longer commutes than other workers (Zhu 2013; Zhu 2012). Telecommuting can be seen as a coping strategy, at least in the short term (Elldér 2020).

To organize my brief discussion of land use variables, I focus on density, diversity, design, destination/job accessibility, and distance to transit stops (Cervero et al. 2009; Cervero and Kockelman 1997; Ewing and Cervero 2010).

Density usually refers to the number of homes, people, or jobs per unit area. It is negatively associated with car ownership, and telecommuting frequency (Van Acker and Witlox 2011).

Diversity, or more specifically "land-use diversity," measures the degree of proximity of various land uses. One example is the job-housing balance, which refers to the spatial relationship between the number of jobs and the number of housing units. An area is considered balanced if resident workers can obtain a job locally, and if available housing can serve the needs of a variety of workers (Giuliano 1991). A better job-housing balance is believed to lower car ownership, and reduce telecommuting (Fu et al. 2012; Ma and Chen 2013; Van Acker and Witlox 2011).

Design refers to road connectivity, which is the degree of connectivity towards destinations. Better road connectivity promotes the use of driving for commuting which should decrease the probability of telecommuting (Bhuiyan et al. 2020; Fu et al. 2012).

Destination/job accessibility refers to the ability of reaching activities or locations (Geurs and van Wee 2004). Ewing and Cervero (2010), and Kockelman (1997) argued that good accessibility can significantly reduce commuting times, which may discourage telecommuting.

Finally, distance to the nearest transit stop may also matter for telecommuting because good transit accessibility favors commuting via transit and may thus reduce telecommuting (Caulfield 2015; Mouratidis and Peters 2022).

Like Islam and Saphores (2022) for commuting, I also expect the cost of housing to play a role in the decision to telecommute because unaffordable housing increases the length of commutes (Sultana 2002), and longer commutes is one of the determining factors of telecommuting (de Abreu e Silva and Melo 2018a-b).

4.2.4 Telecommuting during COVID-19

Stay-at-home restrictions due to COVID-19, better ICT, and an increasing emphasis on reducing VMT to decrease GHG emissions under SB 375 have made telecommuting a popular approach for addressing global health risks while allowing economic activity to continue (Nguyen 2021). As more data become available, the number of studies concerned with the impacts of the pandemic on telecommuting is growing. I review below some selected studies, starting with US studies.

Based on a nationally representative sample of around 50,000 respondents, Brynjolfsson et al. (2020) found that younger people are more likely to switch to telecommuting. Moreover, telecommuting is more prevalent in states with a higher share of ICT jobs.

Bick et al. (2021) reached slightly different conclusions from their analysis of data collected during an online nationwide survey with 46,450 respondents: for them, women, older, better educated, and higher income workers are more likely to telecommute. Moreover, while the share of workers who only telecommute jumped from 7.6% to 31.4% between February and May 2020, it declined back to 20.4% by the end of 2020.

Jiao and Azimian (2021) examined the relationship between socio-economic characteristics and telecommuting using Household Pulse Survey data collected between April 23, 2020, and March 1, 2021, by the US Census Bureau. They found that adults 35 or older are less likely to telecommute than those under 35, and that the likelihood to telecommute is higher in larger households and for people with an individual annual income over $100,000. Conversely, males, Whites, and workers without graduate degrees are less likely to telecommute.

Asfaw (2022) confirmed racial differences in telecommuting after analyzing data from the Current Population Survey (May 2020-July 2021): the odds of telecommuting for Black and Hispanic workers were 35% and 55% lower respectively than for White workers, and 44% higher for Asian workers.

After analyzing survey data from 4,045 residents of the greater Los Angeles region collected in the Fall of 2020, Malik et al. (2023) reported that non-telecommuters are more likely to be non-White, younger, and with a lower household income than telecommuters. Moreover, their use of motor vehicles and active travel modes increased for non-work travel.

A few studies from other regions are also directly relevant to our work. Astroza et al. (2020) analyzed data from 4,395 adults from Chile collected via an online survey in March 2020. They reported that workers from high-income households, with more education, and women are more likely to telecommute whereas workers from larger households and essential services are not.

In Australia, Beck et al. (2020) examined the frequency of telecommuting based on 2020 data. They concluded that a higher household income and living in large metropolitan areas increases the probability of telecommuting while working in some technical and trade occupations reduces it. In a related paper, after analyzing the impact of working from home on modal commuting in 2020 in two large Australian cities, Hensher et al. (2022) reported an increase in many types of non-commuting trips.

In Oslo, Norway, and the surrounding Viken region, Mouratidis and Peters (2022) found an increase in several teleactivities during the pandemic based on data collected in March-May 2020. While the increase in telework and virtual meetings was more pronounced in denser neighborhoods, lower density neighborhoods saw a sharper increase in online learning. Similarly, in Germany, Ecke et al. (2022) showed that public transport has lost importance for commuting, and that people with more education and a higher income are more likely to telecommute, which confirmed findings from another Germany study by Reiffer et al. (2022).

Two telecommuting studies covered multiple countries. The first one (4,628 observations from online panel surveys conducted between August and December 2020) covered eight countries (Balbontin et al. 2021). The authors reported that older people and women tend to telecommute more often in South America. A higher income increases telecommuting in Australia and Chile, and so does commuting time in Australia and South Africa. As expected, car availability has a negative impact on the number of telecommuting days. The second study analyzed data collected between March 23 and May 12, 2020 in fourteen countries (Shibayama et al. 2021). Results indicate that in workplaces with essential workers, the shift to telecommuting does not typically exceed 30%, whereas in workplaces compatible with telecommuting it reaches 60% to 80%.

Another strand of the literature explored whether telecommuting changes will stick after the pandemic. My paper selection emphasizes US studies but I also mention below some studies from Canada and the EU. Barrero et al. (2021) examined data from 28,597 Americans collected by the Survey of Working Arrangements and Attitudes. They found that employees with higher earnings and a better education tend to telecommute more, which reduces spending in major city centers but could increase productivity by 5% post-pandemic relative to before.

Mohammadi et al. (2022) analyzed two waves of survey data collected between April and October 2020, and from November 2020 to May 2021. They reported a shift in preferences for telecommuting post-pandemic for millennials, employees with long commutes, high-income earners, and highly educated workers.

Likewise, Javadinasr et al. (2022) analyzed data from a longitudinal two-wave panel survey conducted in the US between April 2020 and May 2021. They found that 48% of workers anticipate having the option to telecommute after the pandemic. These workers are mostly younger, with a higher education and/or a higher income, and they tend to be more concerned about the environment. As a result, car and transit commuting may drop by 9% and 31% after the pandemic compared to before.

Based on an online survey with 1028 respondents conducted in South Florida in May 2020, Asgari et al. (2022) reported substantial heterogeneity in preferences for telework across many variables. Before COVID-19, males, full-time students, people with PhDs, and those with a higher income were more likely to have jobs with a telework option. They were also more likely to be pro-technology, pro-online education, workaholic, and pro-telework. During the pandemic, workers with professional/managerial/technical jobs and with lower physical-proximity measures had the highest telework frequency. The authors also concluded that teleworking during the pandemic reshaped preferences for teleworking in the future.

Changes in telecommuting were also explored in other parts of the world. In the Canadian province of British Columbia, for example, Rahman Fatmi et al. (2022) found that part-time female workers, mid-age individuals, full-time workers with children, and full-time workers with longer commutes have a significantly higher probability of telecommuting every day after the pandemic. In the Netherlands, Olde Kalter et al. (2021) reported that office workers and teaching staffs were more likely to telecommute during the lockdown, but that after the lockdown, only office workers expected to experience increases in telecommuting. Also in the Netherlands, de Haas et al. (2020) reported that 27% of home-workers expect to telecommute more often in the future. However, In Padova, Italy, Ceccato et al. (2022) concluded that the end of COVID-19 could see a rebound effect with shifts towards non-sustainable modes (e.g., driving personal vehicles).

Based on this literature review, a quantitative assessment based on a random survey of how COVID-19 impacted telecommuting in California, and how telecommuting frequency may evolve after the pandemic are still missing from the literature.

4.3 Data

My dataset was collected in late May 2021 by Ipsos, which surveyed for me California members of KP. With approximately 60,000 members, KP is the oldest and largest probability-based online US panel. Owing to its size and the way its participants were recruited, its subset of Californian panelists is representative of the state’s population.

Conducting surveys using KP offers several advantages (Ipsos 2021). First, it helps to overcome non-response bias because survey cooperation rates (i.e., the ratio of panelists who take the survey to the number of panelists invited) typically exceed 70%. Second, it reduces survey fatigue because panelists are only required to participate in two to three surveys per month on average. Third, this approach helps overcome the self-selection bias inherent in online surveys because KP members are recruited using address-based mail sampling based on the Delivery Sequence File of the US Postal Service. Special care is taken to recruit harder-to-reach groups, such as African Americans, Latinos, Veterans, Americans with disabilities, LGBTQ and non-binary people, rural residents, and non-internet households. Upon enrolling, the latter receive a tablet with a mobile data plan. The socio-economic characteristics of panel members are recorded when they enroll and updated annually so they do not need to be collected during surveys.

