**Housing Choice in an Evolving Remote Work Landscape**

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**ABSTRACT**
We estimate a joint model of housing choice along several dimensions to account for changing valuations of housing outcomes due to the COVID-19 pandemic. We consider housing outcomes including housing type, tenure type, the presence of a patio or yard, the number of bedrooms, neighborhood population density, median housing cost, accessibility of amenities, school quality, crime rate, and commute distance. Data used for this analysis were collected in October and November of 2021 from 24 metropolitan areas across the United States. A Generalized Heterogeneous Data Model (GHDM) is used to estimate these housing outcomes as a function of exogenous household sociodemographic characteristics and latent lifestyle propensities. The GHDM also captures jointness caused by unobserved factors, allowing for the estimation of accurate causal effects between outcomes. The results reveal that lifestyle preferences have significant impacts on housing outcomes. Specifically, individuals with a preference for teleworking are more likely to reside in single-family homes in highly populated areas, experience longer commute distances, and exhibit a higher sensitivity to the presence of amenities in their neighborhoods. Additionally, the analysis of tradeoffs between housing outcomes reveals the relative valuations of various housing outcomes. An increased commute distance is found to lead to an increase in single-family homes, reductions in density, and an increased crime rate. Choosing an apartment in a high-density neighborhood is found to lead to reductions in school quality and significant increases in crime rates. Implications of the results for land-use planning, travel demand analysis, and equity considerations are identified and discussed.

**Keywords:** Housing choices, dwelling unit characteristics, residential location, latent lifestyles, urban planning, travel demand analysis

# 1. INTRODUCTION

The social distancing protocols implemented during the COVID-19 pandemic have led businesses and individuals across the world to consider innovative workflows, lifestyles, and routines. In the United States, the share of workers reporting fully remote work arrangements increased significantly from approximately 7% to about 62% throughout 2020 and 2021 (Bureau of Labor Statistics, 2022). With society now managing the spread and impact of COVID-19, many employers are reverting to their pre-pandemic workplace structures, asking employees to return to the in-person workplace for at least a few days per month. Other employers, however, are embracing the changes brought about by the pandemic and exploring the possibility of continued flexible work arrangements. Overall, the prevailing view is that some level of flexible work arrangements is here to stay, with about 35% of employees retaining the option to work from home full-time and 23% part-time as of spring 2022 (McKinsey, 2022).

The increasing prevalence and popularity of remote work have led individuals and households to reconsider their housing choices and reevaluate the multitude of factors that influence their housing decisions (Fatmi et al., 2022; Puppateravanit et al., 2022). With remote work becoming more common, the physical proximity of residence to the in-person workplace may no longer be the primary determinant of residential choice, as it was for many before the pandemic (Song et al., 2023). Instead, the features of the dwelling unit (such as the presence of a study/office in the home, yard space, house square footage, and number of bedrooms and bathrooms) and the characteristics of the neighborhood (such as crime rate, school quality, and proximity to nature and recreational areas) are becoming increasingly important in determining housing choices (Fatmi et al., 2022; Navas-Martín et al., 2022). This impact of increased remote work, engendered by the pandemic, on housing decisions is reflected in two spikes in residential mobility during initial pandemic lockdowns and in early 2021. These spikes also stand out in contrast to the long-term trend of declining residential mobility observed since the 1980s (Frost, 2023, 2020). Further, a survey sample of US households revealed that housing and location-related concerns are now the primary motivators for moving, replacing job-related factors that were dominant before the pandemic (Frost, 2023). Additionally, households moving away from dense urban neighborhoods report the ability to telework as a motivation for moving (Salon and Conway, 2022). Therefore, traditional residential choice modeling approaches (such as a gravity-type formulation or a bid-rent model) that primarily focus on the trade-off between commuting time and land prices may no longer adequately reflect the behavioral process that drives housing choices (in the rest of this paper, we will use the terms "residential" and "housing" interchangeably).

To be sure, even before the pandemic, the concepts underlying the gravity-type and bid-rent modeling approaches were being embedded within more general discrete choice models (DCMs) for studying housing choice. This is because DCMs provide added flexibility and versatility in capturing individuals' multi-dimensional preferences and decision-making processes that include, but are not limited to, commuting time and land prices (Zolfaghari et al., 2012). However, most of the available housing-related DCMs focus on residential location (such as neighborhoods or zones) as the primary outcome, rather than the specific characteristics of the dwelling units. However, some researchers have expanded the discrete choice framework by incorporating individual dwelling units as outcomes (using each house as a specific alternative) instead of residential locations (Habib and Miller, 2009; Lee et al., 2010). In such studies, the attributes corresponding to the dwelling units (such as area, number of rooms, and presence of a backyard or patio) and the characteristics of the residential location (such as population density, availability of amenities, and school quality) are used as determinants of the preference for a joint combination of a specific dwelling unit within a specific residential neighborhood. However, since this approach uses an individual dwelling unit as the outcome alternative, the universal choice set becomes infeasibly large (Zolfaghari et al., 2012), which can then pose challenges for model estimation and forecasting as the probabilities for each alternative become miniscule (Bhat, 2015a; Lee and Waddell, 2010). To avoid these challenges, many discrete choice modeling studies consider choices at a zonal level to limit the size of the choice set (Andrew and Meen, 2006; Pinjari et al., 2011). Unfortunately, using a zonal unit of analysis limits these studies to considering only residential location and not dwelling unit characteristics. Other studies (see, for example, Eliasson, 2010; Guevara and Ben-Akiva, 2013b; Vandeviver et al., 2015) use sampling approaches in estimation when considering a dwelling unit level of analysis, but as discussed in detail later, such sampling approaches do not represent the housing choice-making process satisfactorily, and the issue of miniscule probabilities in forecasting still remains. Additionally, in such dwelling unit studies, heterogeneity across individuals in the valuation of different dwelling units and neighborhood characteristics is not adequately considered. For example, when deciding on a dwelling unit, the importance ascribed to the number of bedrooms is likely to differ based on whether a household has children or not. While such heterogeneity can be incorporated in a dwelling unit choice model through an interaction of the presence of children and number of bedrooms, doing so to accommodate possible heterogeneity in each dwelling unit dimension and based on multiple individual/household characteristics leads to an explosion in the number of parameters to be estimated.

In the current paper, to overcome the challenges associated with the traditional discrete choice formulation, we partition the overall housing choice into its multiple dimensions and consider each dimension separately within a joint model of housing outcomes. In particular, because we are not using the dwelling unit as the single endogenous outcome of analysis from which to extract relative valuations of the many dimensions characterizing that choice but are using the individual dimensions themselves as multiple endogenous outcomes, we do not have the problem of an infeasible number of alternatives. Besides, we are able to explicitly and directly incorporate heterogeneity across individuals along each dimension. Additionally, while our direct modeling of the individual dimensions characterizing dwelling unit choice precludes a straightforward trade-off analysis (as is possible from a discrete choice model with dwelling units as outcomes), we propose a novel approach that is still able to tease out these relative valuations.

In addition to directly modeling the many housing choice dimensions, we also explore the housing decision-making process within a new pandemic-disrupted terrain, especially due to the increased emergence and embrace of remote work. We do so using a Generalized Heterogenous Data Model (GHDM) framework (Bhat, 2015b) and consider a variety of attitudes, lifestyle preferences, and household sociodemographic characteristics as explanatory variables. The data used for this study are drawn from multiple sources, including the COVID Future Survey Wave 3 and the American Community Survey 2021 five-year estimates.

The following section provides an overview of the broad literature on housing choice modeling, with an emphasis on the development of joint models of housing outcomes. Section 3 presents the modeling framework along with the context and characteristics of the datasets used. Section 4 includes the model estimation results and interpretations. Section 5 discusses several important implications of this research for land use planning, travel demand modeling, and equity considerations. Finally, Section 6 concludes the paper with a brief summary of important findings as well as identification of future research directions.

## 2. LITERATURE OVERVIEW

As already discussed, the housing choice literature has primarily investigated housing location choice, with relatively few studies on non-location housing choices or housing location choice along with non-location housing choices. Accordingly, we first provide a brief overview of the methodologies used for housing location choice models, followed by the methodological challenges when considering non-location housing attributes along with location choice. We end the section by discussing empirical findings from earlier housing choice studies and the salient aspects of the current study.

### 2.1 Housing Location Choice

Traditional approaches in the literature for modeling housing location choice have focused on commute distance as the primary determinant, especially as exemplified in Alonso's (1960, 1964) bid-rent model and the aggregate gravity model. The bid-rent model assumes that households compete for land closest to a monocentric employment center based on willingness-to-pay for location attributes, leading to reduced housing density farther away from the monocentric employment center. This approach has been extended to include an evaluation of additional dwelling location characteristics (crime rates and location of good schools) and housing cost (Ellickson, 1981; Heldt et al., 2018), as well as to account for spatial heterogeneity, the varying attributes of different locations that impact individual preferences for housing in different areas (Cox and Hurtubia, 2021). Another approach is the aggregate gravity model, which uses a distance-decay function to describe the aggregate allocation of households around points of interest, generally employment centers. The approach has been used to characterize distributions of households around workplaces (Wilson, 1970), describe relative distances of household relocations based on cost and area familiarity (Hipp and Boessen, 2017), and identify the effects of ethnic heterogeneity on neighborhood migration (Bakens et al., 2018). However, the predominant approach to housing location choice employs McFadden's microeconomic theory-based discrete choice model (McFadden, 1978; Lerman, 1976), which, unlike the bid-rent and aggregate gravity models, immediately and conveniently facilitates the consideration of multiple attributes in analyzing the tradeoffs manifested in housing location choice (see, for example, Pagliara and Wilson, 2010; Fatmi et al., 2017; Acheampong, 2018).

The discrete choice approach to housing location choice has typically used a zone-level spatial unit or a parcel-level spatial unit for the analysis. The zone-level studies focus on households' choice of the spatial zone as a function of zone characteristics (such as zone-based accessibility measures to pursue out-of-home activities, crime rates, quality of schools in the zone, commute times of workers in the household, zonal race and income distributions relative to household's race and income, respectively) and interactions of household characteristics with the zonal characteristics (see, for example, Bhat and Guo, 2007; Pinjari et al., 2011; Jin and Lee, 2018; Hu and Wang, 2019). Unfortunately, the zonal level of analysis is saddled with the Modifiable Areal Unit Problem (MAUP) because the modeling results are a function of how space is partitioned into zones (Openshaw, 1978; Bhat and Guo, 2004). The parcel-level studies use a specific parcel of land or a building as the analysis unit, thus resolving the MAUP problem of the zone-level studies. Individual parcel-level characteristics (such as square footage of the parcel and topography of the parcel) can also be used along with broader zone-level (or other spatial-level) characteristics (see, for example, Lee et al., 2010; Lee and Waddell, 2010; Marois et al., 2019). The problem with parcel-based models, however, is that, similar to the zone-based models, they do not consider dwelling unit attributes. Besides, parcel-based models share the same "high number of alternatives" problem as dwelling unit-level models, as discussed next.

**2.2. Methodological Challenges when considering Non-Location and Location Attributes**

The consideration of non-location housing characteristics can be accommodated if the analyst uses the dwelling unit as the basis for modeling. The challenge, though, in using the dwelling unit as the outcome variable is that the universal choice set explodes in size quickly. While some studies (for example, see Bhat and Guo, 2007; Habib and Miller, 2009; Eliasson, 2010; Vandeviver et al., 2015; Lopez and Greenlee, 2016) attempt to "band-aid" this problem through a random sampling approach in estimation (combined with correction terms as needed; see Guevara and Ben-Akiva, 2013a, 2013b), the implicit assumption in such studies is that households consider all dwelling units in the universal choice set when making decisions (see Bhat, 2015a for an extended discussion of this point). In contrast, there is a relatively vast body of literature in the information search and social-behavioral science literature now clearly establishing that decision-makers, when confronted with a vast array of possible options, use heuristics and short-cuts to quickly circumscribe (whittle down) the set of possibilities to choose from (Simon, 1986). That is, there is a dynamic spatial choice process at play in which households continually search, construct, and update what they believe to be a set of credible and feasible alternatives in a first stage decision process, and then make a final choice at a specific time point from the alternatives remaining in the credible/feasible set (Habib and Miller, 2007). But, of course, traditional outcome data does not provide information directly on the first stage search process, which has led analysts to develop ways to mimic this first stage process. To conserve space, we do not provide a review of such methodologies. Interested readers will find an extensive review in Zolfaghari et al. (2013) and Bhat (2015a). A problem, though, with the implementation of such methods is that the first stage process becomes cumbersome when a number of search criteria are used to characterize it. As a result, almost all earlier studies use a single search dimension, typically using a maximum threshold of commute distance or commute time, for whittling down the alternative set to the consideration set (see, for example, Thill and Horowitz, 1997; Bhat and Zhao, 2002; Rashidi et al., 2012; Haque et al., 2019). While this threshold is allowed to be a function of household demographics, such as the number of vehicles and number of workers in the household, the net effect is that other housing dimensions, and the heterogeneity in the other dimensions, seldom feature in the housing choice set formation process. In reality, it is a combination of housing dimensions that jointly (and at once) play a role from the very start of the housing search process. This is particularly so in a post-pandemic setting, as discussed previously. The solution is to directly model the many housing dimensions as separate endogenous outcomes (see Bhat, 2015b; Frenkel and Kaplan, 2015). Doing so immediately offers the ability to extract the determinants of each dimension and accommodate heterogeneity across households in the preference for each dimension. Econometrically, by directly investigating preferences along each housing dimension, there is a substantial efficiency gain relative to attempting to determine preferences based on the single outcome of dwelling unit.

**2.3 Empirical Findings on the Determinants of Housing Choices**

Most earlier residential location choice studies use a zone-level or census tract-level analysis within a discrete choice framework, without considering dwelling unit characteristics (see, for example, Chen et al., 2008; de Palma et al., 2007; Pinjari et al., 2011; Yu et al., 2017). Some studies have focused on a single non-location dimension of housing choice, primarily tenure type (owning or renting the home). Examples include Abramsson and Andersson (2016), Carter (2011), Hartono et al. (2020), Manoj et al. (2015), and Tang et al. (2017). In general, these studies, some of which also control for the supply of rental and non-rental units available in the market (see, for example, Manoj et al., 2015), find that high income earning households, households with middle aged and highly educated individuals, and those with children are particularly likely to own their homes, while urban households tend to be more likely than non-urban households to rent. Some other studies examine both dwelling unit characteristics along with residential location, but have considered the outcomes along each dimension to be independent (see Acheampong, 2018; Jansen, 2012; Kaplan et al., 2011). For example, Acheampong (2018) observes that households with children, high income households, and households living in low density areas are more likely to live in detached housing units than other households, similar to the results related to tenure type. Only two published studies that we are aware of have used joint models that integrate both dwelling unit attributes and housing location characteristics into a unified framework that recognizes the interdependence and interactions among the different dimensions: Frenkel and Kaplan (2015) and Bhat (2015a).

