A Rank-Based Model of Residential Location Preferences Before and During the COVID-19 Pandemic

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ABSTRACT
Residential location decisions have widespread implications for individual-level life satisfaction and broader aggregate urban form trends. In this context, the current study examines the importance of a multitude of factors affecting residential location choices. Using data from the 2021 Puget Sound Regional Travel Survey and employing a rank-based modeling approach to capture the multifaceted nature of residential location choices, the study highlights the significant heterogeneity across households in residential location preferences as well as the changes in these preferences between those moving before and after the onset of the COVID-19 pandemic. The results indicate higher priority being placed on "living near friends and family" during the pandemic, particularly for retired adults, high income groups, and Hispanic individuals. Having space and separation from others is simultaneously important for retired adults. Walkable environments appear to be particularly important in the during-COVID residential location choices of families with children, Access to highways has become more important for almost all population subgroups and quality of schools has come down in the priority list of factors sought in residential locations even for households with children. These evolving preferences for residential location factors have important implications for urban planners, real estate developers, and transportation policymakers.

Keywords: Residential Location Choice, COVID Impacts, Rank-Ordered Model, Urban Planning, Travel Demand

1. INTRODUCTION

The home serves as a core location for the start and end of the daily activity-travel behavior patterns of most individuals. The residential location also influences the intensity of activity-travel patterns of individuals, as land-use characteristics (including land-use diversity and number/diversity of activity opportunities) and transportation system characteristics (including street network design, traffic volumes on roadways, transportation infrastructure capacity, availability and distance to public transportation, and parking characteristics) impact travel mode availability and overall travel experiences (Ewing and Cervero, 2010; De Vos et al., 2018). At the same time, the preferences for specific travel modes (such as walking and bicycling), and the general desires for particular activity-travel experiences, also impact the selection of the residential location of families (see, for example, Bhat and Guo, 2007; van Wee and Cao, 2022). In the reverse direction, the residential location decisions across families, in the aggregate, influence urban form through the supply of housing availability relative to spatial out-of-home activity opportunities, and the affordability and range of dwelling unit characteristics (Doling and Arundel, 2022), all of which then influence individual family residential location decisions in a cyclical fashion. This intricate relationship among the demand-side residential location choices, the supply-side market availability and range of housing options, and urban form has been the basis for a vast literature in the land-use transportation field (see, for example, Wilson, 1970; Putman, 1975; Ben-Akiva and de Palma, 1986; Waddell, 2011; Moeckel et al., 2018; Alipour and Dia, 2023).

In recent years, in addition to urban form considerations of out-of-home activity accessibility, the proliferation of convenient virtual activity platforms, along with pandemic-related experiences, has triggered profound shifts in residential location choices, driven by changes in people's attitudes and behaviors through the widespread adoption of remote work, online shopping, and online schooling. For instance, a study by the Pew Research Center reported that approximately 22% of U.S. adults either changed their residence location due to the pandemic or know someone who did (Cohn, 2020). Other studies noted the emergence of an "urban exodus" phenomenon, where the number of urban residents moving away from dense urban areas increased substantially in 2020 following the onset of the pandemic (Whitaker, 2021; González-Leonardo et al., 2022). Monthly data on address changes from the United States Postal Service (2023) also provide compelling evidence of the significant shifts in relocation patterns attributable to the COVID-19 pandemic. In particular, there was a notable increase in relocations during the period from September to December 2020, relative to the same months in 2019, with December registering a peak increase of 13%. However, in 2021, relocations began to decrease, and, on average, they were approximately 5% lower than the levels observed in 2019. By 2022, there was a further reduction in the percentage of address changes, averaging 14% lower than the 2019 figures. These evolving relocation statistics paint a good picture of how the pandemic not only triggered immediate changes in housing decisions, but also has had enduring effects on relocation behaviors over an extended period.[1]

The aggregate residential relocation statistics above have been supported by analyses at the individual level. In this context, for the most part, before-COVID studies (for ease in presentation, in this study, we will refer to the period before the onset of the pandemic as the before-COVID

[1]We acknowledge that, in the housing relocation statistics just provided, there is some confounding between temporary moves during the pandemic (for example, moving to a rented home in Florida from a small apartment in downtown New York, with the intent to return to the apartment after the worst of COVID) from longer-term moves. However, the reduced percentage of address changes in 2021 and 2022 also show that there were longer-term moves that contributed to the overall moves immediately after the onset of the pandemic.