4.3.1 Questionnaire

My questionnaire had two parts. In Part I, I inquired about commuting and telecommuting before, during, and potentially after the COVID-19 pandemic. In Part II, I explored how Californians shopped for groceries and prepared meals during the same periods.

My questionnaire was first written in English and pre-tested by graduate students. Ipsos then conducted a pilot study with 25 California members of KP in early May 2021. I modified our questionnaire to include the feedback received. The median completion time was 12 minutes.

To include Californians more comfortable with Spanish (according to the US Census Bureau, ~30% of Californians speak Spanish at home, and 55% English), I translated my survey in Spanish and pre-tested it with native speakers. Both versions of the survey were administered in late May 2021. Data collection was stopped after receiving answers from 1,026 respondents.

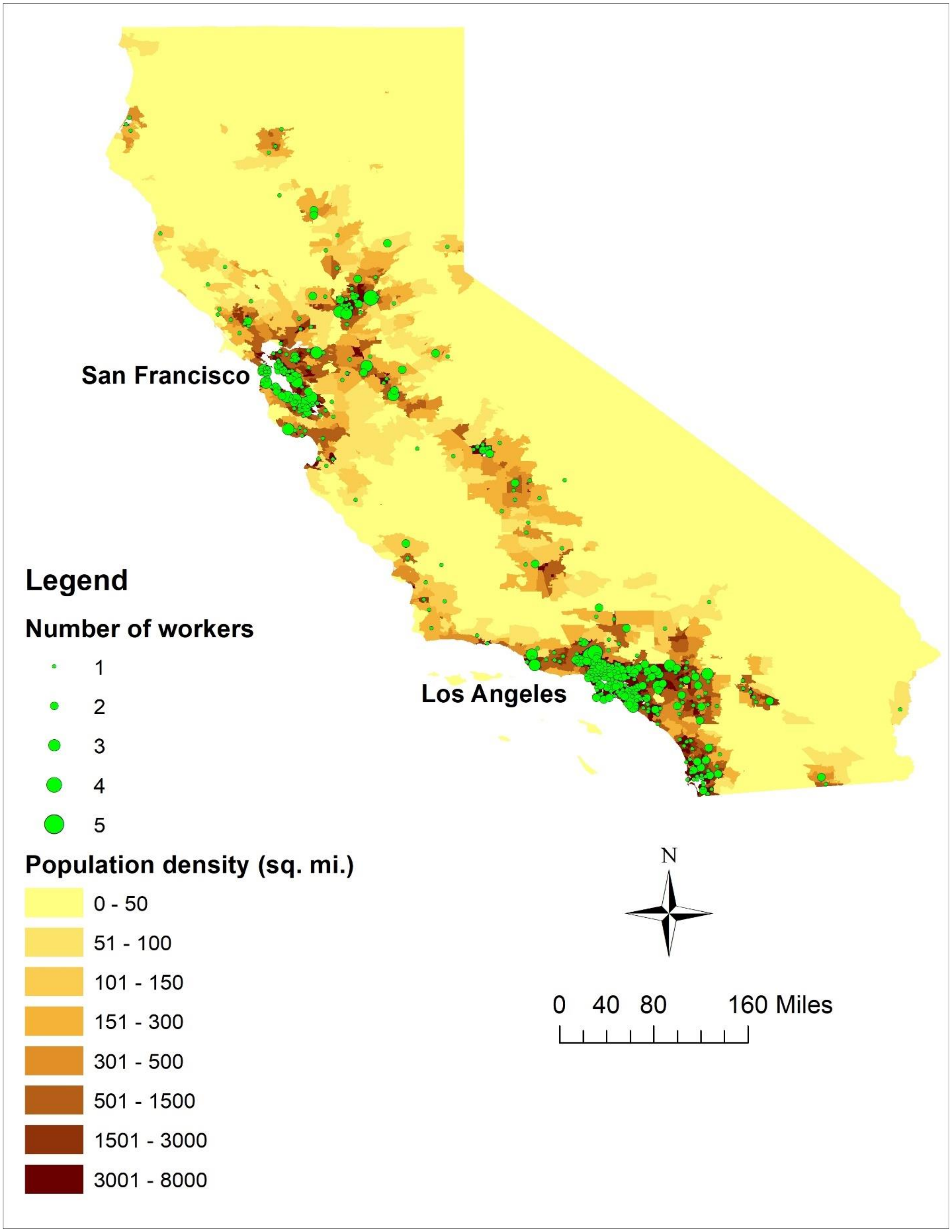


Figure 4.1: Home location of employed respondents in each ZIP code

KP members must remain anonymous, but I was allowed to ask for their residential and work (when applicable) ZIP codes, which allowed me to derive land use variables and add them to my models. Figure 4.1 shows the residential locations of employed Californians in my sample. As expected, more respondents (the size of a green dot is proportional to the number of workers who live in a ZIP code) reside in more populated areas (e.g., Los Angeles and the Bay area), but I also have employed respondents in central California, which is much more thinly populated.

4.3.2 Survey timing and COVID-19

To contextualize the timing of this study, it is useful to look back at the evolution of the pandemic in California.

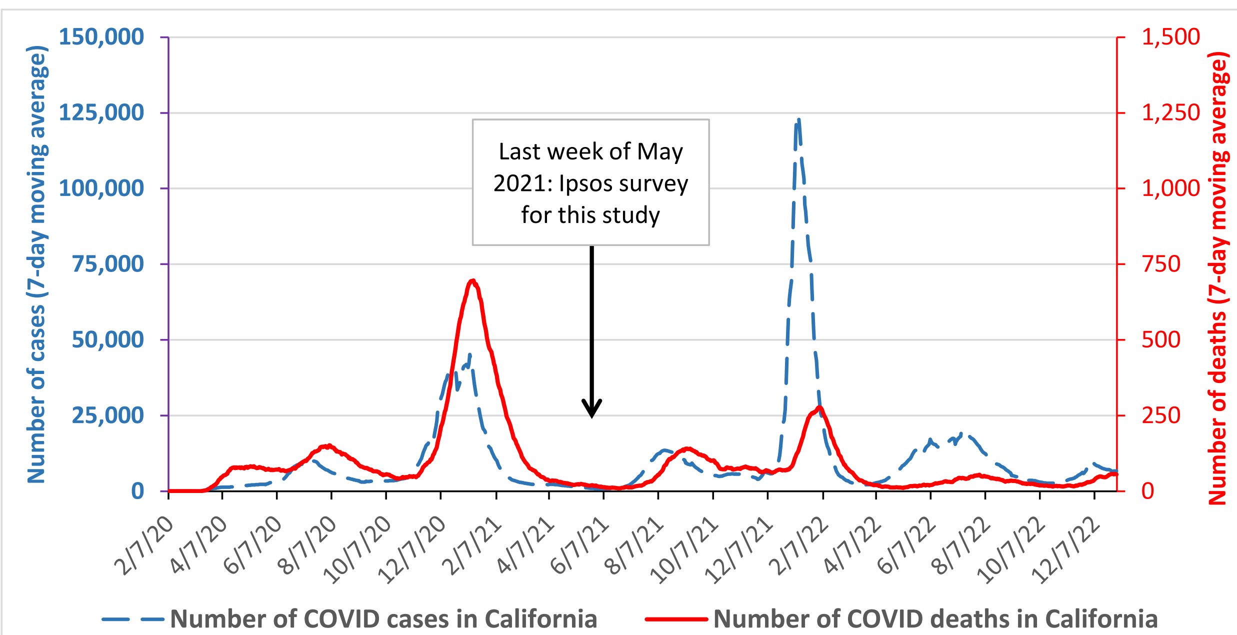


Figure 4.2: Evolution of the pandemic in California and survey timing
Data source: https://covid19.ca.gov/state-dashboard/#county-statewide

From Figure 4.2 and Table 4.1, I see that my survey was conducted after the main wave of deaths (December 2020 to February 2021) had subsided, at a time when Californians were hoping for life to get back to normal as vaccinations were ramping up (the Pfizer–BioNTech and the Moderna vaccines were granted emergency use on December 11 and 18, 2020, respectively).

Table 4.1: Key COVID-19 policy action in California between March 2020 and June 2021

Date	Policy action
March 4, 2020	State of emergency issued.
March 19, 2020	State-wide stay-at-home order issued.
April 1, 2020	Closure of all public and private schools (including institutions of higher education) for the rest of the 2019-20 academic year.
May 7, 2020	California enters Stage 2 of the 4-stage reopening roadmap.
May 18, 2020	Businesses that are part of Stage 3 allowed to reopen.
June 18, 2020	Universal masking guidance issued by the CA Department of Public Health.
June 28, 2020	Bars ordered to close in several counties.
July 1, 2020	Most indoor businesses, including restaurants, wineries, and movie theaters ordered to close in several counties.
July 13, 2020	Closure of gyms, indoor dining, bars, movie theaters, and museums re-imposed.
August 28, 2020	New guidelines for lifting restrictions: "Blueprint for a Safer Economy" (BSE). Four tiers: 1 (Widespread), 2 (Substantial), 3 (Moderate), and 4 (Minimal)
August 31, 2020	BSE county-level restrictions: ≥80% of Californians under Tier 1 restrictions.
September 29, 2020	Most Californians under BSE Tier 2 or lower.
November 10, 2020	Most Californians back up to BSE Tier 1.
November 21, 2020	Nighttime curfew implemented for counties under BSE Tier 1.
December 3, 2020	Regional stay-at-home orders issued.
January 25, 2021	Nighttime curfew and regional stay-at-home orders lifted.
March 13, 2021	Most Californians back under BSE Tier 2 or lower.
April 6, 2021	Most Californians under BSE Tier 3 or lower. Announcement of plan for reopening the economy and scrapping the BSE system on June 15.
May 27, 2021	"Vax for the Win" incentive program.
June 8, 2021	Most Californians under BSE Tier 4 (Minimal).

