AN L.A. STORY:

THE IMPACT OF HOUSING COSTS ON COMMUTING

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The authors declare no conflict of interest.

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ABSTRACT

The empirical impact of housing costs on commuting is still relatively poorly understood. This impact is especially salient in California given the state's notoriously high housing costs, which have forced many lower- and middle-class households to move inland in search of affordable housing at the cost of longer commutes. To investigate this linkage, we relied on Generalized Structural Equation Modeling and analyzed 2012 CHTS data for Los Angeles County – the most populous county in the U.S. Our model, which jointly explains commuting distance and time, accounts for residential self-selection and car use endogeneity, while controlling for household characteristics and land use around residences and workplaces. We find that households who can afford more expensive neighborhoods have shorter commute distances (-2.3% and -3.1% per additional $100k to median home values around workplaces and residences respectively). Job density, distance to the CBD, and land-use diversity around workplaces have a relatively greater impact on commuting than the corresponding variables around commuters' residences. 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, while college educated workers have shorter (-2.6% to -3.6%) commutes. Furthermore, commuters in the top income brackets tend to have faster commutes than lower income workers. Finally, women's commutes are ~41% shorter than men's, possibly because they are balancing work with domestic responsibilities. 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.

Keywords: Land use; Housing cost; Commuting; Generalized Structural Equation Model; California Household Travel Survey.

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 paper 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 our context would alter our understanding of the determinants of commuting (Cao et al., 2009; He et al., 2015).

For this study, we 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, we review selected papers to inform our modeling choices. We then describe our data (Section 3) and present our methodology (Section 4), before discussing our results in Section 5. Finally, in Section 6, we summarize our conclusions, discuss some policy implications, and suggest alternatives for future research.

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 1, recent empirical studies (2010-2020) have examined commuting in Europe, Asia (mostly China), and the U.S. We 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).

Our 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). We 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 us 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.

2.1. Personal and household characteristics

Most of the papers we 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 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).

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, we also included in our 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).

2.3 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.

3. Data

In this paper, we 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. We worked with this slightly older dataset because we obtained access to the location of the residence and the workplace of respondents, which enabled us to create land use characteristics that are essential to our models.

Since our goal is to analyze the time and distance of commutes reported in travel diaries, we focused on workers who traveled directly from home to work (commuters are not asked to report the typical length of their commute; we need to calculate it from their diary). We 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, we excluded observation associated with unusually high values (> 180 min).

Since we want to investigate the impact of housing cost on commuting while controlling for other variables, we selected the household as our basic unit of analysis because the choice of a residential location is a household decision. After linking the workers in our dataset to their households, we 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), we 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 our focus to workers who live and work in Los Angeles County gave us 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.

3.1 Explanatory variables

3.1.1 Personal and household characteristics

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

For simplicity, we reclassified the ten income groups of the 2012 CHTS into four groups. To reflect the presence of children in the household, we 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, we 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, we defined binary variables for the age of the household worker based on definitions from the Pew Research Center (2018). We started with Millennials (18-31 years) since workers from Generation Z (<18 years) were too young in 2012 to commute to work. We 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, we 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, we lumped other ethnicities into "Other" because of their relatively small number. We did not change the education variable, that tracks the education level of a commuter.

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

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

To capture car availability, we 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. Our final sample size was 1,267.

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

We 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. We 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 our sample, we 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, we 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.

We found 33 subcenters (see Panel C of Figure 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 we used, is the ratio of the number of jobs to the number of resident workers (Cervero, 1989).

Finally, we purchased year 2012 median home values at the census tract level from CoreLogic (CoreLogic, 2012).

Summary statistics for our variables are provided in Table 2. Variance Inflation Factors (VIF) for our 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.

4. Methodology

4.1 Conceptual model

Most of the commuting studies we reviewed (see Table 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.

Our conceptual model is shown in Figure 2. We 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 our model), determines commuting distance. For simplicity, we 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), we 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. Our 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.