period, and the period after the onset of the pandemic as the during-COVID period) considered the commute distance between the home and the primary out-of-home workplace as one of the strongest determinants (if not the strongest determinant) of residential location choice (Alonso, 1960; Wilson, 1970; Sermons and Koppelman, 2001; Pinjari et al., 2011; Bhat, 2015).[2] In contrast, during-COVID studies have increasingly pointed to non-commute considerations rising in importance in residential location decisions. For example, Van Acker et al. (2024) revealed a growing valuation of neighborhood safety impacting residential location satisfaction and attachment. This includes the importance of safe conditions for walking and cycling, low crime rates, and low traffic volumes. Additionally, Liu and Su (2021) and D'Lima et al. (2022) found that preferences are shifting toward lower population density areas in the wake of the pandemic, due to a desire for more space both in and outside the home. Other during-COVID studies have reported an elevated desire for better accessibility to non-work activity opportunities such as parks, shopping centers, and local grocery stores (see, for example, Gür, 2022; Monterde-i-Bort et al., 2022; Haslag and Weagley, 2022; Lei and Liu, 2022; Asmussen et al., 2024; Wolday and Böcker, 2023; Komaki et al., 2023; Robbennolt et al., 2024; Wang et al., 2025). Rajabi et al. (2024), however, found that low-income households, many of whose members do not have the opportunity to telework, continue to have stronger preferences for access to the workplace. They also observed that households with children placed more emphasis on access to proximity to relatives, physical closeness to schools, and good access to public transportation. Schouten and Kawano (2024) similarly observed that, while remote work has made lower density areas more attractive, demand for areas in the central city with access to good public transportation continues to be high. In contrast, Yang et al. (2023) found a general across-the-board lower valuation for public transportation access after the onset of the pandemic.

Broadly speaking, then, the growth of opportunities for online activity participation (including telework), along with the lifestyle-shifting experiences during the height of the COVID pandemic, appear to have impacted residential location valuations of in-person accessibility to employment and other types of activities and spaces (Caldarola and Sorrell, 2022; Robbennolt et al., 2024), as well as changed the ways that families view and use their homes in the wake of the pandemic. Motivated by these observations, the current study aims to investigate how COVID-19 has altered housing priorities and preferences for different housing attributes. Using data from the 2021 Puget Sound Regional Housing Survey (Puget Sound Regional Council, 2022), we compare the relative importance placed on a range of factors in the relocation decision for individuals moving before the onset of the pandemic compared to after the onset of the pandemic. We account for a variety of factors that play a role in the residential location decision, including commute distance, affordability, access to various destinations, transportation infrastructure, space needs, and cultural considerations.

In our analysis, we use a Rank Ordered Probit (ROP) model to analyze the relative importance that individuals place on different factors in their most recent residential relocation. But, because individuals may have some difficulty in providing their rankings when multiple factors may be at play, the survey used in our analysis first asked individuals to rate the importance of each factor using an ordinal Likert scale. While this way of eliciting importance information is

[2]This is not to say that before-COVID studies have not considered non-commute distance factors in residential location choice. Examples include the consideration of land-use factors (Chen et al., 2008; Marois et al., 2019), neighborhood crime rates and safety (McIlhatton et al., 2016; Olanrewaju and Wong, 2020), activity accessibility (Wang and Li, 2006; Li et al., 2016), and local school quality (Li et al., 2016; Lee et al., 2019). However, the general before-COVID emphasis has been on commute distance.

convenient and intuitive, directly analyzing such ratings data can be tricky because participants can interpret the Likert rating scale quite differently (Abrudan et al., 2020; Emami and Sadeghlou, 2021). That is, one respondent may interpret a rating of 4 ("somewhat important") the same way that a second interprets a rating of 5 ("very important"). For instance, regardless of their actual location preferences, respondents who have more cautious lifestyles may tend to cluster their ratings around the midpoint of the scale even if they have fairly strong preferences (for instance, see the discussion of Kreitchmann et al., 2019). These types of systematic individual differences in response style mean that, while the order conveyed by these responses is still likely to be reliable, the actual distance gaps between the ratings is not generally reliable. A good analysis approach then is to translate the collected ratings data into a ranking scale that retains the ordering of importance but not the scale, and which is then more stable and comparable across individuals (Layton and Lee, 2006; Nair et al., 2018; Sharma and Mishra, 2023). Accordingly, we use the ROP model for analysis. The ROP model is also to be preferred over the more commonly used rank-ordered logit (ROL) model because it is much more robust to error distribution misspecification than the ROL model, as demonstrated in Nair et al. (2019). Also, recent developments have improved approximation techniques for estimating cumulative multivariate normal distribution functions, making ROP models much more practical (see Bhat, 2018). Recent applications of ROP models in several transportation contexts have demonstrated its reliability and many advantages for rank-ordered modeling (Asmussen et al., 2020; Presley et al., 2021; Mondal and Bhat, 2022; Simionescu, 2022).