Source : https://en.wikipedia.org/wiki/COVID-19_pandemic_in_California

4.3.3 Dependent variables

In this study, I analyzed data collected in Part I of my survey, where I asked about (tele)commuting before, during (between the March 2020 stay-at-home order from Governor Newsom and May 2021), and potentially after the pandemic. I characterized the latter as a time when there would be no more cases in the US, which in retrospect was overly optimistic since COVID-19 is likely to stay in the background like the flu. My starting hypothesis was that the pandemic will increase post-COVID telecommuting, although much less than the high levels experienced during the pandemic. My goal was to quantify these changes and understand who will be impacted most. To test that hypothesis, I estimated three models.

In my first and second model, the dependent variable is the average number of days per week an employed respondent telecommuted before and during the pandemic respectively (i.e., a number between 0 and 7). In my third model, the dependent variable is the number of days per week an employed respondent is expecting to telecommute after the pandemic.

4.3.4 Explanatory variables

4.3.4.1 Personal and household characteristics

I considered a wide range of personal and household variables that characterize households and workers based on the data that Ipsos collects annually from KP members.

For simplicity, I reclassified the seven income groups received from Ipsos into four groups. To reflect the presence of children in the household, I defined three binary variables: no child, one child, and two or more children. Like Dai et al. (2016), Ding et al. (2017), and Van Acker and Witlox (2011), I included household size as a count variable.

To capture generational effects, I defined binary variables for the age of employed respondents based on definitions from the Pew Research Center (2018). I combined members from Generation Z (18-24 years) with Millennials (25-40 years), and members from the Silent Generation (76-96 years) with Baby Boomers (57-75 years) because the numbers of workers from Generation Z and Silent Generation respondents are small.

To create a model with a manageable number of explanatory variables, I also reclassified the 25 categories of occupations into 9 groups based on the North American Industry Classification System (NAICS). I merged ‘primary industry’ and ‘art/ entertainment/recreation’ with ‘others,’ since their percentages are very small.

For ethnicity, I lumped ethnicities different from White, African American, and Asian into "Other" because of their relatively small numbers. I did not change the education variables. Moreover, I included in my models the gender of the respondent, Hispanic status, whether the survey was taken in Spanish, marital status, and full-time/part-time work status.

Finally, I relied on factor analysis to summarize the twelve variables that represent attitudes toward communication technology because telecommuting requires some familiarity with ICT.

4.3.4.2 Land use characteristics

Most empirical studies of commuting include land use characteristics around residences since commuting trips originate from home (Manaugh et al. 2010; Sun et al. 2017). Van Acker and Witlox (2011) showed that land-use around workplaces significantly influences car ownership, and telecommuting frequency but since 46% of workers in my sample worked fully from home during the pandemic, they did not have a work location to report (Ipsos 2021). To characterize land use patterns around residences, I relied on the following variables: job density, intersection density, distance to the nearest transit stop and to the nearest employment center, a measure of the job-housing balance. I also considered median home values.

For density, I considered job density but not population density since the former is more influential for explaining commuting (Van Acker and Witlox 2011). I obtained job density from Zip Code Tabulation Areas (ZCTAs) from the 2019 Longitudinal Employer-Household Dynamics (LEHD).

To calculate intersection density, I used a measure of road connectivity that characterizes intersections with three or more links in each ZCTA (Cervero et al. 2010). My road network data come from the 2020 TIGER/Line shapefiles from the US Census.

The only location information I have for my respondents is their ZIP codes, so I approximated the location of a residence by its ZIP Code centroid. I then computed the network distance to the nearest transit stop using transit stops data from the General Transit Feed Specification (GTFS) dataset (https://gtfs.org).

To estimate job accessibility, I relied on distance to the nearest employment center. Following Giuliano and Small (1991), I found 45 subcenters in California using a '90%-10k' approach applied to the 2019 LEHD data at the ZCTA level. These 45 subcenters offer a total of 5,846,238 jobs over 413,102.44 acres in 167 ZCTAs.

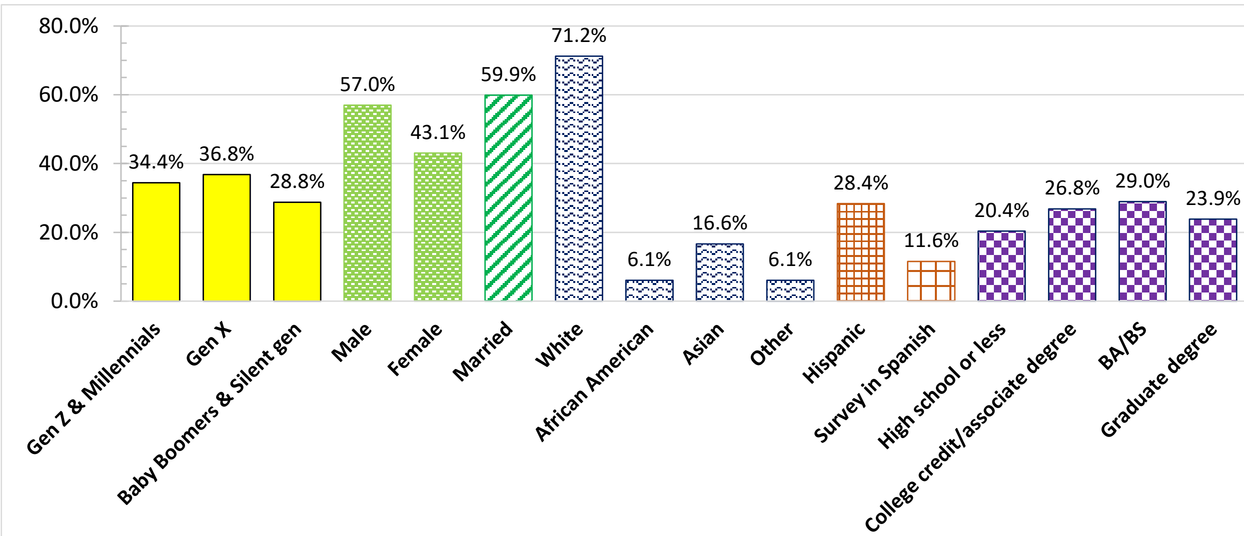
The simplest and most common measure of the job-housing balance in each ZCTA is the ratio of the number of jobs to the number of resident workers (Cervero 1989). Finally, I obtained median home values at the ZCTA level from the 2015-2019 American Community Survey.

4.3.4.3 COVID-19 severity

The decision to telecommute during the pandemic was likely impacted by public health restrictions. To capture the impact of COVID-19 on telecommuting, I therefore included in my models a COVID-19 severity variable defined as the cumulative number of cases from March 2020 to May 2021 in a respondent's county divided by county population (California Open Data Portal 2020). Most of the COVID-19 policies and restrictions were enacted at the state level. They include stay at home orders, non-essential business closures, bar and restaurant closures, mask mandates, gathering restrictions, and quarantine mandates (COVID19StatePolicy 2022; Hale et al. 2021). I therefore did not reflect county-level restrictions in our models.

4.3.5 Sample sizes

My telecommuting frequency model before the pandemic was estimated with 511 observations out of the 594 respondents who were employed because I lost 83 observations to missing variables. Summary statistics are provided in Figure 4.3 and Table 4.2. Models of telecommuting frequency during and after the pandemic were estimated with 498 respondents (I lost 72 observations to missing variables).