4.2 Model

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

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

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 our 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; **C***i*=1 if commuter "*i*" drives to work and 0 otherwise;
- **T** is an n × 1 vector of commuting times (minutes);
- $\mathbf{X}_k$ ($k \in \{1, \ldots, 5\}$) is an n × 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 × 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 our 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, we report only direct and total effects. They are discussed in the next section.

5. Results

Results for our best model, obtained using Stata 15.1, are presented in Table 3. Only significant results are shown for conciseness. We estimated our 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 our explanatory variables are binary.

We 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 our continuous explanatory variables. Comparing different plausible models using AIC and BIC (models with lower values are preferred) gave us our preferred model, which is presented below. Unfortunately, common fit statistics developed for SEM are not available for GSEM, so we 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, we multiply its coefficient by 100 to get results in thousands of dollars ($1k).

Since Equations (2B) and (2D) describe logit models, we 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 our discussion below with Table 3, we refer to the value of statistically significant odds by writing "OR=" before its value shown in Table 3.

As indicated in the Methodology section, we 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 our discussion of the results for Equations 2C and 2E, we 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 we simply report its value preceded by "elasticity=".

5.1 Direct effects

Residence home value (Equation 2A; Column I)

Starting with commuter characteristics, we 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.

Car availability (Equation 2B; Column II)

As shown in Column II of Table 3, 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, we 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).

Commuting distance (Equation 2C; Column III)

Starting with commuter characteristics, we 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 we 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 us 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.

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***). We 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. We 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 us) 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.

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).

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.

5.2 Indirect and total effects

The last five columns of Table 3 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, we discuss total effects for variables with significant indirect effects, which were shaded in Table 3 to make them stand out.

Given the structure of our model (see Figure 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). First, we 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 (see Column VIII of Table 3). 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 3) come from both the "Commuting distance" and the "Car availability" variables. We 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 3), indirect effects come from the "Commuting by car" and "Commuting distance" variables. We 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).

6. Conclusions

In this paper, we 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. Our 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. Our results confirm the presence of residential self-selection since residential home values are partly explained by personal and household socio-economic variables.

Our 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), we quantified the impact of land use characteristics of both residences and workplace on commuting. However, unlike other papers in this literature, we 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 our 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.

Our 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.

We 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.