2. ANALYSIS FRAMEWORK

2.1 Data Description

The data used for this study are drawn from the 2021 Puget Sound Regional Household Travel Survey (Puget Sound Regional Council, 2022), collected between April and June 2021. The study area was the Puget Sound (Greater Seattle, Washington) region, encompassing the King, Kitsap, Pierce, and Snohomish counties, a region including 82 cities and towns with a total population of over four million people. The survey consisted of both a probability address-based sample and a non-probability online panel sample. The probability sample was stratified by census block group to meet targets for race, ethnicity, and county-level targets. 48,024 mailed invitations were sent to households in the study region inviting them to participate online or via phone call, resulting in a sample of 1,929 households. An additional non-probability sample was collected by inviting a panel of respondents to participate via email, resulting in an additional 864 households (see RSG, 2022 for additional details of the survey administration procedure). The survey collected individual and household socioeconomic and demographic information at the time of the survey. It also collected travel, mode use, commute, and telework details, both at the time of the survey and from before the COVID-19 pandemic. Additionally, the survey collected, from a reference adult in the household who completed the initial recruitment survey, the reasons/factors for the household's most recent residential relocation, which constitutes the main vector of outcomes considered here. Specifically, the survey prompted respondents to assess, using a 5-level Likert scale (from "not at all important" to "very important"), the significance of nine distinct residential location factors when deciding to relocate to the current place of residence. The factors were:

1. Affordability
2. Being close to family and friends
3. Access to cultural centers and activities (e.g., museums, sporting events, restaurants)
4. Being close to the highway

5. Quality of schools (K-12)
6. Having space and separation from others
7. Being close to public transit
8. Having a walkable neighborhood and being near local activities
9. Being within a reasonably short commute to work

The ratings on the nine factors above were converted to a set of rankings. An issue that arises in this translation is that an individual may have chosen the same Likert scale category for multiple factors, which results in ranking ties. But, as discussed later in Section 2.2, such ties can be handled in a straightforward way in a ranking model.

Households whose reference person (61 of them) had the same rank for all the factors (that is, assigned the same ordinal level of preference to every factor in the original rating) were removed from the sample, because such households do not provide any information for priority extraction. An additional 292 households with incomplete data were also removed, and households with relocations more than five years prior to survey distribution were also removed. This was done because the demographics collected at the time of the survey are not likely to represent the demographics at the time of the relocation for those relocations occurring in the distant past.[3] The final sample in our analysis included 1,284 households. Finally, since the survey design included more factors than importance levels, every household exhibits tied rankings. Of the 1,284 households considered, 381 used the full spectrum of the five Likert scale levels in the responses across the nine factors, resulting in five ranking levels. Further, 567 households employed four Likert scale levels across the nine factors (while not assigning the fifth Likert scale level to any residential location factor), 202 employed three Likert scale levels, and the remaining 134 used only two Likert scale levels. However, regardless of the number of tied factors for any household, it is straightforward using the ROP approach to accommodate such ties in the modeling approach and distinguish between preferences for the residential location factors rated at different levels (as discussed in Section 2.2).

2.1.1 COVID Segmentation

As the modeling effort in this study aims to determine the effect of the COVID-19 pandemic on the valuation of a host of residential location factors, the sample was segmented based on the timing of each household's most recent residential relocation (in the rest of this paper, we will use the term "factors" to refer exclusively to "residential location factors," which constitute the endogenous outcomes of interest). For the current analysis, we deemed those households who reported moving in the second half of 2019 or after (within 2 years of the survey) as the during-COVID movers, and others (between 2 and 5 years prior to the survey) as the before-COVID movers, which resulted in a total of 617 households in the before-COVID group and 667 households in the during-COVID group.