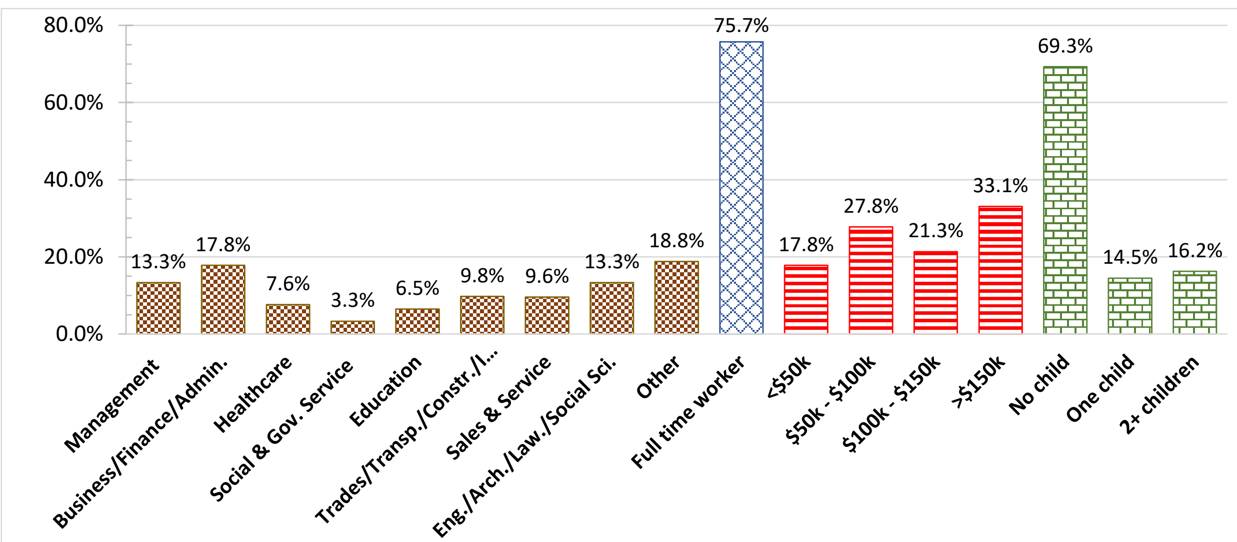


Figure 4.3: Descriptive statistics for binary explanatory variables - before COVID-19 (N=511)

Table 4.2: Descriptive statistics for non-binary explanatory variables - before COVID-19 (N=511)

Variable	Mean	Std. Dev.	Min	Max
Telecommuting frequency	1.280	2.096	0	7
Explanatory variables				
Car ownership	2.207	1.150	0	7
Household size	2.890	1.459	1	10
Land use variables (these variables describe land use around a respondent's residence)				
Jobs-housing ratio	0.940	1.084	0.109	16.952
Median home value ($100k)	6.285	3.608	1.210	20.000
Job density (#1000 jobs per sq. km)	1.046	2.371	0	41.276
Intersection density (# per sq. km)	3.284	2.847	0	15.142
Distance to nearest subcenter (km)	31.496	51.748	0	443.007
Distance to nearest transit stop (km)	3.454	8.353	0.004	74.194
Variables for tech-savviness factor				
1. Others rely on me for advice about technology	1.820	0.941	1	4
2. I often buy a new technology or device, as soon as it goes on sale	1.468	0.769	1	4
3. I like surfing the internet for fun	2.505	0.976	1	4
4. I tend to watch less TV on a traditional television because I watch videos online	2.057	1.116	1	4
5. I like to post online video content that I create (such as on YouTube)	1.284	0.660	1	4
6. I use social networks to communicate with others more than email and instant messenger	1.806	0.988	1	4
7. I am fine with advertising on mobile phones	1.554	0.739	1	4
8. I would pay to watch a TV show or movie to avoid commercials	1.918	0.893	1	4
9. I have had to delay some technology purchases because I didn't have the money	1.932	1.030	1	4
11. I like to buy technology brands that are environmentally friendly	2.172	0.895	1	4
12. I always buy the lowest priced electronics or technology	1.722	0.752	1	4

Summary statistics of explanatory variables in models during and after COVID-19 (N=498) are typically within 1% of the summary statistics for the explanatory variables for the model before COVID-19 (N=511). Answers to questions 1-12 were on a Likert scale ranging from 1 ("Do not agree") to 4 ("Strongly agree".) Question 10 (dropped from the savviness factor) is "I like to buy electronics or technology from a physical retail store."

4.4 Methodology

4.4.1 Conceptual model

My conceptual model is shown in Figure 4.4. For an explanation of the symbols used, see the notes below Figure 4.4 and refer to Kline (2015).

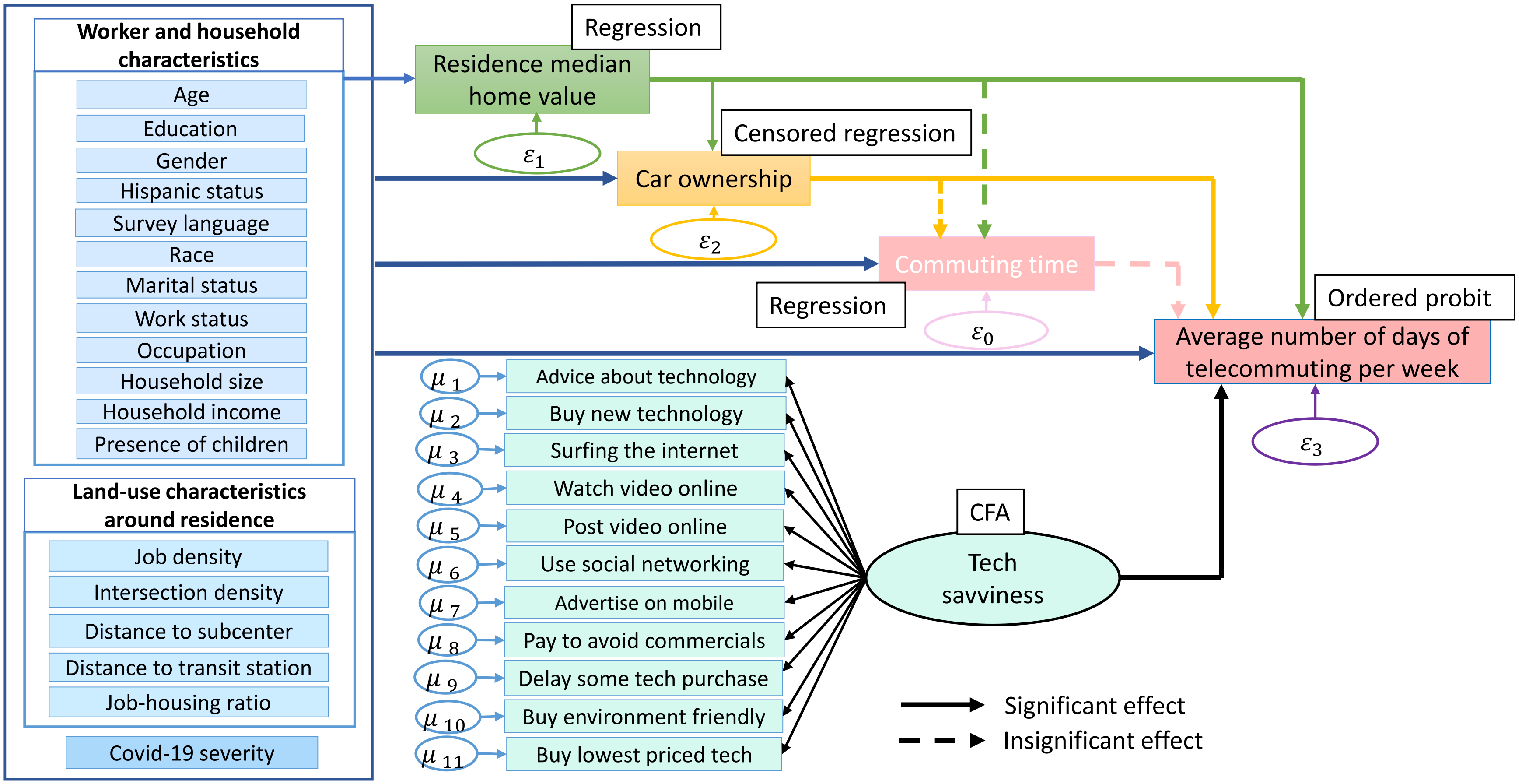


Figure 4.4: Conceptual model

Notes. Following standard practice in structural equation modeling (Kline 2015), a one-way arrow between variables implies that variables at the start of the arrow have a direct effect on the variable at the tip of the arrow. The symbols μ_1, …,μ_{11}, ε_0, ε_1, ε_2 and ε_3 are error terms. "Tech savviness" is an unobserved endogenous variable estimated via confirmatory factor analysis using the variables listed in the lower half of Table 4.2. I initially assumed that how much workers telecommute would depend on the length of their commute, but it was not the case, so I simplified my final model by omitting the commuting time equation.

In my model, I assumed that the socio-economic characteristics of a worker and those of her/his household lead her/him to select a dwelling, whose characteristics (structural, locational, environmental) are reflected in its price, in accordance with microeconomics theory. For simplicity, I assumed that the other residential land use variables are exogenous. Like de Abreu e Silva and Melo (2018a), I assumed that telecommuting frequency is influenced by car ownership and land use characteristics around residences, because land use determines the presence and characteristics of other modes. I also assumed that the duration of the work commute would impact whether or not a worker telecommutes, but that relationship turned out to be not statistically significant, so I dropped it from my final model (this explains the dotted lines to and from commute duration).

To control for residential self-selection (namely the fact that households tend to choose their residential location based on their abilities, needs, and preferences for travel; see Mokhtarian and Cao 2008), personal and household characteristics explain median home value around the residence, which implies that personal and household characteristics can indirectly affect telecommuting behavior via residential median home values. To capture the impact of COVID-19, I included a COVID-19 severity variable in the models of telecommuting frequency during and after the pandemic. Finally, tech savviness - a latent factor- estimated from the eleven indicators listed in Table 4.2, influences telecommuting frequency.