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

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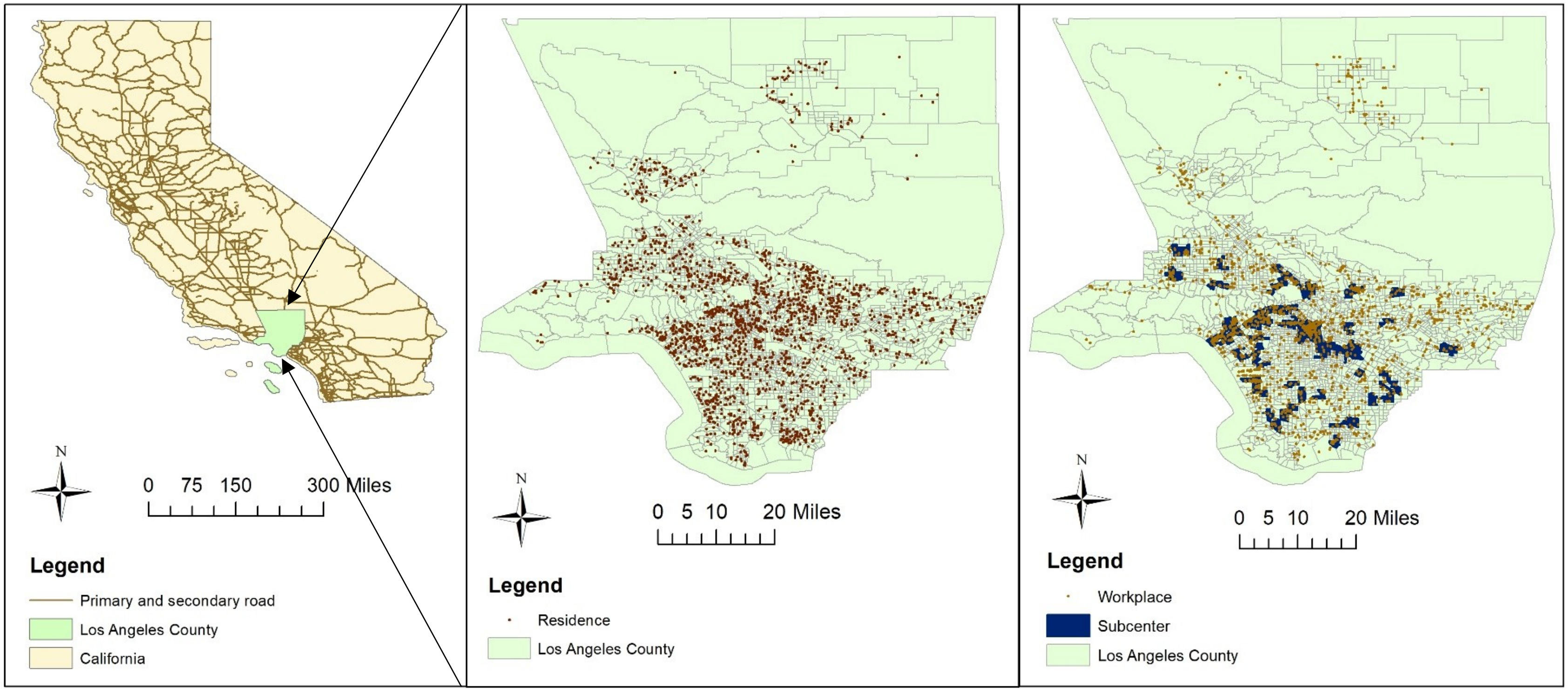

Panel A: Location of LA County **Panel B**: Home locations of respondents **Panel C** Work locations and job centers