Frenkel and Kaplan (2015) estimate a joint model of housing type, tenure type, number of bedrooms, and location choice. The location dimension is limited to a differentiation between central districts and suburban neighborhoods. Using data collected from a revealed preference survey of knowledge workers in Tel Aviv, Frenkel and Kaplan employ a Multinomial Logit-Ordered Response (MNL-OR) model with a single MNL choice for the package decision of housing type, tenure type, and location, along with an OR choice for the number of bedrooms. By estimating correlations between the number of bedrooms and each combination of housing type, tenure type, and location, the researchers observe that home ownership in suburban areas is positively associated with a preference for larger dwelling units. A broad range of exogenous variables are considered, including household-level sociodemographic information, activity patterns (either culture and entertainment-oriented or home-oriented), and accessibility to the workplace. Notably, accessibility to the workplace was exogenous in this model rather than an endogenous outcome.

Bhat (2015a) is the only earlier study of housing choice that we are aware of that models a comprehensive set of dwelling unit attributes and location characteristics, including commute distance, housing type, tenure type, housing cost, square footage of the unit, number of bedrooms, number of bathrooms, lot size, number of stories, and population density of the neighborhood. Bhat utilizes a GHDM model with the latent lifestyle constructs of green lifestyle propensity and luxury lifestyle propensity to explore the relationships among the various outcome dimensions jointly. According to the study, housing type influences housing cost, and both housing type and cost impact tenure type and residential location. Bhat's study also underscores the importance of considering lifestyle preferences in housing choice decisions.

While contributing in important ways to the housing choice literature, Frenkel and Kaplan (2015) and Bhat (2015a) were conducted prior to the pandemic. The two studies also did not consider neighborhood socioeconomic characteristics, such as school quality and crime rates, as part of the package decision.

### 2.4 Study in Context

The current study examines the multitude of housing dimension choices in the period after the onset of the pandemic, employing a joint model incorporating both dwelling unit characteristics and housing location attributes. While many studies after the onset of the pandemic have pointed out the changing preferences for dwelling unit attributes (Kocur-Bera, 2022; Navas-Martín et al., 2022; Salon and Conway, 2022; Li et al., 2021; Liu and Su, 2021) and housing location (Gupta et al., 2022; Huang et al., 2023; Liu and Su, 2021; McCord et al., 2022; Yang et al., 2023), these studies have either (a) used a bid-rent/hedonic pricing approach in which the changing demand for housing services is rather abstract and does not immediately correspond to individual dimensions of the dwelling unit, or (b) employed descriptive or exploratory analysis methods to examine changing housing behaviors. At the same time, many recent studies have suggested that pandemic-induced activity pattern changes, especially those related to remote working conditions, are likely to persist (Florida et al., 2021; Mehta, 2020; Smite et al., 2023; Song et al., 2023). These persisting and widespread changes, induced by the pandemic and the growth of remote work, have led to a growing need to reevaluate housing choices and the long-term implications of evolving housing preferences across the domains of real estate, urban development, and transportation planning.

In the above context, the current paper contributes to the methodological and empirical housing literature in several ways. First, our analysis includes a comprehensive set of outcome variables that are important factors in housing choices, including both dwelling unit attributes and neighborhood socioeconomic characteristics. Only one previous study (Bhat, 2015a) has considered commute distance in a joint model with dwelling unit attributes, and our model is the first such model that we are aware of using data collected since the pandemic. We also go beyond the variables included in any previous joint model by incorporating crime rates, accessibility of amenities, and school quality in a joint model with commute distance and dwelling unit attributes. Second, we incorporate three latent lifestyle-related constructs to recognize the important role played by lifestyle preferences on choice of living spaces (see van Wee, 2009; Van Acker et al., 2014; Fatmi et al., 2017; Guan and Wang, 2020; Maslova and King, 2020). These are green lifestyle propensity (GLP), luxury lifestyle propensity (LLP), and telework lifestyle propensity (TLP), which are modeled as psycho-social constructs using eleven indicators. The inclusion of a telework lifestyle propensity, along with green lifestyle propensity and luxury lifestyle propensity, is, to our knowledge, the first in the literature. Third, we employ Bhat's (2015b) Generalized Heterogeneous Data Model (GHDM) framework to estimate a joint model of housing outcomes. The three stochastic latent constructs, through their effects on different housing outcomes, accommodate unobserved covariance effects among the many outcomes in a parsimonious fashion. After accommodating such unobserved associations, we are able to track the pathway of "true" causal effects among the housing outcome variables. Finally, we develop an approach to impute the importance ascribed to different housing dimensions that reveal tradeoffs between the prioritization of different dimensions. We are not aware of any earlier effort in the econometric literature to extract such insights from joint models of multiple dimensions.

## 3. METHODOLOGY

### 3.1 Analytic Framework

The GHDM framework developed by Bhat (2015b) is used for this analysis. Figure 1 provides a visual representation of this framework. The model is adapted to include three endogenous binary choice outcomes (for the housing type, tenure type, and presence of a patio or yard), six endogenous ordinal choice outcomes (for the number of bedrooms, population density, median housing cost, accessibility of amenities, school quality, and crime rate), and one endogenous continuous outcome (for the logarithm of commute distance). These ten endogenous housing-related outcomes are shown on the right side of Figure 1. A set of individual/household demographics (see left side of figure) affect the ten outcomes in two different ways: (1) directly through the arrow indicated at the bottom of the figure (labeled as "MEM" for the measurement equation model component of the GHDM), as well as (2) indirectly through their effects on a set of latent lifestyle constructs (GLP, LLP, and TLP). These lifestyle constructs have been established in the earlier literature as important lifestyle considerations in housing choices, and are positioned in the middle of Figure 1. The arrow from the individual/household demographics to the latent constructs is labeled as "SEM" for the structural equation model component of the GHDM. The error vector $\boldsymbol{\eta}$ captures the effects of unobserved idiosyncratic individual factors that affect the set of continuous latent constructs for a given individual (all three latent constructs are considered for each individual), after controlling for observed individual/household demographics. As a result, the latent constructs are stochastic, not deterministic. The SEM component is estimated (imputed) based on the loading of the stochastic latent constructs on a set of observed indicator variables for the latent constructs (these indicator variables are positioned at the center top of the figure) as well as the effects of the latent constructs on the set of endogenous outcomes. These loadings and effects are identified by arrows originating from the latent constructs in the figure, which are labeled as "MEM" to indicate that these relationships are estimated as part of the MEM component of the GHDM. Finally, a set of regional exogenous variables (positioned at the top right of the figure) are also included as part of the MEM component to capture the effect on the endogenous housing outcomes of (1) generic variations in housing preferences across different regions of the U.S. and (2) potential geographic heterogeneity in the effects of the individual/demographic variables (as discussed in the next section, the sample used for our analysis includes housing choices of individuals/households from across the U.S.).

In addition to capturing lifestyle preferences that influence housing choice, the inclusion of stochastic latent constructs also facilitates a parsimonious correlation structure among the outcome variables. For example, if the green lifestyle propensity construct positively affects the population density of the residential location and negatively affects the commute distance, the immediate implication because of the stochastic nature of the construct is a negative correlation between the residential location population density and commute distance dimensions of housing choice; that is, unobserved individual factors that favor a high density of living also lead to a reduction in commute distance. In addition to these unobserved associations created by the stochastic latent constructs, the inter-relationships among outcome variables are captured in our model system through recursive causal effects of some endogenous housing outcome variables on other endogenous housing outcome variables, as discussed further in Section 3.2.4.

### *3.1.1 Mathematical Formulation of the GHDM for the Current Study*

As mentioned previously, the main outcomes considered in this study consist of three binary, six ordinal, and one continuous outcome. The binary outcomes are specific instances of ordinal outcomes (with only two ordinal categories), and so the overall GHDM framework for this study is formulated with ordinal and continuous outcome variables (shown on the right side of Figure 1). For ease in presentation, we will suppress the index for decision-makers in our exposition below and assume that all error terms are independent and identically distributed across decision-makers. Following Bhat's (2015b) notations, let $l$ be an index for latent variables ($l$=1, 2,…, $L$). In our case, $L$=3, corresponding to the three latent constructs (GLP, LLP, and TLP). Consider the latent construct $z_l^*$ and write it as a linear function of covariates in the SEM component:

$$z_l^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l , \qquad (1)$$

where $\boldsymbol{w}$ is a $(D\times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l'$ is a corresponding $(D\times 1)$ vector of coefficients, and $\eta_l$ is a random error term assumed to be standard normally distributed for identification purposes ($\boldsymbol{\alpha}_l'$ in Equation (1) represents the transpose of the vector $\boldsymbol{\alpha}_l$). The error vector $\eta_l$ captures the effects of unobserved factors that affect the latent constructs, after controlling for observed demographics.Next, define the $(L\times D)$ matrix $\boldsymbol{\alpha}=(\boldsymbol{\alpha}_1,\boldsymbol{\alpha}_2,...,\boldsymbol{\alpha}_L)'$, and the $(L\times 1)$ vectors $\boldsymbol{z}^*=(z_1^*,z_2^*,...,z_L^*)'$ and $\boldsymbol{\eta}=(\eta_1,\eta_2,\eta_3,\ldots,\eta_L)'$ We allow a multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables. $\boldsymbol{\eta}\sim MVN_L[\mathbf{0}_L,\boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L\times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L\times L)$ correlation matrix. In matrix form, we may write Equation (1) as:

$$\boldsymbol{z}^*=\boldsymbol{\alpha w}+\boldsymbol{\eta}\,. \tag{2}$$

Next consider $N$ ordinal outcomes (indicator variables for the latent constructs presented at the center top of Figure 1 as well as main outcomes) and let $n$ be the index for the ordinal outcomes $(n=1,\ 2,...,\ N)$. In our empirical context, $N$=20, corresponding to a total of eleven indicators of the three latent constructs and the nine ordinal main outcomes (all outcomes except commute distance). Also, let $J_n$ be the number of categories for the $n^{th}$ ordinal outcome $(J_n\geq 2)$ and let the corresponding index be $j_n$ $(j_n=1,\ 2,...,\ J_n)$. Let $\tilde{y}_n^*$ be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the $n^{th}$ ordinal variable. Assume that the individual under consideration chooses the $a_n^{th}$ ordinal category. Then, in the usual ordered response formulation, for the individual, we may write:

$$\tilde{y}_n^*=\tilde{\boldsymbol{\gamma}}_n'\boldsymbol{x}+\tilde{\boldsymbol{d}}_n'\boldsymbol{z}^*+\tilde{\varepsilon}_n,\ \text{and}\ \tilde{\psi}_{n,a_n-1}<\tilde{y}_n^*<\tilde{\psi}_{n,a_n}\,, \tag{3}$$

where $\boldsymbol{x}$ is an $(A\times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous variables, $\tilde{\boldsymbol{\gamma}}_n$ is a corresponding vector of coefficients to be estimated, $\tilde{\boldsymbol{d}}_n$ is an $(L\times 1)$ vector of latent variable loadings on the $n^{th}$ ordinal outcome, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_n$ is the standard normal random error for the $n^{th}$ ordinal outcome (note, however, that for the indicators (but not the main outcomes), the $\boldsymbol{x}$ vector will not appear on the right side of Equation (3); also, there are specific identification conditions for the number of non-zero elements of $\tilde{\boldsymbol{d}}_n$ that can be present in each indicator equation and across all indicator equations; please see Bhat (2015a) for additional details). For each ordinal outcome, $\tilde{\psi}_{n,0}<\tilde{\psi}_{n,1}<\tilde{\psi}_{n,2}...<\tilde{\psi}_{n,J_n-1}<\tilde{\psi}_{n,J_n}$; $\tilde{\psi}_{n,0}=-\infty$, $\tilde{\psi}_{n,1}=0$, and $\tilde{\psi}_{n,J_n}=+\infty$. For later use, let $\tilde{\boldsymbol{\psi}}_n=(\tilde{\psi}_{n,2},\tilde{\psi}_{n,3},...,\tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}}=(\tilde{\boldsymbol{\psi}}_1',\tilde{\boldsymbol{\psi}}_2',...,\tilde{\boldsymbol{\psi}}_N)'$. Stack the $N$ underlying continuous variables $\tilde{y}_n^*$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{y}}^*$, and the $N$ error terms $\tilde{\varepsilon}_n$ into another $(N\times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define $\tilde{\boldsymbol{\gamma}}=(\tilde{\boldsymbol{\gamma}}_1,\tilde{\boldsymbol{\gamma}}_2,...,\tilde{\boldsymbol{\gamma}}_N)'$ [$(N\times A)$ matrix] and $\tilde{\boldsymbol{d}}=\left(\tilde{\boldsymbol{d}}_1,\tilde{\boldsymbol{d}}_2,...,\tilde{\boldsymbol{d}}_N\right)$ [$(N\times L)$ matrix], and let $\mathbf{IDEN}_N$ be the identity matrix of dimension $N$ representing the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$. Finally, stack the lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}\left(n=1,2,...,N\right)$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the upper thresholds $\tilde{\psi}_{n,a_n}\left(n=1,2,...,N\right)$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes for the decision-maker may be written as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{up}. \tag{4}$$

Next, consider $H$ continuous variables $(y_1, y_2, ..., y_H)$ with an associated index $h$ $(h = 1, ..., H)$. In our case, $H$=1 for the logarithm of commute distance, but we present the model formulation for a general $H$, because the presentation simplicity is not affected by using a general formulation. In the usual linear regression form, we may write:

$$y_h = \boldsymbol{\gamma}_h' \boldsymbol{x} + \boldsymbol{d}_h' \boldsymbol{z}^* + \varepsilon_h, \tag{5}$$

where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant), as well as potentially the observed values of other endogenous variables. $\boldsymbol{\gamma}_h$ is an $(A \times 1)$ column vector of the coefficients associated with $\boldsymbol{x}$, and $\boldsymbol{d}_h$ $(L \times 1)$ is the vector of coefficients of the latent variables for continuous outcome $h$. $\varepsilon_h$ is a normally distributed error term corresponding to the $h^{th}$ continuous variable. By vertically stacking the $\varepsilon_h$ elements, we obtain $\boldsymbol{\varepsilon} = (\varepsilon_1, ..., \varepsilon_H)'$. $\boldsymbol{\varepsilon}$ follows a multivariate normal distribution centered at zero with covariance $\boldsymbol{\Sigma}$, which is is restricted to be diagonal. Next, stack the $H$ continuous outcomes into an $(H \times 1)$ vector $\boldsymbol{y}$, and the $H$ error terms into another $(H \times 1)$ vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_H)'$. Also, define the $(H \times A)$ matrix $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, ... \gamma_H)'$ and the $(H \times L)$ matrix of latent variable loadings $\boldsymbol{d} = (\boldsymbol{d}_1, \boldsymbol{d}_2, ..., \boldsymbol{d}_H)'$. Then, one may write, in matrix form, the following measurement equation for the continuous outcomes:

$$\boldsymbol{y} = \boldsymbol{\gamma}\boldsymbol{x} + \boldsymbol{d}\boldsymbol{z}^* + \boldsymbol{\varepsilon}. \tag{6}$$