To determine effects of the COVID-19 pandemic on residential location in the modeling effort, we used a binary indicator that takes the value of 0 for the before-COVID group and 1 for the during-COVID group. This indicator variable is then interacted with the exogenous variables in the model to create three sets of effects. First, each exogenous variable is included (without any interaction with the during-COVID binary indicator) to generate a before-COVID baseline effect

[3]We had to go back up to five years to obtain a reasonable number of households who relocated before the pandemic. Admittedly, it is quite possible that some demographics may have changed even through this five-year period, but that is the data we have. On the positive side, the 2021 Puget Sound Regional Household Travel Survey provides the opportunity for a very timely investigation of residential location decisions in the during-COVID period.

valuation ("utility") of each factor. Second, the COVID-effect indicator is included in the model alone to represent a generic COVID shock effect on each factor compared with the baseline preference for that factor. Finally, the indicator interacts with each exogenous variable to reveal the shifting effects of each exogenous variable since the onset of pandemic. As this final set of interactions represents the shocks, it is possible to add the baseline effects and COVID shifts to determine the total effect of the exogenous variables in the during-COVID period. If an exogenous variable does not appear in its interaction with the binary indicator for a specific factor, but in the baseline effect for that factor, this implies that the baseline effect also permeates to the during-COVID valuation of the factor with no change because of the pandemic.

We should note two potential limitations of our approach here. First, the reference person of each household was asked to recall a decision-making process that may have happened up to five years back, and thus the responses may be susceptible to recall bias. However, there is evidence suggesting that residential location choices are particularly likely to be accessible to respondents (both in terms of their general understanding of their own motivations and in terms of their ability to access and accurately recall these motivations even after time has passed) because they activate several specific cognitive processes. First, housing and residential location decisions represent major life transitions that have significant personal meaning. These decisions are central to identity (Jacobs and Malpas, 2013; Coulter, 2023) and reflect core values and priorities (Collen and Hoekstra, 2001; Jansen, 2014), making the decision processes particularly salient and more easy to recall over time. Second, residential location choice processes activate cognitive centers aligned specifically towards future planning and temporal reasoning, as such decisions involve long-term planning and commitments. Evidence suggests that people are particularly well suited to inspect the motivations behind such long-term planning processes compared even with other major lifestyle decisions (Szpunar et al., 2014; Bulley and Schacter, 2020). Third, residential choice decisions activate elaborative processing mechanisms, creating multiple pathways to memory retrieval as individuals consider a broad range of relevant factors that are relevant across life domains (such as affordability, commute times, access to high quality schools, and community characteristics; all of which are considered directly in the current study, also helping activate these pathways for respondents). This elaborative process creates strong semantic autobiographical memories containing detailed contextual information about the decision and motivations that remains accessible over time (Martinelli et al., 2012; Hawco et al., 2013). Finally, housing and residential location choices involve significant amounts of social coordination among family members. This coordination forces family members to inspect and articulate their own motivations during the housing search and decision process as they negotiate and navigate differing motivations. Doing so serves to move the decision process even more firmly towards the conscious and deliberate reasoning processes as family members (together) weigh various factors, and such negotiations activate memory centers aligned specifically with social dynamics and interpersonal coordination, again serving to make these memories and motivations more accessible (Levy et al., 2008; Leblanc and Ramirez, 2020). For additional detailed discussion of the issue of recall bias when using retrospective data for housing decisions see Hollingworth and Miller (1996) and Müggenburg (2021).

A second potential limitation is that the approach used here, strictly speaking, only studies the changes in individual-level decision making across time through a comparison of the choices of different decision makers in the before-COVID and during-COVID periods. Because such a methodology simply compares changes in the relative preferences across these two periods, it is not appropriate to squarely attribute changes to the COVID-19 pandemic, as other changing social and economic conditions over the sample period (many of which have been discussed in Section 1) may have led to changing residential location preferences. Of course, as in any repeated cross-sectional analysis, the effects of exogenous variables in the before-COVID and during-COVID periods are also captured through variations across individuals in the exogenous and endogenous outcomes. Future studies can complement our study with multi-year longitudinal data that elicits importance ratings from the same set of individuals over time, which would control for time-invariant individual-specific unobserved (to the analyst) factors that affect residential moves (and the motivations for such moves). However, longitudinal data would still not resolve the issue of disentangling COVID-caused changes from changes in other confounding social/environmental factors between the before- and during-COVID periods. Indeed, our notion of linking variations in the effects of exogenous variables over time to pandemic effects in the current paper is in epistemic terms (that is, as our best interpretation of COVID-engendered effects within the modeling structure adopted; see Williamson, 2006). In fact, in any modeling exercise even at a single point in time, the effect of any exogenous variable cannot be strictly interpreted as a "causal" effect of that variable, since there could be a whole host of other related factors at play that have not been controlled for. Fundamentally speaking, all that we really observe is a multivariate distribution of observed exogenous variables and outcomes, whether from cross-sectional or longitudinal data. Regardless of the type of data available, the best we can do as analysts is to use a structured methodological framework to tease out variable effects in an epistemic way (at a single point in time or across time) through the decomposition of this multivariate distribution into plausible cause-effect relationships (see Wunsch et al., 2010).[4]