4.4.2 SEM models

Structural Equation Models (SEM) can estimate the statistical relationships among a set of observed and unobserved variables represented as latent factors based on a theoretical model that reflects the influence of exogenous variables on endogenous variables, and the influence of endogenous variables on each other (Kline 2015). Each of my models is a system of simultaneous equations plus a latent factor (estimated via confirmatory factor analysis) that jointly reflect the causal paths shown in Figure 4.4. Excluding commuting time, which was not significant, and the equations for the technology savviness factor, my model can be written:

Regression equation for residential home value:

$$\boldsymbol{L} = \boldsymbol{X_1}\boldsymbol{\Gamma_1} + \boldsymbol{\varepsilon_1}, \tag{1}$$

Censored (from below at zero) regression equation for car ownership:

$$\boldsymbol{C} = \mathbf{Max}(0, \boldsymbol{C}^* = \beta_{21}\boldsymbol{L} + \boldsymbol{X_2}\boldsymbol{\Gamma_2} + \boldsymbol{\varepsilon_2}), \tag{2}$$

Ordered probit equations for telecommuting frequency:

$$y_i = j \text{ if } \tau_j < y_i^* \leq \tau_{j+1} \tag{3a}$$

for $j \in \{0, \ldots, 7\}$ and $i \in \{1, \ldots, n\}$, where the corresponding latent variable is

$$y_i^* = \beta_0 + \beta_{31}L_{\boldsymbol{i}} + \beta_{32}C_{\boldsymbol{i}} + \boldsymbol{X_{i3}}\boldsymbol{\Gamma_3} + \varepsilon_{3i}. \tag{3b}$$

In the above:

- $\boldsymbol{L}$ is an n × 1 vector of residential median home values (in $100,000);
- $\boldsymbol{X}_\mathbf{k}$ ($k \in \{1,2\}$) is an $n \times p_k$ matrix of explanatory variables (personal and household characteristics, land use characteristics, and COVID-19 severity), assumed to be exogenous; likewise, $\boldsymbol{X}_{i\mathbf{3}}$ ($i \in \{1, \ldots, n\}$) is the $1 \times p_3$ matrix of explanatory variables (personal and household characteristics, land use characteristics, and COVID-19 severity), for respondent *i*;
- $\boldsymbol{C}$ is an n × 1 vector of numbers of household cars, and $\boldsymbol{C^*}$ is the associated latent vector;
- y_i is the average number of days of telecommuting per week for respondent *i*, and y_i^* is the associated latent variable for the ordered probit model;
- $\boldsymbol{\Gamma}_1$, $\boldsymbol{\Gamma}_2$, and $\boldsymbol{\Gamma}_3$ are unknown $p_k \times 1$ vectors of model parameters to estimate jointly with the unknown scalar parameters $\beta_0, \beta_{21}, \beta_{31}$ and β_{32}, and ordered probit model thresholds $\tau_1, \ldots, \tau_7$ ($\tau_0 = -\infty$, $\tau_8 = +\infty$); and

- ε_1 and ε_2 are n × 1 error vectors, and ε_{3i} is a scalar error, all with standard normal distributions.

L and ***C*** are endogenous. Since my model is recursive, it is identified (Kline 2015). Unknown model parameters were estimated by minimizing the difference between the sample covariance and the covariance predicted by the model (Bollen 1989).

SEM decomposes the impacts of exogenous and endogenous variables on the dependent variable into direct, indirect, and total effects. Direct effects quantify the impact of one variable on another without mediation. Indirect effects are mediated by at least one other variable. Finally, total effects are the sum of direct and indirect effects (Bollen 1989).

4.4.3 Exploratory factor analysis

My SEM models include a latent factor designed to capture technology savviness based on answers to the questions listed in the bottom half of Table 4.2. Using exploratory factor analysis, I first explored the adequate number of factors needed to summarize these questions. Based on the Kaiser criterion (Fabrigar and Wegener 2012), I retained only one factor as only one eigenvalue is >1. I then discarded question 10 because its loading was below 0.3 (de Abreu e Silva et al. 2012; Antipova et al. 2011).

To assess the adequacy of the resulting factor, I performed some common diagnostics. I calculated Cronbach's alpha (which indicates how well a set of variables measures a single underlying construct), conducted a Bartlett test for sphericity (which checks whether the correlation matrix of the variables differs significantly from the identity matrix; if not, the factor is inappropriate), and computed the Kaiser-Meyer-Olkin (KMO) statistic (which measures the proportion of the variance common to the variables considered for factorization; a lower proportion is better and leads to a higher KMO value) (Azevedo 2003; Kline 2015).

For my before-pandemic telecommuting model, alpha and KMO are 0.73 and 0.81 respectively, and for the telecommuting models during and after the pandemic, they are 0.74 and 0.82 respectively, which is adequate (Azevedo 2003; Kline 2015). For all three models, the Bartlett test (the null hypothesis was rejected) supported our "Tech-savviness" factor.

4.5 Results

4.5.1 COVID-19 and telecommuting in California

Before analyzing the results of my SEM models, let me briefly consider how working from home has changed and is likely to change in California because of COVID-19. To match my sample to the California population aged 18 and over, Ipsos calculated sample weights by raking the following distributions of Californians aged 18 and over from the 2019 American Community Survey: gender by age, race and Hispanic status, education, household income, and language proficiency (for English and Spanish). I used these weights to calculate the percentage of different telecommuting frequencies before, during, and after the pandemic shown on Figure 4.5.

First, I see that the pandemic had a substantial impact on telecommuting: while 42.2% of Californians never telecommuted before, that percentage shrank to 22.8% during the pandemic. At the same time, the percentage of Californians who telecommuted some almost doubled to 36.0% (4.5% + 7.5% + 24.0%), up from 19.2% before. The frequency that increased the most is "5+ days a week," which jumped from 9.3% pre-pandemic to 24.0%. I also note an uptick in the percentage of Californians who are not employed (which includes homemakers, retirees, and Californians seeking employment) at the time of my survey (40.6%), up from 37.9% before the pandemic.

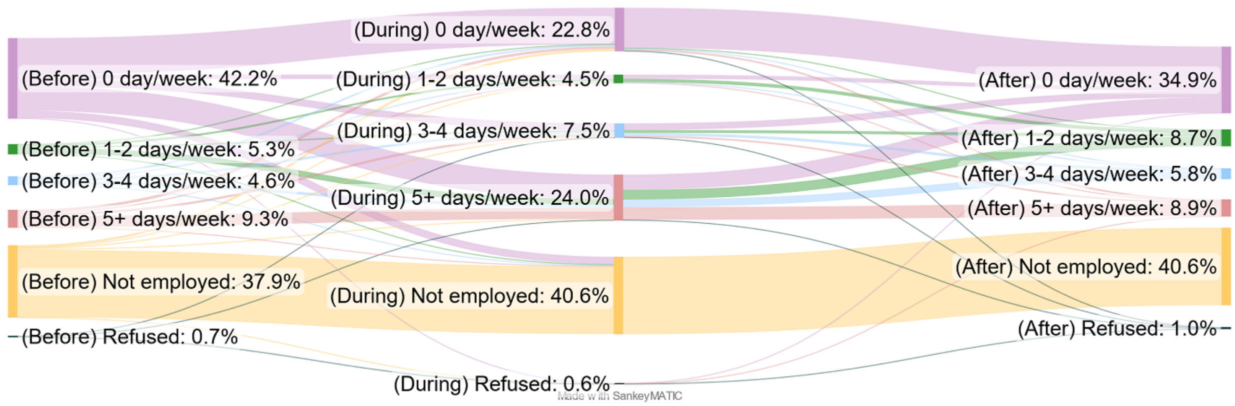


Figure 4.5: Changes in telecommuting frequency

Notes: the thickness of a flow line is proportional to the percentage of people who telecommuted at that frequency at the start of a period. Unemployed Californians are included because I am mapping my results to all Californians 18 and over.

Post-pandemic, my respondents expect the percentage of Californians who never telecommute to drop to 34.9% (down from 42.2% pre-pandemic). Two telecommuting frequencies are also expected to increase: "1-2 days per week" (to 8.7%, up from 5.3% pre-pandemic), and "3-4 days per week" (to 5.8%, up from 4.6% pre-pandemic). Conversely, "5+ days per week" could go down to 8.9% (from 9.3%), which echoes findings from a 2020 survey that only 12% of American workers want to work from home full-time (Gensler Research Institute 2020). Totaling the percentage of Californians expecting to telecommute for these three frequencies, the net gain would be 4.2%, which is substantial but not as large as might have been expected. Moreover, these changes did not/will not uniformly affect all Californians, as shown by my multivariate models.

4.5.2 Telecommuting by occupation category

Figure 4.6 shows the weighted percentage by telecommuting frequency for different occupations of my working respondents with a known occupation before, during, and potentially after the pandemic. For each occupation and time period (before, during, and after COVID-19), four frequencies are considered: 1) never; 2) 1-2 times a week; 3) 3-4 times a week; and 4) 5 or more times a week. For each time period, frequencies over all occupations sum to 100%.