To develop the reduced form equations, we start by defining $\ddot{\boldsymbol{y}} = \left( \boldsymbol{y}', \left[ \tilde{\boldsymbol{y}}^* \right]' \right)'$, which is an $[E \times 1]$ vector that holds the $N$+$H$ set of indicator and outcome variables ($E$=21, in our case). Similarly, define $\ddot{\boldsymbol{\gamma}} = (\boldsymbol{\gamma}', \tilde{\boldsymbol{\gamma}}')'$ $[E \times A$ matrix], $\ddot{\boldsymbol{d}} = (\boldsymbol{d}', \tilde{\boldsymbol{d}}')'$ $[E \times L$ matrix], and $\ddot{\boldsymbol{\varepsilon}} = (\boldsymbol{\varepsilon}', \tilde{\boldsymbol{\varepsilon}}')'$. Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vech}(\boldsymbol{\Sigma}), \text{Vech}(\ddot{\boldsymbol{\gamma}}), \text{Vech}(\ddot{\boldsymbol{d}})]$, where the operator "Vech(**.**)" vectorizes all the non-zero elements of the matrix/vector on which it operates. Using the matrix definitions above, the MEM component of the model system may be written compactly as:

$$\ddot{\boldsymbol{y}} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}\boldsymbol{z}^* + \ddot{\boldsymbol{\varepsilon}}, \text{ with Var } (\ddot{\boldsymbol{\varepsilon}}) = \ddot{\boldsymbol{\Sigma}} = \begin{pmatrix} \boldsymbol{\Sigma} & \mathbf{0} \\ \mathbf{0} & \mathbf{I_N} \end{pmatrix} (E \times E \text{ matrix}). \tag{7}$$

By substituting $\boldsymbol{z}^*$ from the SEM component of Equation (2) in the MEM Equation (7), $\ddot{\boldsymbol{y}}$ may be expressed in reduced form as:

$$\ddot{\boldsymbol{y}} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}\boldsymbol{z}^* + \ddot{\boldsymbol{\varepsilon}} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}(\boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}) + \ddot{\boldsymbol{\varepsilon}} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w} + \ddot{\boldsymbol{d}}\boldsymbol{\eta} + \ddot{\boldsymbol{\varepsilon}}. \tag{8}$$

From Equation (8), we observe that $\ddot{y}$ follows the multivariate normal distribution with a mean of $\boldsymbol{b} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w}$ and a covariance matrix of $\boldsymbol{\Omega} = \ddot{\boldsymbol{d}}\boldsymbol{\Gamma}\ddot{\boldsymbol{d}}^{\mathrm{T}} + \ddot{\boldsymbol{\Sigma}}$; that is,

$$\ddot{\boldsymbol{y}} \sim MVN_E(\mathbf{b}, \boldsymbol{\Omega}). \tag{9}$$

For the estimation of the model, partition the vector $\boldsymbol{b}$ into components $\boldsymbol{b}_y$ that correspond to the mean of vectors $\boldsymbol{y}$ (the continuous outcome variable for the logarithm of commute distance), and $\boldsymbol{b}_{\tilde{y}^*}$ corresponding to $\tilde{\boldsymbol{y}}^*$ (the ordinal indicator and outcome variables). Also, partition the matrix $\boldsymbol{\Omega}$ into the corresponding variances and covariances:

$$\tilde{\boldsymbol{B}} = \begin{bmatrix} \boldsymbol{b}_y \\ \boldsymbol{b}_{\tilde{y}^*} \end{bmatrix} (E \times 1) \text{ vector and } \tilde{\boldsymbol{\Omega}} = \begin{bmatrix} \tilde{\boldsymbol{\Omega}}_y & \tilde{\boldsymbol{\Omega}}_{y\tilde{y}^*} \\ \tilde{\boldsymbol{\Omega}}_{y\tilde{y}^*} & \tilde{\boldsymbol{\Omega}}_{\tilde{y}^*} \end{bmatrix} (E \times E) \text{ matrix.} \tag{10}$$

Let the observed value of the continuous outcome vector $\boldsymbol{y}$ for the individual be $\boldsymbol{g}$. The conditional distribution of $\tilde{\boldsymbol{y}}^*$, given $\boldsymbol{y} = \boldsymbol{g}$, is MVN with mean $\vec{\boldsymbol{B}}_{\tilde{y}^*} = \boldsymbol{b}_{\tilde{y}^*} + \tilde{\boldsymbol{\Omega}}'_{y\tilde{y}^*}\ \tilde{\boldsymbol{\Omega}}_y^{-1}\left(\boldsymbol{g} - \boldsymbol{b}_y\right)$ and variance $\vec{\boldsymbol{\Omega}}_{\tilde{y}^*} = \tilde{\boldsymbol{\Omega}}_{\tilde{y}^*} - \tilde{\boldsymbol{\Omega}}'_{y\tilde{y}^*}\ \tilde{\boldsymbol{\Omega}}_y^{-1}\tilde{\boldsymbol{\Omega}}_{y\tilde{y}^*}$. Then, the likelihood function may be written as:

$$\begin{aligned} L(\boldsymbol{\delta}) &= f_H(\boldsymbol{y} = \boldsymbol{g} \,|\, \boldsymbol{b}_y, \boldsymbol{\Sigma}) \times \Pr\left[\vec{\boldsymbol{\psi}}_{low} \le \tilde{\boldsymbol{y}}^* \le \vec{\boldsymbol{\psi}}_{up}\right], \\ &= f_H(\boldsymbol{y} = \boldsymbol{g} \,|\, \boldsymbol{b}_y, \boldsymbol{\Sigma}) \times \int\limits_{D_r} f_N(\boldsymbol{r} \,|\, \vec{\boldsymbol{B}}_{\tilde{y}^*}, \vec{\boldsymbol{\Omega}}_{\tilde{y}^*}) dr, \end{aligned} \tag{11}$$

where the integration domain $D_r = \{\boldsymbol{r} : \vec{\boldsymbol{\psi}}_{low} \le \boldsymbol{r} \le \vec{\boldsymbol{\psi}}_{up}\}$ is simply the multivariate region of the elements of the $\tilde{\boldsymbol{y}}^*$ vector determined by the observed ordinal outcomes. $f_H(\boldsymbol{y} = \boldsymbol{g} \,|\, \boldsymbol{b}_y, \boldsymbol{\Sigma})$ is the MVN density function of dimension $H$ with a mean of $\boldsymbol{b}_y$ and a covariance of $\boldsymbol{\Sigma}$, and evaluated at $\boldsymbol{g}$. Note that for unemployed individuals and those with no physical workplace, the continuous dimension is irrelevant and we only consider the ordinal outcome dimensions. The likelihood function for a sample of $Q$ decision-makers is obtained as the product of the individual-level likelihood functions.

### 3.2 Data Description

The primary data source used for this study is the COVID Future Survey Wave 3 (Salon et al., 2022), which involved collecting responses through an online platform powered by Qualtrics. To ensure a diverse pool of participants, survey invitations were extended through multiple channels, including purchased email lists, social media outreach, and mainstream media articles. The purchased email list comprised approximately 450,000 email addresses of people residing in 24 metropolitan areas across the U.S. An additional list containing approximately 39,000 email addresses specifically from the Phoenix metropolitan area was also included (Chauhan et al., 2021, 2022). To encourage participation, respondents were provided with a small incentive in the form of a gift card upon completing the survey.

The COVID Future Survey Wave 3 was administered to a stratified random sample of households across the United States in October and November of 2021. The dataset includes sociodemographic information about individuals and their households, details of their travel behaviors, attitudes and preferences for a variety of mobility and housing options, and responses to the COVID-19 pandemic. Using data from October and November of 2021 allows for analysis of housing choices with the worst of the pandemic well behind, and the initial shocks caused by lockdowns in the United States in 2020 wearing off. The survey collected data from 2,728 participants. Of these, 2,149 responses with complete data on housing choices were retained for the final analysis.

The research team then appended additional information to the data from the COVID Future Survey. In particular, neighborhood socioeconomic characteristics, including population density and median housing cost (see description below) from the 2021 American Community Survey (U.S. Census Bureau, 2021), were appended based on the respondent's zip code tabulation area (ZCTA). Neighborhood quality of life rating scores were also appended from areavibes.com ("Best Places to Live In the US & Canada," 2023), including an education score and amenities score, and crime rates were added from crimegrade.org ("Find the Safest Areas," 2023).

An important point to note here is that the Future Covid Survey, while providing a timely dataset with comprehensive information on a host of residential attributes as well as important attitudes and indicators of relevant lifestyle preferences, collected information at the individual-level rather than at the level of the entire household. Admittedly, housing choices are made at a household level, considering work/telework arrangements and attitudinal/lifestyle preferences of all family members. However, an individual level analysis of housing choices as undertaken in the current study, although not ideal, may not also be as inadequate as it may initially seem to extract knowledge about the housing choice process. This is because of at least four reasons. First, we use a suite of household-level sociodemographic exogenous variables to accommodate the household level nature of housing choice decisions. For instance, household composition and household income both represent the household as a whole. Second, while race and ethnicity are available only at the individual level, these are highly correlated with the race and ethnicity of other household members, particularly when racial identification is restricted to a small set of categories (this is so even if the individual-household race correspondence has been weakening a little in recent years; see Bratter et al., 2022; Roy et al., 2022). Third, it has been well established in the demography literature that variables such as age and educational attainment of any individual in the household does provide a reasonable indication of the life-stage and structure of the entire household (see Zacher and Froidevaux, 2021; Davis-Kean et al., 2021). Fourth, evidence from the sociology literature (see Zablocki and Kanter, 1976; Glass et al., 1986; Chambers and Gracia, 2021) indicates that the close individual-household correspondence is not just confined to many demographic variables, but also extends to lifestyle preferences. This is particularly so among intimate family members who are likely to be the ones making important family-level decisions such as housing choices.[1]

[1]Also, while not explicitly a justification for using an individual-level analysis of housing choices, we should point out that, similar to our study, there is a vast body of literature that examines household level residential choice decisions using individual-level data (see, for example, Walker and Li, 2007; Pinjari et al., 2011; Frenkel and Kaplan, 2015; Lee et al., 2019; Kim et al., 2020; Zarrabi et al., 2021). Indeed, while there has been more extensive investigation of household-level interactions for other transportation decisions (see Bhat and Pendyala, 2005; Timmermans and Zhang, 2009), only a handful of papers in the housing choice literature have considered the household as the unit of analysis (see Borgers and Timmermans, 1993; Ho and Mulley, 2015; Picard et al., 2015; Huai et al., 2021; Janke, 2021). Additionally, while these papers provide important insights into the dynamics of household interactions in the residential location choice decision, they have almost exclusively focused on location characteristics to the exclusion of other dwelling unit characteristics (except for Borgers and Timmermans, 1993, who, using stated preference data, examined dwelling unit type alongside residential location characteristics). Thus, almost all earlier household-level studies of housing choice ignore that location choice is intricately linked with dwelling unit attributes, a driving motivation for the current investigation. Of course, an important direction for future research is to recognize the household-level nature of decision-making of housing choices, while also explicitly considering the multidimensionality of housing choices including dwelling unit attributes. Of particular importance is to consider the commuting distances of all workers in a household, rather than of only one person as in the current paper (as already discussed, the individual-level survey effort provided information only on the commute of the respondent (if employed), not the commutes of all employed individuals in the respondent's household).

### *3.2.1 Main Outcome Variables*

The study examines a range of outcome variables split into two broad categories: the dwelling unit attributes, and the neighborhood characteristics (which include all the outcomes for the spatial zone encompassing the dwelling unit and the location in relation to other points of interest). The specific variables are discussed below, and descriptive statistics are summarized in Table 1.

The dwelling unit attributes in our analysis include housing type (single family homes or apartments), tenure type (own or rent), presence of a patio or yard, and number of bedrooms. The label "single family homes" includes private homes completely detached from other units or duplexes attached to other units. Those living in mobile homes or on a friend's couch constituted an extremely small number of individuals and were screened out of our analysis. The "number of bedrooms" represents the total number of rooms used for sleeping, including guest rooms, in the house. Studio apartments and other single-room homes are considered to have zero bedrooms. A few respondents reported having large houses with more than five bedrooms, and these were combined into a "five or more bedrooms" category. As may be observed from Table 1, a vast majority of respondents lived in a single-family home, owned the home, and had a patio or yard. A majority of households lived in housing units with 2-4 bedrooms, with very few in units with no bedrooms.

The neighborhood characteristics modeled as endogenous outcomes include commute distance, population density, median housing cost, access to amenities, school quality, and crime rate. The commute distance represents the reported distance in miles (one-way) between the respondent's home and primary workplace outside the home (we will refer to this primary workplace outside the home as the "office"). The logarithm of the commute distance is used in the analysis to recognize the substantial rightward skew, as well as the strictly positive nature, of the variable. Note that commute distance is relevant only for employed individuals with an office location; this is accommodated by considering commute distance as an outcome only for those employed with an office and removing commute distance from the multivariate endogenous outcome set for those unemployed or who have no office (these individuals were retained in the sample but included in the model with only the nine remaining outcomes after removing commute distance). Among those employed with an office (about half of the respondents in the sample were employed with an office, with about 15% employed but with no office), the mean one-way commute distance is 15.15 miles, and the median is 10.00 miles. Table 1 also shows the one-way commute distance distribution in different discrete bins, indicating that most employed individuals had a commute distance below 20 miles, but a non-insignificant percentage of employed individuals also had a commute distance beyond 20 miles. Population density reflects the number of individuals residing per square mile in each ZCTA. The population density is used as an ordered outcome variable, categorized into densities of low (less than 5 people per square mile), medium (5 to 10 people per square mile), and high (more than 10 people per square mile). The Table 1 statistics indicate a relatively even distribution across the three population density categories, though with a higher percentage of individuals residing in medium and higher density neighborhoods. The median housing cost is across all occupied housing units in the ZCTA and is categorized into four monthly cost ranges of low ("≤ $1,000"), medium range 1 ("$1,001-$1,500"), medium range 2 ("$1,501-$2,000"), and high ("≥$2000"). This information, obtained from American Community Survey estimates, is calculated separately for renters and owners. For renters it includes the contract rent plus the estimated average monthly cost of utilities (including water, sewer, electricity, gas, and fuel). For owners it is calculated as the sum of payments for mortgages and other property debts, real estate taxes, residential insurance policies, and utilities (again including water, sewer, electricity, gas, and fuel). The Table 1 statistics point to a relatively low share of individuals living in low- or high-cost neighborhoods, compared to the medium categories. The amenities rating is a score based on the availability of amenities within a 2-mile radius of the center of the zip code. The methodology used to estimate this rating is a function of the number of available locations for groceries, food and drink, shopping, coffee shops, schools, parks, entertainment, fitness facilities, public transportation, and libraries, weighted towards locations for shopping and groceries. From these ratings, five categories are created based on the relation to the national average, such that areas with more amenities have higher scores. As seen in Table 1, the vast majority of respondents fall into the category with many amenities available within two miles of their ZCTA and very few fall into each of the four lower levels.[2] The school quality rating is based on the standardized test scores for students in schools in the area, as well as the average educational attainment of residents in the area (a total rating is calculated as 0.8*school test score percentile + 0.2*average educational attainment percentile). The school rating variable is grouped as an ordered outcome with five levels, where higher levels indicate higher quality education in the area. The statistics indicate a bimodal distribution, with more than a quarter of individuals each living in "very poor" and "excellent" school quality neighborhoods. Finally, the crime rating is based on the total number of crimes reported per 100,000 residents per year. This includes crimes reported to the police and FBI including violent crimes (such as murder, rape, robbery, and assault), property crimes (arson, theft, vehicle theft, and burglary), kidnapping, drug crimes, and vandalism. The crime rating is used as an ordered outcome with levels of (on a crimes per 100,000 residents basis) (i) very low (less than 1.615), (ii) low (1.615 – 2.522), (iii) medium (2.523 – 3.820), (iv) high (3.821 – 7.540), and (v) very high (more than 7.540).