Figure 1: Location maps

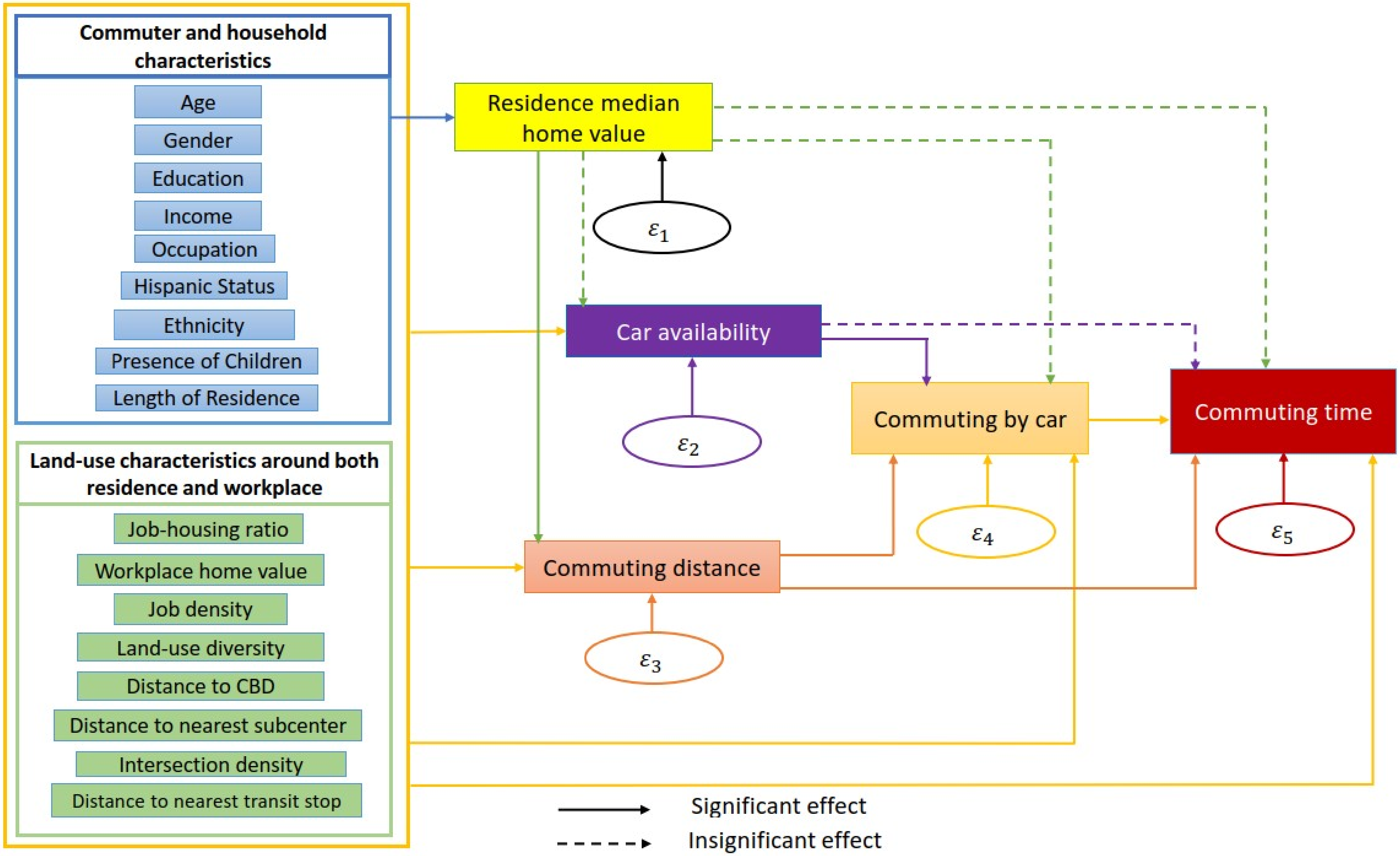

Figure 2 Conceptual model

Table 1: Summary of selected papers (2010-2020)

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 • Residential & employment densities, land use mix, road density, transit accessibility, distance to	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
		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 jobs-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
Ding et al. (2017)	• 8,327 commuters in Washington, DC	• Age, gender, race, household size, occupation, household income, car ownership	Commuting distance is more sensitive to the effects of distance from CBD,

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
	(2007-08) • Multilevel mixture hazard model	• Residential density, employment density, land use mix, average block size, 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 County, Ohio (2000) • OLS	• Race, Hispanic status, education, employment status, income, poverty, household with children • Distance from CBD, bounded community	Commutes between occupation groups vary more than those between gender groups
Li (2010)	• 1500 (2001) and 1200 (2005) households in	• Gender, income, occupation, work unit type	Men in Guangzhou have appreciably shorter commutes than women

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
	Guangzhou, China • OLS		
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) • Multilevel LR and OLS	• Gender, income, age, education, number of family houses, family cars, household size, employment, occupation, number of workers • Housing source, transport accessibility, population density, job-housing balance	Job-housing balance and commuting mode influence both commuting time and distance
He et al. (2015)	• 1242 households from Kunming, China (2011)	• Age, education, income, house ownership, occupation status, household structure • Residential location	Education level, gender, and occupation status significantly impact commute time and distance

Author(s) (year published)	Data (period analyzed) models	Explanatory variables (personal and household variable, land-use variable, others)	Key results
	• OLS		
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

Table 2A: 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 2B: 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

Table 3: Generalized SEM results (N=1,267)

Variables	Direct effects					Total effects				
	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					Total effects				
	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.
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***	-	-

	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.
Land use (Residence)										
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.