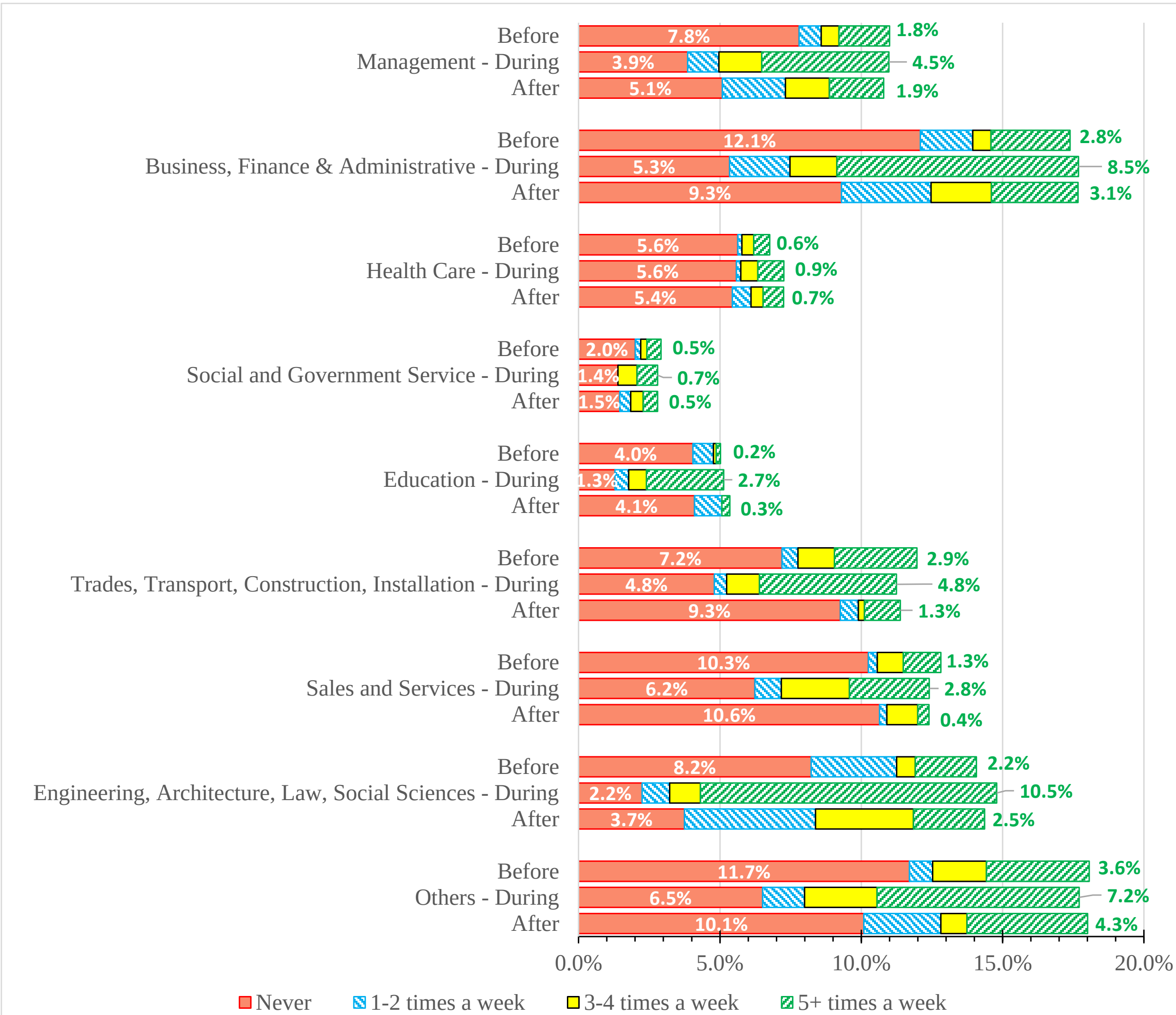


Figure 4.6: Telecommuting frequency of Californian workers before, during, and after COVID-19

First, I see that the percentage of workers who never telecommute decreased for all occupation categories (the lone exception is health care, which is unchanged) during the pandemic compared to before. That percentage decreased most (in relative terms) for engineering, architecture, law, and social sciences, and for education. Apart from health care, categories where this percentage changed the least include social and government services (which include a number of first responders), trades, transport, construction, installation (either because of essential workers or the impossibility to work remotely), and sales and services (also because of the impossibility to work remotely).

Second, the change in intermediate telecommuting frequencies depends on the occupation category. For example, the percentage of workers telecommuting 1 to 2 times a week decreased for “social and government services,” “education,” “trades, transport, construction, installation,” and “engineering, law, social sciences,” and increased for other categories. However, the percentage of workers telecommuting 3 to 4 times a week increased for all occupation categories, except for “trades, transport, construction, installation.”

Third, although the percentage of California workers who never telecommute is expected to go down after the pandemic (see Figure 4.5), that change varies by occupation, and the percentage of workers who never telecommute in “Education”, “Sales and services” and “Trades, transport, construction, installation” may actually increase slightly.

4.5.3 SEM results

4.5.3.1 Overview

After preparing my dataset with Stata 17.0, I estimated my models using Mplus 8.9 because it offers more SEM tools than Stata. I relied on the weighted least squares mean and variance adjusted (WLSMV) estimator to account for non-normally distributed variables (Muthén and Muthén 2017), since many of my explanatory variables are binary and my telecommuting frequency variable is categorical. For the models discussed below, the maximum value of the variance inflation factors (VIF) for my explanatory variables is under 3.5, so, multicollinearity is not a problem here.

I explored several model specifications, and used common fit statistics (χ^2, the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker-Lewis Index (TLI)) (Kline 2015) to select my preferred models, which are presented in Table 4.3. For conciseness, only significant coefficients are reported. Cut-off criteria for these fit statistics are: χ^2 with p-value >0.05, CFI>0.50, and TLI>0.50, where 1 represents the best fit, RMSEA <0.05 where smaller values indicate a better model fit (Kline 2015). All fit statistics for my models have acceptable values except the χ^2 values because they increase with sample size, so models with larger sample sizes might be rejected even though the differences between the observed and model-based covariance matrices are small (Kline 2015).

Equation 1 is a linear regression model, so its interpretation is straightforward. Its dependent variable (median home value around the residence) is in hundreds of thousands of dollars so to obtain the impact of changing an explanatory variable by one unit, its coefficient needs to be multiplied by 100 to get results in thousands of dollars ($1k).

Likewise, Equation 2 is a censored regression model, so it can be interpreted as a linear regression model for values of the dependent variable that are greater than zero.

Equation 3 is an ordered probit model, so I simply report estimated coefficients. Providing a simple quantitative interpretation of estimated coefficients is not possible here (Train 2009), but I know from Equations (3a-b) that augmenting the variable corresponding to a positive (negative) estimated coefficient would potentially increase (decrease) the average weekly number of telework days.

The last two columns of Table 4.3 report total effects. For conciseness, indirect effects are not shown since they can be simply calculated by subtracting direct effects from total effects. I discuss total effects for variables with significant indirect effects, which are shaded in Table 4.3.

Table 4.3: SEM results

Variables	Direct effects: Before COVID-19 (N=511): **Car ownership** (Eq. 2)	Direct effects: Before COVID-19 (N=511): **Telecommuting frequency** (Eq. 3)	Direct effects: During COVID-19 (N=498): **Car ownership** (Eq. 2)	Direct effects: During COVID-19 (N=498): **Telecommuting frequency** (Eq. 3)	Direct effects: After COVID-19 (N=498): **Telecommuting frequency** (Eq. 3)	Total effects: Before COVID-19 (N=511): **Telecommuting frequency** (Eq. 3)	Total effects: During COVID-19 (N=498): **Telecommuting frequency** (Eq. 3)
Column number	I.	II.	III.	IV.	V.	VI.	VII.
Generation (baseline: Generation Z & Millennial)							
Generation X	•	0.334†	•	•	•	0.334†	•
Baby Boomers & Silent	•	•	•	•	•	•	•
Gender: Male	•	•	•	•	•	•	•
Marital status: Married	0.310‡	•	0.257†	•	•	•	-0.035*
Hispanic status: Hispanic	•	•	•	•	•	•	•
Survey language: Spanish	•	•	•	1.282‡	•	•	1.282‡
Ethnicity (baseline: Caucasian)							
African American	•	•	•	•	•	•	•
Asian	•	•	•	•	•	•	•
Other	•	•	•	•	•	•	•
Education (baseline: high school or less)							
Some college credit or associate degree	•	•	•	•	•	•	•
Bachelor's degree	•	•	•	0.465†	0.383*	•	0.465†
Graduate degree	-0.465†	•	-0.540†	0.630‡	•	•	0.703‡
Occupation (baseline: Management)							
Business /Finance/ Administration	•	•	•	•	•	•	•
Health	•	•	•	-0.985‡	-0.710†	•	-0.985‡
Social and Government service	•	•	•	•	•	•	•
Education	•	•	•	0.486*	-1.023‡	•	0.486*
Trades / Transport / Construction / Installation / Repair	•	•	•	•	-0.754†	•	•
Sales and service	•	•	•	•	-0.567†	•	•
Engineer / Architect / Lawyer/ Social scientist	•	•	•	0.416*	•	•	0.416*