### *3.2.2 Exogenous Variables*

The descriptive statistics of the exogenous variables are provided in Table 2, along with corresponding data for the entire United States from the American Community Survey (ACS) 2021 five-year estimates (U.S. Census Bureau, 2021). These exogenous variables include household and individual demographics.

The sample exhibits an underrepresentation of individuals living alone, and an overrepresentation of those living with related adults. Further, there is an overrepresentation of individuals from households (a) with senior (≥65 years) adults, (b) with no children (a child is defined as a dependent 17 years of age or younger), (c) from middle income households (using reported gross household incomes), (d) with a single motorized vehicle available in the home, and (e) from the western region[3]. In terms of individual demographics, there is a clear over-

[2]The amenity ratings were obtained as such from the areavibes.com website. While the distribution is highly skewed toward the highest amenity level, we decided to retain the five-category classification in our modeling because the ordered-response framework efficiently accommodates multiple categories even with few observations in each category (only one additional threshold parameter needs to be computed for each ordinal category). Besides, there were 50 observations even in the lowest "few" amenities ordinal category.

[3]The four US regions were defined according to the US Census definitions. These regions include the Northeast (Connecticut, Main, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania), Midwest (Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota), South (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas), and West (Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, and Washington).

representation of women, non-Hispanic individuals, white individuals, those who are 65 or above in age, and individuals with high formal education degree attainment. The overrepresentation of the western region of the US can be attributed to the purchasing of more email addresses from the western region, including a specific focus on the Phoenix metropolitan area (Chauhan et al., 2022). Also, it is surprising that single and younger adults are underrepresented, given that the survey was conducted online and advertised through social media. One possible explanation is that older individuals have perceived much more disruption caused by the pandemic in their regular activity-travel rhythms, and so may have been more tuned into the purpose of the survey (which was to investigate shifts in activity-related behavior caused by the pandemic).

The observed skews in the exogenous variables imply that descriptive statistics derived from this sample cannot be generalized to the entire United States population. However, since this study focuses on conducting an individual-level causal analysis, there is no reason to believe that the causal relationships estimated would not apply to the population at large. Indeed, the sample used in this study is sizable, encompasses the entire nation, and demonstrates substantial variation in the exogenous variables, allowing estimation of the effects of exogenous variables on the housing outcomes of interest. Additionally, since the sample is not based on endogenous sampling (i.e., our sampling of respondents was based on a convenience sample, not one targeted toward individuals with specific housing outcomes), an unweighted approach is the preferred one because it is more efficient (see Wooldridge, 1995 and Solon et al., 2015).

#### *3.2.3 Latent Constructs*

The first latent construct is the green lifestyle propensity (GLP), which captures individuals' overall attitudes toward the environment, their preference for outdoor non-motorized activities, and their environmentally conscious behavior. Several existing housing choice studies have highlighted the importance of incorporating a latent construct for GLP in housing choice decisions (Bhat, 2015a; Fleischer, 2007; Tan and Goh, 2018). It is expected that individuals with high GLP will seek to reduce their emissions by choosing shorter commute distances and choose to reside in high population density areas that concords with their desire to use non-motorized modes of travel. The indicators used to measure GLP are presented in Figure 2 and include measures of attitudes toward environmentally conscious actions and revealed walking behavior.

The second latent construct is the luxury lifestyle propensity (LLP), which measures the preference for increased privacy and high levels of consumption. A luxury lifestyle is associated with a preference for privacy, spaciousness, and exclusivity (Bhat, 2015a; Wang, 2022). Thus, we expect that those with high LLP will choose single-family houses rather than apartments, own their homes, live in high-cost dwelling units with more bedrooms, and in neighborhoods with low crime rates. The indicators for this latent construct, shown in Figure 2, include the preference for privacy, a single-family home with a yard, and higher levels of vehicle ownership, all of which point to higher levels of conspicuous consumption.

The third latent construct is the telework lifestyle propensity (TLP), which captures an individual's relative inclination toward working from home rather than from the office. A shift from office to remote work has important lifestyle implications, with a substantial portion of daily activities being relocated from the workplace to the home, thereby transforming the role of the dwelling unit (Doling and Arundel, 2022). Since the onset of the pandemic, significant connections have been established between the preference for telework and housing preferences, motivating its inclusion as a latent construct (see also de Abreu e Silva, 2022). TLP is expected to be an important factor impacting commute distance and dwelling unit characteristics, since those with a high TLP may, for example, have longer commute distances (because they make the commute less frequently) and tend to live in single family homes (rather than in apartment complexes). Indicators for teleworking include attitudes towards working at home, revealed current telework frequency, and anticipated preference for future teleworking arrangements.[4]

### *3.2.4 Endogenous Effects*

Endogenous effects capture the recursive influences and interdependencies among the endogenous outcomes within the model. As mentioned previously, the three stochastic latent constructs serve both to capture lifestyle preferences that influence housing choices and to allow for unobserved covariance effects among the main outcomes. By accommodating these covariance effects through the latent variables, we are better able to discern the causal chain of effects among the housing outcomes through the recursive effects among the endogenous outcomes. While one observed endogenous outcome can affect another dependent outcome, in joint models with limited-dependent outcomes (that is, model systems that include non-continuous dependent outcomes), model identification requires that endogenous outcome effects can only be recursive and triangular (see Maddala, 1983; Bhat, 2015b). That is, the causal relationship between two endogenous outcomes can only be in one direction. The final preferred endogenous causal pathway structure from our analysis is shown in Figure 3 and is discussed later. This structure was determined through testing each direction of causality between each pair of endogenous outcomes, and selecting the causal structure among the many outcomes that achieved the best data fit. In our empirical context, we consistently achieved the best data fit with the causal pathway structure of Figure 3.

## 4. MODEL RESULTS

The final specification presented here is based on an iterative process of including demographic variables in different forms and testing alternative combinations of explanatory variables based on statistical fit. The categorical/bracketed variables were considered as dummy variables in the most disaggregate form available, and progressively combined based on statistical tests to yield parsimonious specifications. In the model estimation process, we used a t-statistic threshold of 1.00 to retain variables (corresponding to a 0.32 level of significance or 68% confidence level), because of the moderate-sized sample used in the analysis and the potential for such included variables to guide future investigations with larger sample sizes. However, it should also be noted that, but for four estimated coefficients in Table 3 and 4, the rest of the 155 estimated coefficients (not including the 26 thresholds and constants that should always be included) have a t-statistic well above the 90% confidence level t-statistic of 1.645. A more parsimonious model excluding these four coefficients had literally no impact on the rest of the model coefficients, indicating that the interpretations and conclusions drawn are not sensitive to our use of a more liberal confidence

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[4]We acknowledge that telework decisions may be endogenous to housing choices. The direction of effects between telework and housing decisions has been an issue of debate for a long time in the literature. In this paper, we assume that telework decisions affect housing choices, in the strand of literature originating in the works of Nilles (1991), Mokhtarian (1991), Melo and de Abreu e Silva (2017), de Vos et al. (2018), Chakrabarti (2018), de Vos et al. (2019), and Lennox (2020). However, workers' teleworking propensity itself may be impacted by their housing location in the reverse direction, as has been assumed in several other studies (de Abreu e Silva, 2022; de Abreu e Silva and Melo, 2018; Fatmi et al., 2022; Liang et al., 2023). We leave the joint modeling of telework arrangements along with housing choices to future efforts, though we will draw attention to a recent paper by Asmussen et al. (2024) that starts to address this issue in the specific context of telework arrangements and commute distance (but this Asmussen et al. paper does not model the many other aspects of housing choices considered in the current paper).

level to keep the four coefficients with a lower t-statistic (these four coefficients correspond to the impact of ethnicity on TLP in the structural equation model, and the following three effects in the measurement equation model – the effect of TLP on housing type, the income effect on population density of residential living, and the endogenous effect of commute distance on housing type). A "—" entry in the results tables indicates that the row exogenous variable/endogenous outcome does not have any statistically significant impact on the column latent construct (for Table 3) and endogenous outcome (for Table 4). In some cases, the entry also implies that the effect is not applicable.

The results are organized in several sections. Section 4.1 presents results related to the latent constructs, including the effects of exogenous variables on the latent constructs (constituting the structural equation model or SEM component of the model) and the relationship between the latent constructs and the indicators (constituting part of the measurement equation model or MEM component of the model). Section 4.2 presents the MEM model component corresponding to the effects on the main endogenous outcomes. The effects of the latent constructs on the main outcomes are presented first, followed by the impacts of exogenous variables, then the endogenous effects between main outcomes, and finally the implied correlations (based on the stochastic latent construct effects) between the outcomes. Section 4.3 discusses the model fit in relation to an independent model that ignores the jointness among the outcomes. Finally, Section 4.4 discusses average treatment effects, to explore the package nature of the housing decision and the tradeoffs between the outcomes.

### 4.1 Latent Constructs

Table 3, displaying the SEM model component, reveals that age significantly impacts all three latent constructs. The green lifestyle propensity (GLP) decreases with age. This finding aligns with previous research indicating that older adults tend to prioritize business and economic growth over environmental concerns, while younger adults prioritize sustainability even if at higher costs (Shi et al., 2016; Smith and Brower, 2012). Conversely, there is a notable increase in luxury lifestyle propensity (LLP) among those aged 40 years and above, and particularly for those 50 years and above. Importantly here, while younger age groups are often associated with conspicuous consumption of smaller products such as clothing and phones, the luxury lifestyle considered in this study refers to the consumption of larger items such as cars and houses, which have been associated primarily with individuals aged 40-60 years of age (Shukla, 2008). Finally, older adults tend to have a lower telework lifestyle propensity (TLP) relative to their younger peers, with the oldest cohort of workers (65 years of age or over) particularly having a disinclination for telework. This is consistent with the human development literature; younger adults are more predisposed to telework because of their expansive social-professional networks in and outside of their work environment (including strong desires for a "digital nomadic lifestyle"), while older adults prefer small and familiar social-professional networks such as those at their work office (Tahlyan et al., 2022; Asmussen et al., 2023).

In terms of formal educational attainment, GLP is positively associated with higher educational attainment, consistent with results in the social-psychological literature suggesting that individuals with a higher education are more self-aware of the negative consequences of degrading the environment (such as the resulting health-related problems and global warming), enabling them to identify actions they can take to reduce harmful environmental impacts (Aklin et al., 2013; Franzen and Vogl, 2013; Chankrajang and Muttarak, 2017; Liu et al., 2020). Higher levels of education degree attainment also are associated with lower LLP, possibly because education plays an important role in shaping consumer behavior through an increased awareness of spending habits and a restraint on extravagant consumption (Jaikumar and Sharma, 2021; Memushi, 2014). Finally, higher levels of education attainment correspond to an elevated TLP, presumably because of the ease of adapting to new technological environments (Adobati and Debernardi, 2022) and the ability to secure jobs that are conducive to teleworking.

Income is positively associated with all three latent constructs. The impact of income on GLP has been a subject of debate in the literature, but may be traced to Maslow's (1943) theory of the hierarchy of human needs. A higher social/economic status of an individual allows consideration of the longer-term and higher-level need for environmental quality, given shorter-term basic biological survival needs are likely to already be satisfied. Higher incomes also provide the financial wherewithal to consume exclusive and expensive goods, as a means to signal wealth, power and status, and uniqueness in the consumer space (see Husic and Cicic, 2009; Chevalier and Gutsatz, 2012). Further, the positive effect of income on TLP aligns with the previous literature suggesting that such high-income earners enjoy more freedom in their work arrangements and in negotiating ability to work remotely (see Tahlyan et al., 2022; Asmussen et al., 2023).

Table 3 also indicates that individuals of Asian origin have a higher GLP (possibly influenced by cultural values of collectivism and community concern that align with prioritizing a green lifestyle; see Deng et al., 2006), while Black individuals have a lower LLP (perhaps because of historical discriminatory social status practices; see Oliver and Shapiro, 1997 and Charron-Chénier et al., 2017). Hispanic individuals, however, are more likely to be luxury-oriented, though also tend to display a lower TLP. This higher LLP among Hispanic individuals may be related to a strong belief in the "American Dream" and focus on financial achievements, educational attainment, and home ownership (see Cervantes et al., 2021). Overall, the latent constructs are related much more to individual demographics than household demographics (except for household income). However, it must be borne in mind that, in general, the individual variables (age, education status, race, and ethnicity) corresponding to the respondent provide a good sense of the demographics of the entire household.

The bottom half of Table 3 presents the loadings of the latent constructs on the indicator variables, corresponding to the MEM component. The signs on the latent constructs for all indicators are positive, consistent with the indicator prompts. The last row panel section of Table 3 includes the correlations between the latent constructs. A negative correlation between GLP and LLP is expected since GLP includes the preference for moderating consumption as one way of being environmentally conscious, while LLP is associated with higher levels of conspicuous consumption. Unobserved individual factors that increase GLP also increase TLP, while unobserved individual factors that increase LLP also decrease TLP. These correlations, while due to unobserved factors, are quite expected, given that teleworking can be viewed as a mechanism to be more "green" through the reduction in motorized commute travel.

### 4.2 Main Estimation

The measurement equation model results are presented in Table 4. These include the latent construct effects, the exogenous variable impacts, and the recursive endogenous variable effects on the latent variables (propensities) underlying the main housing ordinal outcomes. The constant effects and threshold effects listed at the bottom of Table 4 do not have any substantive interpretations, and simply adjust for the range of exogenous variable values in a manner that provides for a good data fit.

### *4.2.1 Latent Construct Effects*

The effects of the latent constructs, shown in Table 4, indicate that individuals with a higher GLP prefer owning a home with a patio or yard in a high-density area, tend to have a shorter commute distance but live in a neighborhood with relatively high median housing cost, and appear less sensitive to crime rates. A lower commute distance facilitates an environmentally friendly lifestyle by reducing travel distances, while also promoting the use of active modes and public transportation (Heinen and Bohte, 2014). GLP is also associated with a preference for more outdoor spaces and activities, explaining the inclination toward properties with outdoor patios and yards. At the same time, GLP has a positive bearing on high density living, presumably as a means to reside in an area that is conducive to the use of non-motorized and public transportation travel modes (areas in which high crime rates are generally also prevalent). The reason for high GLP individuals to live in areas with a high median housing cost may be because additional green household improvements, such as photovoltaic panels, are often adopted by those with a green lifestyle preference, leading to a more sustainable home but a higher housing cost (Grębosz-Krawczyk et al., 2021).

Individuals who prioritize a luxury lifestyle exhibit distinct preferences when it comes to their housing choices. They, too, share a preference for owning a home with a patio or yard, but are more inclined toward single-family homes with more bedrooms. They also tend to have longer commute distances, favor areas with lower population densities, exhibit a reduced sensitivity to the proximity of amenities, and prioritize areas with low crime rates. Greenwood and Holt (2010) suggest that individuals pursuing luxury lifestyles actively compete for exclusive neighborhoods, willingly paying premiums to gain higher social status while also gaining access to better school districts and enhanced safety from crime.

Finally, individuals with a preference for teleworking are more likely to reside in single family homes with high population density, desirous of areas with good amenities, less sensitive to crime rates, and willing to live relatively far from their work office locations. These results are intuitive. For example, accessibility can be appealing to teleworkers who value the convenience of having essential services, shops, and recreational facilities within close proximity to their homes (Caldarola and Sorrell, 2022; de Abreu e Silva and Melo, 2018).

### *4.2.2 Effects of Explanatory Variables*

Table 4 presents the direct effects of the exogenous variables on the housing outcomes, beyond the indirect effects through the latent constructs. Household composition, as one would expect, has several impacts on the many dimensions of housing choices. To conserve space, we discuss the many results briefly and selectively. Households with related adults, seniors, and those with children are more likely to choose single-family homes compared to single adults, and these households are also more inclined to prefer homes with many bedrooms. These effects represent the need for more space and privacy in general. The effect of number of children may also be associated with single-family homes aligning with the prevailing "picket fence" image among American parents of the ideal living arrangement for raising children (Wood, 2014). Conversely, single adults may prefer the increased opportunities for social interaction available in apartment complexes (Frenkel and Kaplan, 2015). Couple households and roommate households appear to prefer to rent, but with a propensity toward more bedrooms. Couple households also prefer to be in low housing cost areas and tend to live further from their office. Compared with single adult households, couple households may need to accommodate commutes for multiple adults working outside the home, resulting in longer commute distances for each working adult. In combination with the strong positive effect (+1.91) of apartment living on the renting utility alternative of tenure choice (as discussed later), the net result is that related adults prefer not to rent but to own their homes (the net effect on renting utility is +1.91*(-0.45)+0.55=-0.31)) and do not appear to be too concerned about school quality in housing choices. On the other hand, roommates prefer to rent dwelling units with many bedrooms. Households with seniors lean toward owning homes that include a patio or yard and a large number of bedrooms, and in areas with lower population densities, higher median housing costs, and proximity to amenities. Among other results, households with children tend to live in areas with lower crime rates, reflecting a strong desire for family safety and security (DeLuca and Jang–Trettien, 2020).

Income is another significant factor driving housing choices. Consistent with their higher purchasing power, households with higher incomes are more likely to own their home rather than rent, even beyond the indirect effect through the latent constructs and the housing type choice effect on tenure choice (see also Carter, 2011). Further, households with higher incomes reside in areas with high housing costs, which also points to income segregation, reinforcing the notion that houses tend to be clustered with others in a similar price range (Heldt et al., 2018). Also, higher income households prefer areas that offer an abundance of amenities and higher-quality schools, which underscores the price premiums placed on these types of services (Li et al., 2019). One difference found here compared with many previous studies (Bhat, 2015a; He and Hu, 2015; Xue et al., 2020) is the absence of a significant direct impact of income on commute distance. Previous studies have suggested that individuals with higher incomes are more willing to undertake long commutes because they tend to maximize their earnings potential by casting a wide spatial net in search of jobs in the first place (Clark and Wang, 2005). Two factors potentially contribute to the difference found in this study. First, growing housing demand coupled with limited supply in many cities has led to increased housing costs in urban areas, pushing low-income workers further away from employment centers (Blumenberg and Wander, 2022). Thus, many low-income workers also have long commutes, tempering any association between income earnings and commute distances. Second, while we observe no direct effect of income on commute distance, this effect is still present indirectly through the latent effects of the latent constructs. The net effect is a substantial positive effect on commute distance with a rise in income, through the LLP and TLP latent constructs. The results also suggest a direct positive association between the highest income household group and residence in high crime rates, though this direct effect is neutralized by the indirect effect of income through the latent constructs (this indirect effect of income of $200,000 or more may be computed from the estimates in Table 3 and Table 4 as 0.10*0.305-0.19*1.935+0.13*1.309=-0.17, which pretty much wipes out the +0.20 direct income effect on crime rate). The net result then is that household income has no effect on crime rate of residence. Perhaps future studies should consider a better disaggregation of crime by crime type, rather than combining violent and property crimes into a single aggregate category as web-scraped in our study from crimegrade.org.

In terms of race and ethnicity, we assume that the race/ethnicity of the individual closely corresponds to the race/ethnicity of the entire household. Households identifying racially as Black or other, or ethnically as Hispanic, tend to reside in apartments rather than single-family homes. Additionally, Black families are more likely to rent than own relative to white and other non-Black families, attributable, at least in part, to the long history of racial discrimination in the housing sector in the United States. For instance, New Deal policies in the 1930s offered the possibility of homeownership to white families through government-insured mortgages, but Black families were denied these benefits because their neighborhoods were deemed too risky (Faber, 2020; Bhat et al., 2022). Continued systematic racial segregation in housing has prevented many Black families from becoming homeowners and constrained them to the rental market (Desmond, 2016). Black families are also more likely to live in constrained spaces with no patio or yard, and in areas with higher population densities, lower-quality schools, and higher crime rates. This is consistent with previous findings (see, for example, Wood, 2014; Simms and Talbert, 2019; Cuddy et al., 2020) indicating that Black families prioritize dwelling unit attributes over neighborhood characteristics when choosing a home. Hispanic families seem to value neighborhood characteristics similar to non-Hispanic families but appear to have a stronger preference for areas with high population densities. Finally, Asian families are more likely to live in dwelling units with more bedrooms and in areas with a high median cost. One potential reason is that Asian households tend to be larger than other households, with more adults and extended family members (Glick and Van Hook, 2002).

The effect of the number of motorized vehicles in the household on housing choices turns up some interesting (and not always expected) results. Households with more vehicles are more likely to live in apartments than single-family homes, consistent with the explanation that those living in apartments have a more socially active lifestyle and prefer a higher level of accessibility (Van Acker et al., 2014; Seo and Nam, 2019). Households with more vehicles also tend to live in areas with lower median housing costs, potentially a trade-off between accessibility to activities and housing amenities/quality (Huang et al., 2018). Additionally, recent research has found that vehicle ownership is becoming increasingly important to meet the needs of younger adults living in urban areas who are now less inclined towards public transportation than before the pandemic, helping to explain why those with more vehicles might exhibit a stronger preference for apartment living and may live in lower-cost areas (Vega-Gonzalo et al., 2023). Importantly, vehicle ownership is considered to exogenously affect housing choice in this analysis, an assumption made in many housing choice models (see, Cho et al., 2008; Kim, 2011; Shin, 2012; Chen et al., 2013; Manoj et al., 2015; Yu et al., 2017; Huang et al., 2018; Jin and Lee, 2018; Gomaa, 2023). We acknowledge that travel attitudes impact both the selection of housing attributes and vehicle ownership decisions, and that vehicle ownership may itself be affected by an individual's existing housing status (see, for example, Bhat and Guo, 2007; Paleti et al., 2013; Fatmi et al., 2017; Yu et al., 2017; Mondal and Bhat, 2023). However, we focus here on the housing choice decision alone, leaving the additional joint modeling of decisions such as vehicle ownership alongside the multidimensional housing choices analyzed here to future efforts.[5]

Finally, there is significant heterogeneity in dwelling unit and neighborhood characteristics based on the region of residence within the United States. Home ownership is more prevalent in the Midwest relative to other regions, while individuals in the Midwest live in low population density areas with low housing costs. In contrast, those residing in the West encounter high housing costs, and those living in the Northeast appear to be burdened with the highest crime rates. Southern households are likely to live in low population density and low school quality areas.

[5]To examine whether ignoring the endogeneity of vehicle ownership may have significantly impacted the results or the causal direction of the endogenous effects between outcomes, the model was re-estimated without the effects of vehicle ownership. The elimination of vehicle ownership led to a very similar set of results, with the vehicle ownership effects being transferred as (a) income effects in the housing type and commute distance outcomes, (b) a slightly reduced income effect in the median housing cost outcome, and (c) a slightly greater coefficient on LLP for the housing type outcome. But the removal of the vehicle ownership variable did not change the proposed causal structure and had little impact on the magnitude of endogenous effects between outcomes.

#### *4.2.3 Endogenous Effects of Dependent Variables*

After accounting for the correlations between the housing outcomes through the latent constructs, endogenous effects among the many outcomes may be considered. Note, however, that the model itself is a joint model of all housing outcomes. As indicated earlier in Figure 3, the recursive pathway of effects begins with commute distance (see also the blank last column of Table 4 corresponding to commute distance under the row panel of "endogenous effects"), followed by housing type (the only effect in the housing type column in Table 4 is the one from commute distance). Both these outcomes have many impacts on other outcomes. In terms of commute distance effects, individuals with long commute distances typically prefer single-family homes, own their dwelling unit, and tend to be in neighborhoods with low population density and low crime rates, suggesting an overall "rural-type" housing preference. Such individuals also are less sensitive to school quality. In the context of housing type effects, individuals living in apartments are more likely to be renters, tend not to have patios or yards, have fewer bedrooms, and are more likely to be in high population density neighborhoods with high housing costs and crime rates, consistent with the trends for apartment living in high-density urban centers.

Population density and median housing costs are next in the recursive sequence, affecting several dwelling unit attributes and neighborhood characteristics. Households residing in densely populated areas tend to prioritize access to amenities but are less sensitive to the quality of schools and to crime rates, while residence in a higher median housing cost area implies dwelling units that have more bedrooms situated in areas with high population densities, high quality schools, and low crime rates. These results are evidence of money being able to buy not only larger-sized houses, but also dwelling units situated in safe neighborhoods with high quality schools. While these effects are similar to those found in earlier studies (see Hasan and Kumar, 2019 and Kang, 2016), the direction of causation is different. Specifically, earlier studies have used neighborhood characteristics as determinants of neighborhood housing costs, but we find that the "true" causal direction (after accommodating for the jointness) is from housing cost to other neighborhood characteristics.

#### *4.2.4 Implied Correlations Among Main Outcomes*

As noted above, the endogenous effects discussed in the previous section represent the "true" causal effects between housing outcomes, after accounting for the effects of correlations engendered by the latent constructs. The correlation matrix among the housing outcomes (corresponding to the covariance matrix estimated in the GHDM) is presented in Table 5 (only the upper diagonal is shown because of the symmetric nature of the matrix). Note that none of the three latent constructs have a significant impact on school quality, so no correlations are generated between school quality and any other housing outcomes.

The correlations shown in Table 5 range from -0.318 to 0.227, with the highest correlations between dwelling unit attributes. These high correlations are to be expected, as people who live in apartments are intrinsically more likely to rent, to live in a home without a patio or yard, and to have fewer bedrooms. Apartment living is also positively correlated with many neighborhood characteristics, particularly population density, which is also expected since apartment living is much more prevalent in high density areas. Correlations between neighborhood characteristics are much lower, ranging from -0.004 to 0.087, indicating that intrinsic valuations of these factors are less closely linked. Without controlling for these correlation effects, estimates of endogenous effects would be biased. For instance, without accounting for the strong negative correlation between commute distance and housing type, we would overestimate the "true" causal impact of commute distance on preference for an apartment.

### 4.3 Model Fit

We assess the proposed joint GHDM with a restricted independent heterogeneous data model (IHDM) that ignores the jointness among the many housing outcomes. This entails ignoring the stochastic latent constructs and removing the MEM component of the GHDM model that links exogenous variables to the latent constructs. Thus, the IHDM has a diagonal covariance matrix for the ten housing outcomes with unit entries along the diagonals rather than the general covariance matrix used in the estimation of the GHDM (corresponding to the correlation matrix shown in Table 5 and discussed in the previous section). However, to ensure a fair comparison, we estimate the IHDM including the determinants of the latent constructs as explanatory variables, while maintaining the recursivity in the outcomes as obtained from the GHDM model. The GHDM and IHDM models are not nested, as the latter lacks a mechanism to incorporate latent constructs. Thus, we use the Bayesian Information Criterion (BIC) and the non-nested likelihood ratio index data fit measures for comparing the models. The BIC metric is computed as follows: (BIC) statistic [= $-\mathcal{L}(\hat{\theta})+$ 0.5 (# of model parameters) log (sample size)] ($\mathcal{L}(\hat{\theta})$ is the predictive log-likelihood at convergence). The model with a lower BIC statistic is the preferred model. Additionally, the non-nested likelihood ratio test uses the adjusted likelihood ratio index for each model (joint and independent) relative to the log-likelihood obtained by considering only the constants in each outcome. The adjusted likelihood ratio index is first calculated as:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\boldsymbol{\theta}}) - M}{L(c)}, \tag{12}$$

where $L(\hat{\boldsymbol{\theta}})$ corresponds to the predictive log-likelihood at convergence and $L(c)$ is the predictive log-likelihood for the constants-only model and $M$ is the number of parameters (excluding the constants) estimated in the GHDM model. Let the adjusted likelihood ratio indices for the GHDM and independent models be $\bar{\rho}^2_{GHDM}$ and $\bar{\rho}^2_{Independent}$, respectively. If the difference in the indices is $(\bar{\rho}^2_{GHDM} - \bar{\rho}^2_{Independent}) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_{GHDM} - M_{Independent})]^{0.5}\}$, with a small value for the probability of chance occurrence suggesting that the difference is statistically significant and the model with the higher value for the adjusted likelihood ratio index is preferred.

Table 6 presents the findings of the goodness of fit assessment. The comparison includes BIC values, predictive adjusted likelihood ratio indices, informal non-nested likelihood ratio statistics, and the average probability of correct prediction. These results collectively demonstrate the superior fit of the GHDM model in comparison to the independent model.

### 4.4 Average Treatment Effects

While the endogenous effects between outcomes discussed in Section 4.2 allow us to track the pathway of "true" causal effects among the many housing outcomes, they do not reveal the relative importance that is ascribed to each dimension in the package housing decision. In this package decision, individuals face tradeoffs between the various dimensions (for instance whether they are willing to accept an increased commute distance to gain an additional bedroom in their home). To compute such relative valuations across housing dimensions, we use the average treatment effects

(ATE) for the endogenous outcomes. ATE is a metric that computes the impact on a downstream posterior outcome of interest due to a treatment that changes the state of an antecedent outcome from A to B. For example, if the intent is to estimate the "treatment" effect of commute distance on housing type, A (which is the "base" level) can be the state where an individual has a commute distance of less than 5 miles, and B (which is the "treatment" level) can be the state where the individual has a commute distance of more than 20 miles. The impact of this change in state is measured in terms of the change in the shares of the outcomes of interest (say, the "apartment" category of the housing type) between the case where all individuals in the dataset are in state A and the case where all the individuals in the dataset are in state B.

To develop the methodology for computing the ATEs, following the notation in Section 3.1.1, denote the ordered outcomes (including the binary outcomes that are a special case of the ordered outcomes) as $\tilde{y}_n$, with the possible ordered levels that $\tilde{y}_n$ can take as $j_n$ ($j_n$=1,2,3,…, $J_n$). In this section, we will confine our attention to only the ordered endogenous outcomes, while, in Section 3.1.1, the index $n$ included the ordinal indicators of the latent constructs too.[6] We will continue to denote the continuous outcome in our empirical analysis as $y$. Since we only have one continuous outcome and because the continuous outcome (the natural logarithm of commute distance), in our results, impacts other ordered variables but is not impacted by any other ordered variables in the causal structure adopted (i.e., the log commute distance variable is antecedent to all other variables), we can confine our ATE analysis to two antecedent/posterior variable structures:

(i) The first structure is when the continuous endogenous outcome is the antecedent variable, and an ordered endogenous outcome is the posterior variable.

(ii) The second structure is when an ordered endogenous outcome is the antecedent variable, and another ordered endogenous outcome is the posterior variable.