Variables	Direct effects: Before COVID-19 (N=511) Car ownership (Eq. 2)	Direct effects: Before COVID-19 (N=511) Telecommuting frequency (Eq. 3)	Direct effects: During COVID-19 (N=498) Car ownership (Eq. 2)	Direct effects: During COVID-19 (N=498) Telecommuting frequency (Eq. 3)	Direct effects: After COVID-19 (N=498) Telecommuting frequency (Eq. 3)	Total effects: Before COVID-19 (N=511) Telecommuting frequency (Eq. 3)	Total effects: During COVID-19 (N=498) Telecommuting frequency (Eq. 3)
Column number	I.	II.	III.	IV.	V.	VI.	VII.
Other	•	•	•	•	•	•	•
Employment status: Full time	•	-0.656‡	•	•	-0.426‡	-0.656‡	-0.008*
Tech savviness	NA	•	NA	0.223†	0.256†	•	0.223†
Number of household vehicles	NA	-0.097*	NA	-0.136‡	•	-0.097*	-0.136‡
Annual household income (baseline: <$50k)							
$ 50k to $ 100k	0.588‡	•	0.500‡	•	•	-0.057*	-0.068†
$ 100k to $ 150k	0.698‡	•	0.707‡	•	•	-0.068*	-0.096‡
>$150k	0.857‡	•	0.864‡	•	•	-0.083*	-0.117‡
Household Size	0.385‡	•	0.430‡	•	-0.126†	-0.037*	-0.058‡
Presence of children (baseline: no child)							
One Child	-0.588‡	•	-0.617‡	•	•	0.057*	0.084†
Two or more Children	-1.009‡	•	-0.903‡	•	•	0.098*	0.122‡
Land use (Residence)							
Job-housing ratio	0.095*	•	0.091*	•	•	•	•
Median home value	-0.055‡	•	-0.058‡	•	•	0.005*	0.008‡
Job density	-0.072‡	•	-0.069‡	•	•	0.007*	0.009†
Intersection density	•	•	•	•	•	•	•
Distance to nearest subcenter	•	•	•	•	•	•	•
Distance to nearest transit stop	•	•	•	•	•	•	•
Residence Covid-19 Severity	NA	NA	•	•	•	NA	•

1) ∗, †, &‡ denote significance at 10%, 5%, & 1% respectively.
2) "Coef." = coefficient; "•" = statistically non-significant coefficient; NA= Not applicable.
3) Median home values are expressed in $100,000; distances are in km; and densities are in persons per square km.
4) Shaded cells indicate statistically significant indirect effects (so total effects differ from direct effects).
5) Model before COVID-19: χ^2=714.118‡, RMSEA= 0.036, CFI= 0.727, TLI= 0.660;
Model during COVID-19: χ^2=735.635‡, RMSEA= 0.036, CFI= 0.727, TLI= 0.660;

Model after COVID-19: χ^2=735.945‡, RMSEA= 0.036, CFI= 0.722, TLI= 0.655.

6) Ordered probit thresholds for before COVID-19: τ_1=0.260; τ_2=0.404; τ_3=0.552; τ_4=0.705*; τ_5=0.798*; τ_6=1.649‡; τ_7=2.002‡.

Ordered probit thresholds for during COVID-19: τ_1=0.332; τ_2=0.440; τ_3=0.600; τ_4=0.830*; τ_5=0.977†; τ_6=2.549‡; τ_7=2.908‡.

Ordered probit thresholds for after COVID-19: τ_1=0.239; τ_2=0.411; τ_3=0.734; τ_4=0.991†; τ_5=1.194‡; τ_6=2.157‡; τ_7=2.456‡.

Since residence home value is not statistically significant in any of the telecommuting frequency equations, I only discuss results for Equations 2 (car ownership) and 3 (telecommuting frequency) before and during the pandemic. After the pandemic, I only discuss Equation 3 (telecommuting frequency) since car ownership is not significant in Equation 3. Finally, I note that the tech-savviness factor is highly significant for all three time periods.

4.5.3.2 Before COVID-19

Car ownership (Equation 2; Column I)

Starting with worker characteristics, I see that married people (0.310‡) are more likely to own more cars than unmarried people, which is expected. Workers with a graduate degree (-0.465†) tend to own fewer cars but a higher household income has the opposite effect (0.588‡, 0.698‡ and 0.857‡ for incomes of $50k to $100k, $100k to $150k and >$150k, respectively). Conversely, household size is positively associated (0.385‡) with car ownership although the presence of children (-0.588‡ for one child; -1.009‡ for two or more) acts as a correction.

For land use characteristics around residences, median home value (-0.055‡) shows a mild negative association with car ownership which is unexpected. Finally, car ownership slightly rises with job-housing ratio (0.095*) while job density shows the opposite effect (-0.072‡).

Telecommuting frequency (Equation 3; Column II)

Starting with worker characteristics, I see that Generation X members were more likely to telecommute (0.334†) before the pandemic because they probably have more experience working independently than younger people (Peters et al. 2004; Sener and Bhat 2011; Zhang et al. 2020).

Full-time workers (-0.656‡) telecommuted less before the pandemic compared to part-time workers, possibly because part-time jobs are often more flexible (Felstead and Henseke 2017).

Among household characteristics, I note that owning more cars had a negative impact on telecommuting (-0.097*), as commuting often requires access to more motor vehicles.

In addition, the "car ownership" equation created a number of indirect effects (as indicated by shaded cells in Column VI) for the "telecommuting" equation. First, households with higher incomes (-0.057*, -0.068*, and -0.083* for incomes $50k to $100k, $100k to $150k, and >$150k respectively) were less likely to telecommute, possibly because their higher income comes with management responsibilities that require them to work on-site. Second, household size had a negative impact on telecommuting (-0.037*), possibly because of the difficulty to find a quiet space to work in many larger households. Conversely, households with children prefer telecommuting (0.057* and 0.098* for households with one child, two or more children respectively) possibly as they seek a balance between work and childcare. Third, households who can afford more expensive neighborhoods (0.005*) tend to telecommute more overall, which agrees with urban economic theory (for which households select their residential locations after considering trade-offs between commuting and housing costs). Finally, telecommuting rises slightly with the job density (0.007*) around residences which is unexpected.

4.5.3.3 During COVID-19

Car ownership (Equation 2; Column III)

The determinants of car ownership during COVID-19 are similar to those before the pandemic, so we do not discuss them further.

Telecommuting frequency (Equation 3; Column IV)

Contrasting Columns IV and II shows that the pandemic had a substantial impact on the determinants of telecommuting.

Starting with worker characteristics, I see that respondents who took my survey in Spanish were more likely to telecommute (1.282‡) compared to respondents who took it in English. However, the Hispanic indicator is not statistically significant.

Whereas before COVID-19 education is not statistically significant, during the pandemic more educated Californians became more likely to telecommute (0.465† for a bachelor's degree; 0.630‡ for a graduate degree) possibly because they were in a better position to negotiate with their employers the option to telecommute (Singh et al. 2013; Zhang et al. 2020).

The occupation variables also saw substantial changes. Unlike before COVID-19, during the pandemic workers in Education (0.486*) and Engineers/Architects/Lawyers/Social Scientists (0.416*) were more likely to work from home, whereas heath care workers had to disproportionately go to work (-0.985‡), despite a shift to telemedicine (Friedman et al. 2021). The greater adoption of telecommuting was made possible by more tech savviness (0.223†), which did not play a role in explaining telecommuting before the pandemic.

Looking at household characteristics, I see that the importance of car ownership for telecommuting waned during the pandemic (-0.136‡) compared to before (-0.097*) as Californians worked more from home. Surprisingly, COVID-19 severity around residences was not significant in my models, possibly because many restrictions were statewide.

Finally, indirect effects (via the car ownership variable) played an important role in the "telecommuting" equation (Column VII). Unlike before COVID-19, they slightly increased the impact of education (0.703‡ for workers with graduate/professional degrees), mitigated the impact of marital status (-0.035*) and dampened the impact of full-time work status (-0.008*).

4.5.3.4 After COVID-19 (Expectations about telecommuting post-pandemic)

Telecommuting frequency (Equation 3; Column V)

Interestingly, generation, race, or Hispanic status do not impact expectations about telecommuting post-pandemic. Education does, however, with more educated workers expecting to telecommute more (0.383* for bachelor's degree) than workers with a high school education or less. This effect depends on occupation, however, with workers in healthcare (-0.710†), education (-1.023‡), trades/transport/construction/installation/repair (-0.754†), and sales and services (-0.567†) expecting to telecommute less than managers (our baseline). Moreover, full-time workers expect to telecommute less (-0.426‡) after the pandemic compared to part-time workers, likely because many part-time jobs offer more flexibility, and are thus more conducive to telecommuting (Felstead and Henseke 2017).

Tech savviness again comes into play for telecommuting (0.256†) post-pandemic. Conversely, household size plays a negative impact on telecommuting (-0.126†), possibly because finding a quiet space to work in larger households can be difficult.

There were no indirect effects for this equation, so total effects equal direct effects here.

4.6 Conclusions

In this essay, I estimated three structural equation models to assess the impact of COVID-19 on the frequency of telecommuting in California before, during, and potentially after COVID-19. My dataset was collected in late May 2021 via a survey of Californians in KnowledgePanel© conducted for me by Ipsos. Compared to papers published until the end of 2022, my study covers a longer period of the pandemic (March 2020 to late May 2021), and my respondents are representative of the California population, which enables me to generalize my results to the whole state.