The formulation of the ATEs is not as straightforward as in a case where there are no recursive endogenous outcome effects. While one can develop ATE formulas for each specific case based on the length of the recursive order effects between the antecedent and posterior outcomes, we present a general formula that works regardless of the order length. To do so, define a vector $S=\{1,2,...\tilde{N}\}$, where $\tilde{N}$ refers to the number of ordered endogenous outcomes ($\tilde{N}$=9 in our empirical case). Also, define the vector $S_{-n}$ as the vector $S$ with the $n^{th}$ ordered outcome removed, and the vector $S_{-n,-c}$ as the vector $S$ with the $n^{th}$ and $c^{th}$ ordered outcomes removed. Let $S_d$ denote the $d^{th}$ element of the vector $S$, $S_{-n,d}$ denote the $d^{th}$ element of the vector $S_{-n}$, and $S_{-n,-c,d}$ denote the $d^{th}$ element of the vector $S_{-n,-c}$. Then, in the first structure, the probability of an ordered outcome $\tilde{y}_n$ taking the ordered level of $j_n$, given the continuous outcome $y$ lies between a lower bound of $l$ and an upper bound of $u$, is:

[6] The reader will also note that, in Section 3.1.1, the level $j_n$ took the specific value of $a_n$, where $a_n$ represented the observed ordered outcome for $\tilde{y}_n$ of the individual. This was because the focus in Section 3.1.1 was on model estimation.

$$P(\tilde{y}_n = j_n \mid l < y < u) = \frac{\int_{y=l}^{y=u} \sum_{j_{S_{-n,1}}=1}^{J_{S_{-n,1}}} \sum_{j_{S_{-n,2}}=1}^{J_{S_{-n,2}}} \cdots \sum_{j_{S_{-n,\tilde{N}-1}}=1}^{J_{S_{-n,\tilde{N}-1}}} P(\tilde{y}_{S_{-n,1}} = j_{S_{-n,1}}, \ldots, \tilde{y}_{S_{-n,N-1}} = j_{S_{-n,N-1}}, \tilde{y}_n = j_n, y) dy}{\int_{y=l}^{y=u} \sum_{j_{S_1}=1}^{J_{S_1}} \cdots \sum_{j_{S_{\tilde{N}}}=1}^{J_{S_{\tilde{N}}}} P(\tilde{y}_{S_1} = j_{S_1}, \ldots, \tilde{y}_{S_N} = j_{S_N}, y) dy}. \quad (13)$$

For example, $\tilde{y}_n$ could be the neighborhood housing cost outcome with $c_n$ being the "high (>$2000 per month)" category, and $l$ and $u$ could be $-\infty$ and ln(5), respectively, for the log commute continuous outcome. Then, the equation above would provide the probability of choosing an expensive residential neighborhood, given the commute distance is less than 5 miles for a specific individual $q$. The average over all individuals would then provide the predicted share of individuals living in expensive neighborhoods for a commute distance less than 5 miles. Then, based on the earlier definition, the ATE (in this first scenario) may be computed as the difference in the conditional probability of $\tilde{y}_n$ taking the value of $c_n$ given the "base" bound of ($b_l < y < b_u$) and the "treatment" bound of ($t_l < y < t_u$) for the antecedent $y$ variable, averaged over all individuals $q$ ($q$=1,2,…,$Q$).

$$ATE = \frac{1}{Q} \sum_q \left[ P(\tilde{y}_{qn} = j_n \mid t_l < y_q < t_u) - P(\tilde{y}_{qn} = j_n \mid b_l < y_q < b_u) \right]. \quad (14)$$

In the second structure, the probability of an ordered outcome $\tilde{y}_n$ taking the ordered level of $j_n$, given another ordered outcome $\tilde{y}_c$ taking the ordered level of $j_c$, would be:

$$P(\tilde{y}_n = j_n \mid \tilde{y}_c = j_c)$$
$$= \frac{\int_{y=-\infty}^{y=+\infty} \sum_{j_{S_{-n,-c,1}}=1}^{J_{S_{-n,-c,1}}} \sum_{j_{S_{-n,-c,2}}=1}^{J_{S_{-n,-c,2}}} \cdots \sum_{j_{S_{-n,-c,\tilde{N}-2}}=1}^{J_{S_{-n,-c\tilde{N}-2}}} P(\tilde{y}_{S_{-n,-c,1}} = j_{S_{-n,-c,1}}, \ldots, \tilde{y}_{S_{-n,-c,\tilde{N}-2}} = j_{S_{-n,-c,\tilde{N}-2}}, \tilde{y}_n = j_n, \tilde{y}_c = j_c, y) dy}{\int_{y=-\infty}^{y=+\infty} \sum_{j_{S_{-c,1}}=1}^{J_{S_{-c,1}}} \cdots \sum_{j_{S_{-c,\tilde{N}-1}}=1}^{J_{S_{-c,\tilde{N}-1}}} P(\tilde{y}_{S_{-c,1}} = j_{S_{-c,1}}, \ldots, \tilde{y}_{S_{-c,\tilde{N}-1}} = j_{S_{-c,\tilde{N}-1}}, \tilde{y}_c = j_c, y) dy}. \quad (15)$$

Then, the ATE (in this second scenario) may be computed as (introducing the index $q$ for individuals) as the difference in the conditional probability of $\tilde{y}_n$ taking the value of $j_n$ between the "base" state when $\tilde{y}_c$ is $b_c$ and the "treatment" state when $\tilde{y}_c$ is $t_c$ (as shown below).

$$ATE = \frac{1}{Q} \sum_q \left[ P(\tilde{y}_{qn} = j_n \mid \tilde{y}_c = t_c) - P(\tilde{y}_{qn} = j_n \mid \tilde{y}_c = b_c) \right]. \quad (16)$$

To keep the presentation simple, in this paper, for ordered response outcomes with more than two categories, we only report the ATEs for a change from the lowest extreme to the highest extreme for the antecedent variables. For the posterior variable, we compute the shares for the highest categorical level. Further, we only compute the ATE effects for antecedent-posterior variable pairs where there is a causal pathway of effect. Based on Section 4.2.3, that leaves four antecedent variables for employed individuals (commute distance, housing type, population density, and median housing cost) and three for unemployed individuals (housing type, population density, and median housing costs). Additionally, in computing the ATEs for commute distance for employed individuals, we only consider those individuals who have a physical workplace outside their home and in the local area of their residence. The results of these ATEs, computed as percentage changes from the base, are presented in Table 7. For example, the first numeric of -31.3% indicates that, among employed individuals with a commute distance of more than 20 miles, the share of those living in an apartment is 31.3% lower than the corresponding share among employed individuals living within 5 miles of their office. Another way to interpret this figure is that employed individuals living more than 20 miles away from their office are 31.3% (0.687 times) less likely to be in an apartment than those living within 5 miles of their office. The results for employed individuals reveal that an increase in commute distance from less than five miles to more than 20 miles would lead to a reduction in the likelihood of choosing an apartment and reduction in the likelihood of renting. In other words, to counterbalance the inconvenience of longer commute distances, individuals place greater importance on the ownership of a single-family home. Additionally, a significant increase in commute distance results in a greater preference for having more bedrooms and a reduced likelihood of living in a high population density area with a very high crime rate. The results also reveal that living in an apartment, rather than a single-family home, and living in an area with a high population density both contribute to a compromise in terms of school quality and crime rate. This is evidenced by the negative ATE observed for housing type and population density variables on school quality (reflected in the second and third rows of the school quality column in Table 7) as well as the positive ATE observed for these variables on crime rate (found in the second and third rows of the crime rate column in Table 7). The effect of moving from an area with a low median housing cost to one with a high median housing cost results in a 386.8% increase in the likelihood of living in an area with excellent school quality. Similar treatment effects are found for unemployed individuals (shown in the bottom panel of Table 7). The most significant difference between employed and unemployed individuals is that the effect of living an apartment rather than a single-family home leads to a smaller increase in the likelihood of renting and a larger reduction in the likelihood of having a patio or yard for unemployed individuals. This is likely because unemployed individuals are less willing to commit to the long-term investment of buying a home without stable employment, even if they live in a single-family home.

## 5. IMPLICATIONS

### 5.1 Land Use Policies and Planning

The ATEs shown in Table 7 demonstrate the relationships between housing outcomes that have important implications for land use policies. Longer commute distances lead to housing choices favoring locations with low population densities and large single-family homes, both of which contribute to suburbanization and urban sprawl. This type of increased suburbanization can have negative impacts, including environmental degradation from the increased consumption of land, negative economic consequences due to higher transportation costs and real estate prices, and increased social vulnerability because of segregated land uses and unequal distribution of public infrastructure (Cocheci and Petrisor, 2023). Policies that reduce the spatial mismatch between housing and employment, including promoting affordable housing near employment centers and zoning for higher-density residential developments, can effectively reduce commute distances and lead to less suburbanization. Relatedly, those who choose areas with lower median housing costs tend to live in low population density areas, indicating that budget considerations also play an important role in considerations of residential density of living, reinforcing the benefits of providing low-income housing near employment centers.

Although Table 7 reveals an overall reduction in access to amenities with increasing commute distance, the results in Table 4 indicate that those with a high TLP have longer commute distances and prefer to have greater access to amenities. This distinction indicates that teleworkers, relative to non-teleworkers, are more inclined to live in mixed-use areas where they have easy access to non-work activities, consistent with the results in Zenkteler et al. (2022). The implications of these changing preferences are wide-ranging. For urban planners, this means designing new developments that incorporate both residential and retail spaces as well as transportation systems that promote active transportation for shorter trips. Retailers, on the other hand, may want to consider moving away from larger shopping centers to instead include a mix of online options and smaller neighborhood locations that are more suited to the local needs of teleworkers. As for cities and government officials, there is a suggestion to promote developments that foster social connectivity and promote positive lifestyles to generate an influx of teleworkers, who will bring in additional capital investments and economic growth, rather than prioritize the further development of commercial centers.

**5.2 Travel Demand Shifts**

The growth of commute distances for teleworkers also has important implications for individual activity-travel patterns and broader travel demand patterns. Many teleworkers have begun splitting their time between their home and physical workplace (see Asmussen et al., 2024). The greater commute distances facilitated by the reduction in trips to the office lead to increased travel distances for any remaining commute trips. At an individual level, these new commuting patterns imply daily variations in work location and timing, as well as significant daily variations in travel investment for work activities and different time allocations for work and non-work activities. This, of course, raises the need for more serious consideration of multi-day activity-travel demand models rather than current models that predict travel for an “average” weekday. These and related considerations offer intriguing new challenges, as the profession works toward adapting travel demand models to a new era of work arrangements. This is particularly the case because our results show that teleworkers self-select dwelling units and neighborhoods that fit their lifestyle, which may lead to changing commuting patterns in some areas but not in others.

In addition to the impacts of teleworking, the land use changes discussed in Section 5.1 impact both commute patterns and non-work travel behaviors. Mixed-use developments, along with smaller and more distributed office sites, can lead to new distributions of commute patterns. For example, Jun (2020) found that mixed-use developments can help reduce commute distances and commute times by providing more jobs near residential areas. They can also make public transportation more economically feasible, providing additional improvements to commuting times. Changing land use patterns will also impact non-work travel. Mixed-use areas that provide access to amenities, such as shopping centers, gyms, and parks near their homes, allow individuals to reduce their travel for these non-work activities. In fact, several recent studies have found that teleworkers take more recreational trips than office workers (Asgari and Jin, 2017; Chakrabarti, 2018; Wöhner, 2022), indicating that the promotion of mixed-use developments in the increasing era of teleworking may be particularly beneficial to curtail motorized travel.

### 5.3 Equity Implications

The tradeoffs captured by the ATEs presented in Table 7 have significant equity implications, particularly since not all families have the financial means to choose locations with high quality schools and low crime rates. For instance, those who possess the financial wherewithal to live in neighborhoods with high median housing costs reap the benefits of significantly higher school quality. The ability to move from a neighborhood with a low median housing cost to a high median housing cost results in a 386.8% increase in the likelihood of living in a neighborhood with excellent school quality for employed individuals (372.2% for unemployed individuals). This premium on school quality is directly tied to the funding of schools through property taxes, leading schools in areas with high property values to have increased funding (Chetty and Friedman, 2010). The result, however, is that families without the financial means to acquire homes in these expensive neighborhoods are unable to access the highest quality schools, even if they have school-aged children and place significant value on school quality. This feature of the housing market has far-reaching implications, as low-income families are constrained to send their children to lower quality schools, which in turn limits their life-chances and earning potential, perpetuating a cycle of income inequality (Rothstein, 2015). Additionally, families living in apartments in densely populated neighborhoods are faced with reduced school quality and higher crime rates. For instance, the effect of living in an apartment rather than a single-family home is to reduce the likelihood of living in a neighborhood with excellent school quality by 24.9% (29.3%) for employed (unemployed) individuals and to increase the likelihood of living in a neighborhood with a very high crime rate by 203.5% (218%). The effect of living in a high population density neighborhood is even larger, reducing the likelihood of living in a neighborhood with excellent school quality by 36.9% (43.7%) and increasing the likelihood of living in a neighborhood with a very high crime rate by 533.7% (531.2%). However, the disadvantages associated with living in apartments are not distributed equitably across households based on income and race. Black and low-income households, in particular, are significantly more likely to rent apartments than own single-family homes, as discussed in Section 4.2.2. Consequently, these groups are disproportionately exposed to lower quality schools and high crime rates. The strong connections between these housing dimensions provide one mechanism through which existing racial inequalities continue to be perpetuated in the housing market. Continued systematic segregation and the lack of capital accumulation gained from homeownership restricts many Black families to the rental market where they face the additional challenges of low-quality schools and high crime rates (Rothstein, 2015; Desmond, 2016). Based on our results, there are multiple possible avenues to reduce this cycle of inequality. The first would be to prioritize investments for safety and education in low-income and high-density neighborhoods, thereby improving school quality for those without the capital to pay premiums to move elsewhere. A second strategy would be to plan more balanced neighborhoods with a mix of apartments and larger single-family homes. Reducing the existing geographic segregation of housing types and income distributions could help limit the associated geographic disparities in access to quality schools and safe neighborhoods.

## 6. CONCLUSIONS

In this paper, we have examined the housing choice decision as a joint decision across a range of dwelling unit attributes and neighborhood socioeconomic characteristics. The focus on a broader range of housing outcomes is driven by the changing role of the home due to the growth of remote work opportunities. Our analysis framework enables the consideration of multiple dimensions of housing choice as a package decision and to understand the tradeoffs among the many dimensions.

The approach incorporates household demographic, regional variables, and latent psycho-social constructs within the behavioral framework. The estimation results indicate that individuals with different attitudes and lifestyles make different housing decisions, both in terms of the attributes of the dwelling unit and the characteristics of the neighborhood. The results also point to the significant impacts of changing commute distances on the characteristics of the dwelling unit and the sensitivity to various neighborhood characteristics, which, in turn, have implications for understanding evolving mobility patterns and real estate demands. Telework preferences and changing commuting patterns also impact urban planning as we consider evolving housing needs and the increased preference for mixed-land use developments among teleworkers.

There are, of course, several avenues for additional research. First, although this study includes a comprehensive set of outcome variables, there are many more that can be considered in a joint model, including the availability of various transportation alternatives, access to public spaces, and additional dwelling unit features. Additionally, a detailed investigation of the preferences for different types of amenities (such as access to parks and sports activities, museums and cultural activities, restaurants, grocery stores, and medical facilities) in residential neighborhoods, rather than an aggregate amenities metric as used in the current paper, would be a valuable direction for future research. Second, an analysis of housing choices along with other major life decisions, such as vehicle purchases/ownership and employment/telework decisions, could reveal the relationships between these major decisions that were not considered here. In this context, it is also important to consider the interactions among household members rather than modeling the decision based on individual level data. Third, additional research into the causal relationships between the many factors at play in housing decisions would be fruitful. While our model accounts for unobserved correlation effects across many dimensions and controls for aggregate regions of the U.S., additional research within specific disaggregate housing markets of the U.S. would be helpful to examine the spatial stability of the causal pathway effects found in the current study. This would require adequate sample sizes from the specific housing markets. Also, additional research that examines potential heterogeneity in the causal pathway relationships across different sociodemographic groups is another direction for research. Finally, continued analysis of housing choices with recent datasets would provide important insights on the changing housing choice patterns since the pandemic. After all, housing choices are long-term decisions, and behavioral shifts in these brought about by the pandemic may not yet be completely manifested. Subsequent studies should continue to consider the impacts of the pandemic as well as the broader interlinkages between remote work trends and housing choices.

In conclusion, while there remain many areas for future investigations, the research has highlighted the intricate inter-relationships among the multiple choice dimensions characterizing housing decisions, and established a methodological and empirical foundation for studying the housing-transportation nexus within a fast evolving technological, demographic, and remote work landscape.

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**Table 1: Sample Distribution for Outcome Variables**

| Variable | % | Variable | % |
|---|---|---|---|
| **Housing Type** | | **Population Density (pop/sq mi)** | |
| Single Family Home | 76.73 | Low (≤5) | 28.11 |
| Apartment | 23.27 | Medium (>5 & ≤10) | 36.48 |
| **Tenure Type** | | High (>10) | 35.41 |
| Own | 72.13 | **Median Housing Cost ($1,000)** | |
| Rent | 27.87 | Low (≤1) | 16.75 |
| **Presence of Patio or Yard** | | Medium Range 1 (>1 & ≤1.5) | 40.48 |
| Yes | 84.32 | Medium Range 2 (>1.5 & ≤2) | 28.62 |
| No | 15.68 | High (>2) | 14.15 |
| **Number of Bedrooms** | | **Amenities Rating** | |
| 0 | 0.88 | None (1) | 3.12 |
| 1 | 10.84 | Few (2) | 2.37 |
| 2 | 22.99 | Average (3) | 4.00 |
| 3 | 36.44 | Above Average (4) | 4.33 |
| 4 | 21.64 | Many (5) | 86.18 |
| 5+ | 7.21 | **Schools Quality Rating** | |
| **One-Way Commute Distance (mi)** | | Very poor (1) | 25.27 |
| Not Employed | 35.32 | Poor (2) | 12.28 |
| No Physical Workplace | 15.08 | Neutral (3) | 13.26 |
| ≤5 | 14.94 | Good (4) | 20.43 |
| >5 & ≤10 | 12.19 | Excellent (5) | 28.76 |
| >10 & ≤20 | 13.68 | **Crime Rating (per 1,000 residents)** | |
| >20 | 8.79 | Very low (< 1.615) | 17.96 |
| Mean: 15.15 | | Low (1.615 – 2.522) | 22.15 |
| Median: 10.00 | | Medium (2.523 – 3.820) | 26.66 |
| | | High (3.821 – 7.540) | 24.99 |
| | | Very high (> 7.540) | 8.24 |

**Table 2: Sample Distribution of Exogenous Variables**

| Variable | % in sample | % in ACS | Variable | % in sample | % in ACS |
|---|---|---|---|---|---|
| **Household composition** | | | **Region** | | |
| Single | 26.4 | 40.3 | Northeast | 10.5 | 17.2 |
| Couple | 50.9 | 48.2 | Midwest | 23.1 | 20.7 |
| Related adults | 16.2 | 4.9 | South | 25.7 | 38.4 |
| Roommates | 6.6 | 6.6 | West | 40.7 | 23.7 |
| **Presence of seniors (age ≥ 65 years)** | | | **Education** | | |
| Yes | 41.0 | 30.2 | Less than bachelor's degree | 37.4 | 66.3 |
| No | 59.0 | 69.8 | Bachelor's degree | 33.8 | 20.6 |
| **Presence of adult students** | | | Graduate degree | 28.8 | 13.1 |
| Yes | 12.4 | 10.5 | **Race** | | |
| No | 87.6 | 89.5 | White | 83.9 | 74.5 |
| **Presence of children (age ≤ 17 years)** | | | Asian | 5.1 | 6.9 |
| Yes | 20.6 | 27.2 | Black or other | 11.0 | 18.6 |
| No | 79.4 | 72.8 | **Ethnicity** | | |
| **Household Income (gross)** | | | Not Hispanic | 92.8 | 81.6 |
| Less than $25,000 | 10.9 | 17.2 | Hispanic | 7.2 | 18.4 |
| $25,000-$49,999 | 18.6 | 19.6 | **Age** | | |
| $50,000-$99,999 | 34.6 | 29.6 | 18-29 | 7.1 | 20.8 |
| $100,000-$149,999 | 19.7 | 16.3 | 30-39 | 14.8 | 17.2 |
| $150,000-$199,999 | 7.5 | 7.8 | 40-49 | 13.4 | 16.5 |
| $200,000+ | 8.7 | 9.5 | 50-64 | 31.9 | 24.9 |
| **Number of motorized vehicles** | | | 65+ | 32.8 | 20.7 |
| 0 | 7.2 | 8.1 | **Gender** | | |
| 1 | 41.5 | 32.9 | Male | 37.9 | 49.5 |
| 2 | 38.3 | 37.1 | Female | 62.1 | 50.5 |
| 3 | 9.4 | 14.6 | | | |
| 4+ | 3.6 | 7.3 | | | |

**Table 3: Determinants of Latent Variables**

| Latent Variable Structural Equation Model | Green Lifestyle | | Luxury Lifestyle | | Telework Lifestyle | |
|---|---|---|---|---|---|---|
| | Coefficient | T-stat | Coefficient | T-stat | Coefficient | T-stat |
| Age (base: 18-29) | | | | | | |
| 30-39 | -0.304 | -2.652 | -- | | -- | |
| 40-49 | -0.344 | -3.486 | 0.287 | 2.704 | -0.222 | -1.980 |
| 50-64 | -0.344 | -3.486 | 0.328 | 3.878 | -0.882 | -9.716 |
| 65+ | -0.344 | -3.486 | 0.328 | 3.878 | -1.904 | -17.670 |
| Education status (base: less than bachelor's degree) | | | | | | |
| Bachelor's degree | 0.185 | 2.852 | -0.180 | -2.281 | 0.503 | 6.012 |
| Graduate degree | 0.345 | 4.787 | -0.407 | -4.564 | 0.859 | 9.053 |
| Household Income (base: less than $25,000) | | | | | | |
| $25,000-$49,999 | -- | | 0.514 | 4.636 | 0.330 | 2.246 |
| $50,000-$99,999 | 0.169 | 2.534 | 1.184 | 10.500 | 0.563 | 4.110 |
| $100,000-$149,999 | 0.259 | 3.251 | 1.702 | 13.170 | 0.912 | 6.097 |
| $150,000 or more | 0.305 | 3.433 | 1.935 | 13.296 | 1.309 | 8.479 |
| Race: (base: white) | | | | | | |
| Asian | 0.207 | 1.744 | -- | | -- | |
| Black or other | -- | | -0.250 | -1.972 | -- | |
| Ethnicity: (base: not Hispanic) | | | | | | |
| Hispanic | -- | | 0.260 | 1.676 | -0.219 | -1.454 |
| **Latent Variable Measurement Equation Model** | **Loading** | **T-stat** | **Loading** | **T-stat** | **Loading** | **T-stat** |
| I am committed to an environmentally friendly lifestyle | 0.711 | 15.729 | -- | | -- | |
| I am committed to using a less polluting means of transportation as much as possible | 0.969 | 13.440 | -- | | -- | |
| Sometimes I worry about the effects of airplane trips on the environment | 0.860 | 17.016 | -- | | -- | |
| Number of days in previous week traveling by Walking | 0.315 | 10.629 | -- | | -- | |
| Apartment living doesn't provide enough privacy | -- | | 0.144 | 5.541 | -- | |
| I like to have a yard at home | -- | | 0.251 | 8.642 | -- | |
| Number of household vehicles | -- | | 0.622 | 10.436 | -- | |
| I like working from home | -- | | -- | | 0.494 | 19.322 |
| How often would you want to work from home | -- | | -- | | 0.730 | 17.941 |
| Number of days with business meetings online | -- | | -- | | 0.639 | 12.594 |
| Number of days working from home | -- | | -- | | 0.818 | 14.038 |
| **Correlation between Latent Variables** | | | **Coefficient** | **T-stat** | **Coefficient** | **T-stat** |
| **Green Lifestyle** | -- | | -0.246 | -7.261 | 0.158 | 4.237 |
| **Luxury Lifestyle** | -- | | -- | | -0.150 | -2.895 |

**Table 4: Main Estimation Results**

| Variables (base) | Housing Type: Apt. (single family) | | Tenure Type: Rent (own) | | Presence of Patio or Yard | | Number of Bedrooms | | Population Density | | Median Housing Cost | | Amenities Rating | | School Quality | | Crime Rate | | Commute Distance | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| **Latent Constructs** | | | | | | | | | | | | | | | | | | | | |
| Green lifestyle propensity | -- | | -0.09 | -1.83 | 0.15 | 2.86 | -- | | 0.15 | 4.57 | 0.13 | 4.39 | -- | | -- | | 0.10 | 3.41 | -0.14 | -8.27 |
| Luxury lifestyle propensity | -1.66 | -5.33 | -0.30 | -3.03 | 0.44 | 3.84 | 0.35 | 6.25 | -0.22 | -4.43 | -- | | -0.16 | -2.86 | -- | | -0.19 | -3.85 | 0.13 | 4.85 |
| Telework lifestyle propensity | -0.09 | -1.23 | -- | | -- | | -- | | 0.11 | 3.31 | -- | | 0.09 | 2.25 | -- | | 0.13 | 4.68 | 0.05 | 3.62 |
| **Exogenous Variables** | | | | | | | | | | | | | | | | | | | | |
| Household Composition (single adult) | | | | | | | | | | | | | | | | | | | | |
| Couple | -- | | 0.26 | 2.53 | -- | | 0.16 | 2.34 | -- | | -0.17 | -3.05 | -- | | -- | | -- | | 0.10 | 2.95 |
| Related Adults | -0.45 | -2.58 | 0.55 | 4.09 | -- | | 0.57 | 6.84 | -- | | -- | | -- | | -0.22 | -3.02 | -- | | -- | |
| Roommates | -- | | 0.63 | 4.07 | -- | | 0.33 | 3.28 | -- | | -- | | -- | | -- | | -- | | -- | |
| Presence of adults over 65 | -0.42 | -2.63 | -0.56 | -5.88 | 0.21 | 1.88 | 0.13 | 2.11 | -0.15 | -2.17 | 0.16 | 2.97 | 0.32 | 3.31 | 0.14 | 2.50 | -- | | -- | |
| Presence of adult students | -- | | -- | | -- | | -- | | -- | | -- | | -- | | 0.18 | 2.27 | 0.14 | 1.73 | -- | |
| Presence of children | -0.63 | -3.71 | -- | | -- | | 0.66 | 8.79 | -- | | -- | | -- | | -- | | -0.18 | -2.73 | -- | |
| Household Income (< $25,000) | | | | | | | | | | | | | | | | | | | | |
| $25,000-$49,999 | -- | | -0.37 | -2.55 | -- | | -- | | -- | | 0.37 | 3.58 | -- | | -- | | -- | | -- | |
| $50,000-$99,999 | -- | | -0.62 | -4.19 | -- | | -- | | -- | | 0.74 | 7.41 | -- | | 0.18 | 2.79 | -- | | -- | |
| $100,000-$149,999 | -- | | -0.84 | -4.86 | -- | | -- | | -- | | 1.02 | 9.24 | 0.19 | 1.63 | 0.21 | 2.98 | -- | | -- | |
| $150,000-$199,999 | -- | | -0.84 | -4.86 | -- | | 0.26 | 3.30 | -- | | 1.28 | 9.49 | 0.37 | 2.62 | 0.21 | 2.98 | -- | | -- | |
| $200,000+ | -- | | -1.21 | -5.16 | -- | | 0.26 | 3.30 | 0.15 | 1.32 | 1.50 | 11.64 | 0.37 | 2.62 | 0.29 | 2.65 | 0.20 | 2.17 | -- | |
| Race: (white) | | | | | | | | | | | | | | | | | | | | |
| Asian | -- | | -- | | -- | | 0.19 | 1.66 | 0.68 | 5.20 | 0.74 | 5.59 | -- | | -- | | -- | | -- | |
| Black or other | 0.38 | 1.65 | 0.28 | 1.96 | -0.31 | -2.32 | -- | | 0.26 | 2.69 | -- | | -- | | -0.44 | -5.27 | 0.33 | 3.60 | -- | |
| Ethnicity (not Hispanic) | | | | | | | | | | | | | | | | | | | | |
| Hispanic | 0.39 | 1.57 | -- | | -- | | -- | | 0.45 | 3.86 | -- | | -- | | -- | | -- | | -- | |
| Number of Motorized Vehicles | | | | | | | | | | | | | | | | | | | | |
| 1 | 0.30 | 1.66 | -- | | -- | | -- | | -- | | -0.22 | -1.94 | -- | | -- | | -- | | 0.49 | 5.26 |
| 2-3 | 1.35 | 3.18 | -- | | -- | | -- | | -- | | -0.26 | -2.13 | -- | | -- | | -- | | 0.55 | 5.41 |
| 4+ | 2.32 | 2.14 | -- | | -- | | -- | | -- | | -0.44 | -2.51 | -- | | -- | | -- | | 0.55 | 5.41 |
| Region (northeast) | | | | | | | | | | | | | | | | | | | | |
| Midwest | -- | | -0.32 | -3.15 | -- | | -- | | -0.49 | -6.83 | -0.41 | -5.94 | -- | | -- | | 0.41 | 4.64 | -- | |
| South | -- | | -- | | -- | | -- | | -0.77 | -11.12 | -- | | -- | | -0.16 | -2.64 | 0.73 | 8.61 | -- | |
| West | -- | | -- | | -- | | -- | | -- | | 0.37 | 6.21 | -- | | -- | | 1.40 | 16.68 | -- | |