My results show some generational impacts (for Generation X), but no gender and race effects. However, workers with more education started telecommuting more during the pandemic, a trend that is likely to continue post-pandemic. As expected, occupation type and full time work status matter (full time workers are less likely to telecommute). Although household income has no direct impact on telecommuting, it had significant indirect and total effects before and during the pandemic (higher income workers telecommuted less). Household size and the presence of children also matter, but their effect is complex. Finally, although some residential land use variables are significant, their impact is small, and so is the magnitude of residential self-selection.

The nature of an occupation plays a key role in telecommuting both during and potentially after the pandemic since ICT-supported jobs are suitable for telecommuting. My results show that during the pandemic workers in Education and Engineers / Architects / Lawyers / Social Scientists were more likely to work from home, whereas heath care workers (e.g., nurses) had to be at work in person. However, after the pandemic workers in healthcare, education, trades / transport / construction / installation / repair, and sales and services are expecting to telecommute less since most of these jobs require their presence in the workplace.

Overall, My results suggest that an additional 4.2% of Californian workers could engage in some level of telecommuting post-pandemic which is substantial but much less than suggested by Conway et al. (2020), who analyzed data from a 2020 nonprobability US sample.

To support a switch to (at least partial) telecommuting, employers may consider offering a mix of in-person and remote work, which would allow workers to maintain or create ties with colleagues while reducing their commuting expenses. Although employer decisions will play a major role in defining the future forms and adoption of telecommuting, employee preferences and constraints, such as access to appropriate technologies to work from home and the home environment will also be important (Tahlyan et al. 2022).

In 2021, ~91% of California households had access to high-speed internet, and ~85% of California residents used a desktop, laptop, or tablet to connect to the internet, but income remains a digital gatekeeper as ~29% of households who earn under $40,000 a year have no internet connection or have internet access only through a smartphone (Mackovich-Rodriguez 2021). Although only around half of all jobs in California are suitable for telework (US Census Bureau 2019), the state should continue its efforts to give broadband access to all Californians (see EO N-73-20, the Governor's 2020 "Broadband For All" Executive Order, and the December 2020 Broadband For All Action Plan), because, in addition to telework, fast access to the internet opens the door to telemedicine, cultural programs, education opportunities, and better online shopping.

As mentioned in the introduction, one of the initial motivations for promoting telecommuting was the desire to reduce traffic congestion. In California, the South Coast Air Quality Management District (the regulatory agency responsible for improving air quality in Los Angeles, Orange, Riverside, and San Bernardino counties) allows firms to use telecommuting as part of a menu of options to reduce VMT under Rule 2202, which applies to worksites with 250 or more employees. In 2021, California also published Statewide Telework Policy 0181, whose purpose is to provide a structure to establish effective telework programs that incorporate telecommuting as a work option (California Department of General Services 2021). Monetary incentive were also put in place, including stipends for represented state employees under the Telework Stipend Program (California Department of Human Resources 2022). Some lawmakers tried to go further and proposed in early 2022 an income tax credit (which was not adopted) funded by the Greenhouse Gas Reduction Fund of $1,000 for telecommuting at least 25 hours per week. However, monetary inducements for telecommuting run counter state and local tax breaks granted to many large employers for locating some of their facilities in California to spur economic activity and increase the tax base by bringing in well paid jobs. Many of these agreements, which were concluded well before COVID-19, do not consider that a substantial percentage of the workforce at these worksites could work remotely, which would sharply limit the intended benefits of these tax breaks (Spring 2023). It would therefore make sense to revisit some of these agreements (and not just in California) to better reward firms that hire local telecommuters and discourage hiring out-of-state telecommuters who do not contribute to the local or state tax base.

One limitation of this study is that my dataset does not contain the exact residential location of my respondents (I just know their ZIP code). I also know the work ZIP code of only a subset of Californian workers in my dataset, although models estimated on that subset showed that commuting time to work was not statistically significant. A more extensive dataset that captures time use and travel behavior over several days is needed to better explore the impact of commuting time on the decision to telecommute.

There are multiple avenues for future research. First, ongoing analysis is needed as behaviors are still shifting as the pandemic is waning. For example, as a number of companies have allowed their workers to work from home (Howington 2023), some households moved to more affordable areas, possibly out of state (Walczak 2021) or even abroad (Masterson and Shine 2022) because they were attracted by relocation incentives. Capturing changes in residential location and travel to investigate the long-term impacts of the pandemic is of interest but will take a longer time frame. Second, it would be useful to examine the impact of attitudes and perceptions (related, for example, to productivity at home, or impacts of telecommuting on family life) on telecommuting since they often affect the decision to telecommute. Finally, I agree with Elldér (2020) about the value of conceptualizing telecommuting as a coping strategy for organizing everyday activities, which suggests that it should be analyzed in the context of daily activities.

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Chapter 5. Conclusions

In this dissertation, I presented three essays on commuting in the United States, which address important gaps on the relationship between commuting, housing cost, and the impact of COVID-19 on telecommuting. In all three essays, I used Structural Equation Model (SEM) which is a model of simultaneous equations. SEM can estimate the statistical relationships among a set of observed and unobserved variables (represented as latent factors) based on a theoretical model that reflects the influence of exogenous variables on endogenous variables, and the influence of endogenous variables on each other.

In my first essay, I analyzed 2012 CHTS data for Los Angeles County – the most populous county in the U.S. – to tease out the impacts of housing costs on commuting of one-worker households. My model jointly explains commuting distance and time, accounts for residential self-selection and car use endogeneity, while controlling for commuter and household characteristics, and land use around residences and workplaces. My results confirm the presence of residential self-selection since residential home values are partly explained by commuter and household socio-economic variables.

Moreover, my results show that households who can afford more expensive neighborhoods have on average a commute 3.1% shorter per additional $100k to their residence median home values. Likewise, a $100k increase in their workplace median home value raises the average commuting distance by 2.3%. This suggests that longer commutes are to some extent a consequence of California's high housing costs. Surprisingly, the job-housing ratio is hardly significant in my study, possibly because the dwellings near employment centers tend to be unaffordable.

My second essay analyzed 2017 NHTS data for five metropolitan areas in three US states - Los Angeles and San Francisco in California, Dallas and Houston in Texas, and Atlanta in Georgia - to tease out the impact of gender on commuting in heterosexual two-worker households. My model jointly explains commuting distance and time for each worker in each two-worker household in my dataset and the feedback between their commuting time, accounts for residential self-selection and the endogeneity of commuting by car, while controlling for commuter and household characteristics, and land use around residences and workplaces.

My results show that households who can afford more expensive neighborhoods have on average a commute 14.5% and 22.7% faster respectively for both workers per additional $1000 to median monthly housing cost in their residence census tract, which is also corroborated with the findings from one-worker households in Los Angeles County (see Chapter 2). This suggests that longer commutes are to some extent a consequence of high housing costs in MSAs. Moreover, my results show that both commuting times appear to be slightly complementary which means commuting trips of both workers are adjusted together (both trips get longer or shorter together). To some extent, this complementary effect may reduce the gender gap in commuting in two-worker households. Finally, compared to San Francisco, both commuters in Los Angeles, Dallas, Houston, and Atlanta are more likely to commute by car and tend to have faster commutes, possibly because other modes (e.g., transit, bike) are typically slower compared to car.

My third essay estimated three SEM models on a unique dataset collected in late May 2021 via a random survey of Californians in KnowledgePanel© conducted by IPSOS. My study covers a longer period of the pandemic (March 2020 to late May 2021), and respondents are representative of the California population, which enables me to generalize my results to the whole state. My models characterize the telecommuting frequency of Californian workers based on their socio-economic characteristics, household car ownership, and residential land use before, during and potentially after the pandemic to understand the impacts of COVID-19 on telecommuting.

Results show that workers with more education started telecommuting more during the pandemic, and this trend is expected to continue post-pandemic. Likewise, occupation matters, as well as full time work status. Household income has significant indirect effects on telecommuting during the pandemic (higher income workers telecommuted less). Moreover, my results suggest that an additional 4.2% of Californian workers could engage in some level of telecommuting post-pandemic. To support this change, employers may consider offering a mix of in-person work and telecommuting. While employer strategies will play a major role in defining the future forms and adoption of telecommuting, employee preferences and constraints, such as access to appropriate technologies to work from home and the home environment will also be important.

In my first essay, data limitations precluded me to examine the impact of attitudes and lifestyle (e.g., pro-transit or pro-active mode behavior) on commuting. Although I focus on LA County in this essay, my methodology is widely applicable so it could be used to investigate how housing costs impact commuting in other parts of the world. In my second essay, data limitations on income (wages) for each worker in the 2017 NHTS restricted me to analyze the impact of income on commuting for each worker which might be of interest for future research. Moreover, instead of gender, it would be of interest to explore the variations in commuting with respect to education and occupation potentials of both male and female workers. In my third essay, it would be of interest to examine the impact of attitudes and perceptions (related, for example, to productivity at home, or impacts of telecommuting on family life) on telecommuting since they often affect the decision to telecommute. Moreover, ongoing analysis is needed as behaviors are still shifting in response to the evolving pandemic. For example, capturing changes in residential location (e.g., to more affordable areas, possibly out of state) to investigate the long-term impacts of the pandemic will take a longer time frame. Finally, the value of conceptualizing telecommuting as a coping strategy for organizing everyday activities suggests that it should be analyzed in the context of daily activities.