## Table 4: Main Estimation Results (cont.)

| Variables (base) | Housing Type: Apt. (single family) | | Tenure Type: Rent (own) | | Presence of Patio or Yard | | Number of bedrooms | | Population Density | | Median Housing Cost | | Amenities Rating | | School Quality | | Crime Rate | | Commute Distance | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| **Endogenous Effects** | | | | | | | | | | | | | | | | | | | | |
| Commute Distance (base varies; miles) | | | | | | | | | | | | | | | | | | | | |
| <5 | -- | | 0.38 | 3.71 | -- | | -- | | -- | | -0.11 | -1.94 | 0.20 | 1.60 | -- | | -- | | -- | |
| 5-10 | -- | | -- | | -- | | -- | | -- | | -0.11 | -1.94 | -- | | -- | | -- | | -- | |
| 10-20 | -- | | -- | | -- | | -- | | -- | | -- | | -- | | -- | | -0.18 | -1.50 | -- | |
| >20 | -0.30 | -1.37 | -- | | -- | | -- | | -0.40 | -4.01 | -- | | -- | | -0.24 | -2.42 | -0.18 | -1.89 | -- | |
| Housing Type (single family) | | | | | | | | | | | | | | | | | | | | |
| Apartment | -- | | 1.91 | 14.08 | -1.87 | -12.31 | -1.97 | -17.67 | 0.62 | 5.69 | 0.36 | 5.14 | -- | | -- | | 0.28 | 2.86 | -- | |
| Population Density (low ≤5 pop/sq mi) | | | | | | | | | | | | | | | | | | | | |
| Medium > 5 & ≤10 | -- | | -- | | -- | | -- | | -- | | -- | | 0.89 | 9.76 | -0.23 | -3.41 | 0.17 | 2.46 | -- | |
| High >10 | -- | | -- | | -- | | -- | | -- | | -- | | 1.61 | 12.11 | -0.77 | -11.09 | 0.88 | 11.18 | -- | |
| Median Housing Cost (low ≤ \$1,000) | | | | | | | | | | | | | | | | | | | | |
| Medium 1 > \$1,000 & ≤ \$1,500 | -- | | -- | | -- | | 0.24 | 3.00 | 0.54 | 6.85 | -- | | -- | | 0.41 | 5.48 | -0.70 | -8.42 | -- | |
| Medium 2 > \$1,500 & ≤ \$2,000 | -- | | -- | | -- | | 0.25 | 3.05 | 0.64 | 7.51 | -- | | -- | | 0.84 | 10.22 | -1.22 | -14.03 | -- | |
| High > \$2,000 | -- | | -- | | -- | | 0.25 | 3.05 | 0.64 | 7.51 | -- | | -- | | 1.62 | 16.16 | -1.54 | -14.39 | -- | |
| **Constant** | -- | | -- | | -- | | -- | | -- | | -- | | -- | | -- | | -- | | 1.46 | 18.02 |
| Threshold 1\|2 | -0.32 | -1.51 | 0.34 | 2.28 | -1.34 | -10.08 | -3.13 | -19.35 | -0.66 | -5.71 | -0.48 | -3.67 | -1.32 | -11.41 | -0.43 | -4.92 | -0.95 | -7.31 | -- | |
| Threshold 2\|3 | -- | | -- | | -- | | -1.31 | -10.77 | 0.51 | 4.63 | 0.83 | 6.26 | -1.00 | -8.93 | -0.02 | -0.22 | -0.07 | -0.56 | -- | |
| Threshold 3\|4 | -- | | -- | | -- | | 0.12 | 1.05 | -- | | 1.87 | 13.66 | -0.65 | -5.75 | 0.38 | 4.43 | 0.81 | 6.66 | -- | |
| Threshold 4\|5 | -- | | -- | | -- | | 1.49 | 12.02 | -- | | -- | | -0.38 | -3.37 | 1.01 | 11.57 | 1.98 | 16.54 | -- | |
| Threshold 5\|6 | -- | | -- | | -- | | 2.63 | 18.95 | -- | | -- | | -- | | -- | | -- | | -- | |

**Table 5: Implied Correlations between Main Outcomes**

| Housing Outcomes | Housing Type (Apartment) | Tenure Type (Rent) | Presence of Patio or Yard | Number of bedrooms | Population Density | Median Housing Cost | Amenities Rating | School Quality | Crime Rate | Commute Distance |
|---|---|---|---|---|---|---|---|---|---|---|
| **Housing Type (Apartment)** | 1.000 | 0.227 | -0.318 | -0.282 | 0.216 | 0.026 | 0.140 | 0.000 | 0.185 | -0.139 |
| **Tenure Type (Rent)** | | 1.000 | -0.110 | -0.088 | 0.056 | -0.002 | 0.044 | 0.000 | 0.050 | -0.036 |
| **Presence of Patio or Yard** | | | 1.000 | 0.123 | -0.077 | 0.005 | -0.061 | 0.000 | -0.069 | 0.051 |
| **Number of Bedrooms** | | | | 1.000 | -0.086 | -0.010 | -0.056 | 0.000 | -0.074 | 0.045 |
| **Population Density** | | | | | 1.000 | 0.027 | 0.055 | 0.000 | 0.087 | 0.012 |
| **Median Housing Cost** | | | | | | 1.000 | 0.007 | 0.000 | 0.021 | -0.004 |
| **Amenities Rating** | | | | | | | 1.000 | 0.000 | 0.050 | 0.020 |
| **School Quality** | | | | | | | | 1.000 | 0.000 | 0.000 |
| **Crime Rate** | | | | | | | | | 1.000 | 0.026 |
| **Commute Distance** | | | | | | | | | | 1.000 |

**Table 6: Disaggregate Data Fit Measures**

| Summary Statistics | Model | |
|---|---|---|
| | Joint (GHDM) Model | Independent Model |
| Predictive log-likelihood at convergence | -20046.13 | -21464.82 |
| Number of parameters | 174 | 165 |
| Bayesian Information Criterion (BIC) | 20713.66 | 22097.82 |
| Constants-only predictive log-likelihood | -26641.42 | -26641.42 |
| Predictive adjusted likelihood ratio index | 0.242 | 0.189 |
| Informal non-nested adjusted likelihood ratio test: joint model versus independent model | $\Phi[-53.226] \approx 0.000$ | |

## Table 7: Average Treatment Effects

| Variable | Base Level | Treatment Level | Housing Type | Tenure Type | Presence of Patio or Yard | Number of bedrooms | Population Density | Median Housing Cost | Amenities Rating | School Quality | Crime Rate |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Apartment | Rent | Yes | 5+ | High | High | Many | Excellent | Very High |
| **ATEs for Employed Individual with an Office** | | | | | | | | | | | |
| **Commute Distance** | ≤ 5 miles | > 20 miles | -31.3% | -47.7% | 10.5% | 39.2% | -39.7% | 12.2% | -9.4% | -4.7% | -50.4% |
| **Housing Type** | Single-Family | Apartment | -- | 639.4% | -68.5% | -99.8% | 64.1% | 10.2% | 12.0% | -24.9% | 203.5% |
| **Population Density** | Low | High | -- | -- | -- | -- | -- | -- | 52.1% | -36.9% | 533.7% |
| **Median Housing Cost** | Low | High | -- | -- | -- | 36.4% | 174.3% | -- | 15.6% | 386.8% | -61.6% |
| **ATEs for Unemployed Individual** | | | | | | | | | | | |
| **Housing Type** | Single-Family | Apartment | -- | 88.3% | -220.1% | -99.9% | 135.7% | 8.7% | 13.8% | -29.3% | 218.3% |
| **Population Density** | Low | High | -- | -- | -- | -- | -- | -- | 53.0% | -43.7% | 531.2% |
| **Median Housing Cost** | Low | High | -- | -- | -- | 113.9% | 166.0% | -- | 15.4% | 372.2% | -65.7% |

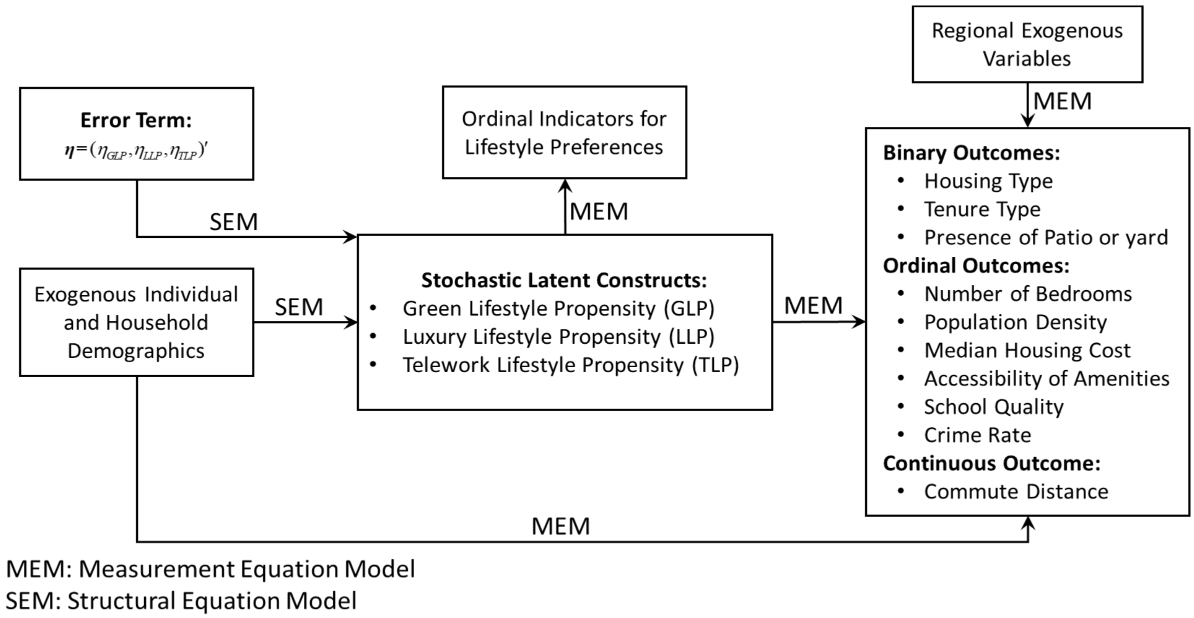


**Figure 1: GHDM Analytic Framework**

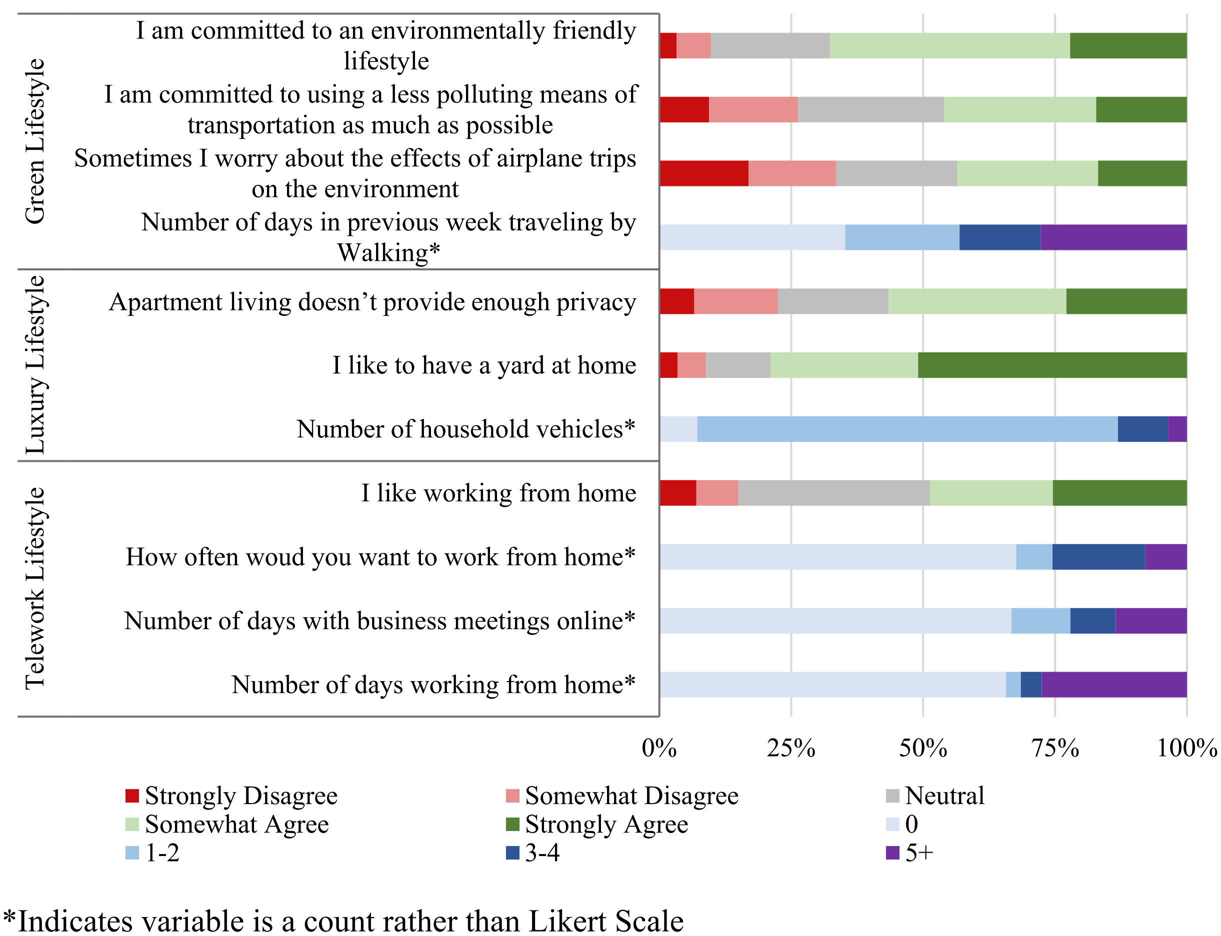


**Figure 2: Distribution of Indicators of Latent Constructs**

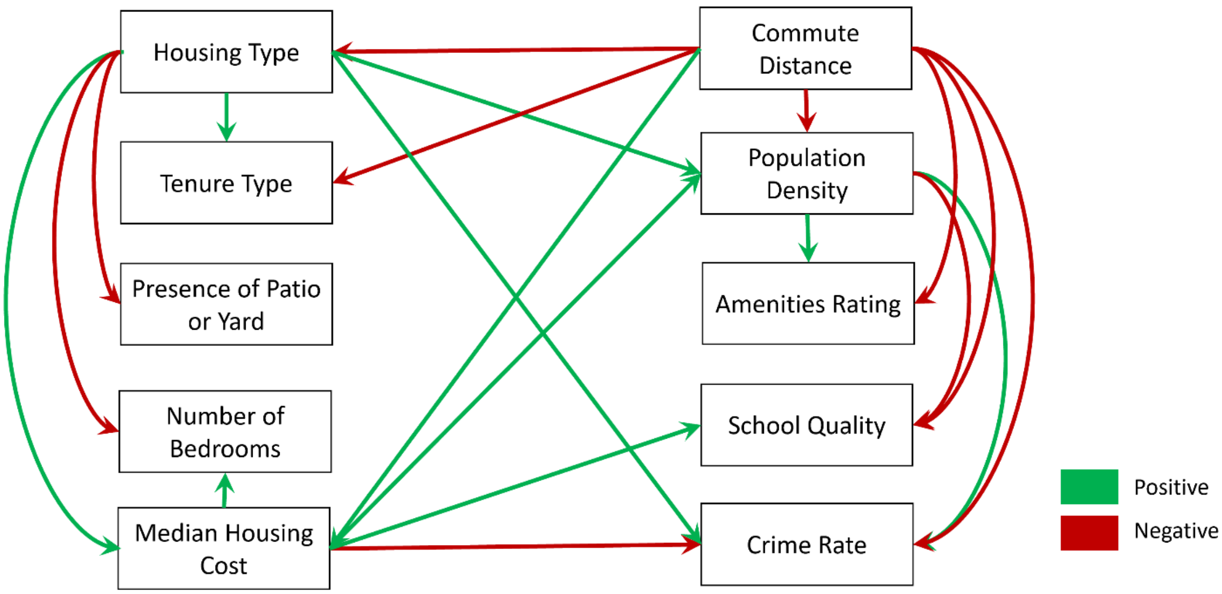


**Figure 3: Structure of Endogenous Effects**