2.1.2 Outcome Variables

Table 1 presents the ranking preferences of the respondents among the nine residential location factors. The table presents, for each of the before- and during-COVID periods, the percentage share of individuals selecting each factor as the top-ranked, in the top 2 ranks, and so on until the last-ranked factor.[5] The sample statistics reveal that affordability is by far the most significant factor, with more than 25% of respondents ranking it first in both the before-COVID and during-COVID segments and more than 60% ranking it in the top three in each segment. Also, less than 5% of

[4]We should also point out that there are many other limitations in the use of longitudinal data that can be avoided using repeated cross-sectional data. For instance, an application of longitudinal data for our purpose would necessitate collecting data from a large enough sample of individuals who moved both in the before-COVID and during-COVID periods. Given that residential moves are not frequent occurrences, this would likely mean extending the time horizon beyond the three-year period that is considered as the before-COVID period in the current survey to get a large enough sample of individuals who moved in both periods. This would further exacerbate issues of confounding of COVID-caused and other social/environmental factors over the longer time horizon. Besides, such a long-term longitudinal data collection would also raise issues of initial self-selection into a protracted survey process, drop-outs during the data collection period, fatigue effects, and cost. Another problem with the use of longitudinal data in the current context is that, when repeatedly querying the same respondent on the same topic, responses may be biased due to panel conditioning, where the respondents' answers to the repeated queries are based on their responses to the initial queries (Warren and Halpern-Manners, 2012; Struminskaya and Bosnjak, 2021). For a broader review of these types of challenges with longitudinal data, see Thompson (2015) and Johal et al. (2023). A good path forward, in general, would be to harness the full potential of cross-sectional and longitudinal data, either individually or in combination, and asking respondents about the factors motivating their move immediately before or after the actual move.

[5]In this table, we allocated ties equally across the tied rank categories. For example, if an individual identified factors 1, 2, and 3 as tied for rank 1, the individual's contribution of each factor toward rank #1 was assigned as 0.33, toward rank #2 as 0.33, and toward rank #3 as 0.33. Thus, the sum of the percentages in each column for the top-ranked factor and last-ranked factor in each period sum to 100%.

respondents rank affordability as the last-ranked factor. Other highly significant factors include a short commute to work and living in a walkable neighborhood. Conversely, at the opposite end of the spectrum, quality of schools, being close to a highway, and being close to public transit were rated as relatively unimportant factors by respondents in both the before-COVID and during-COVID periods (these three factors have a share higher than 10% in the column labeled "last-ranked" in both periods, identifying them as the least important factors).

A comparison of the priorities of respondents who relocated before the pandemic to those who relocated after the onset of pandemic in Table 1 shows notable shifts in the rankings. In particular, there is evidence that, across the entire sample, the importance of being close to friends and family has risen in the during-COVID period, while the importance of quality of schools has fallen in the during-COVID period. Of course, Table 1 does not provide the entire picture of rises and falls in the importance of different factors because the table does not include the relative rankings in the three intermediate categories (that is, ranks #4 through #6). Also, in a ranking model, the utility of each alternative (housing factor in the current study) as a function of exogenous variables (see Section 2.2 for the model formulation) is determined based on the complete ranking of all alternatives across all individuals, which is not considered in the aggregate statistics of Table 1. Besides, the aggregate statistics mask variations in the rankings, and changes in the rankings, between the before- and during-COVID periods across different households. For instance, while quality of schools gets relatively low rankings overall, particularly in the during-COVID period, it may not be that unimportant a factor for families with young children. To comprehensively understand the heterogeneity in preferences, and the heterogeneity in the changes in preferences between the before- and during-COVID periods, while also using the entire depth of nine rankings of factors, the rigorous multivariate ranking analysis undertaken in this study is needed.

2.1.3 Exogenous Variables

The socioeconomic and demographic characteristics of the households in the sample are provided in Table 2, along with corresponding data from the 2020 United States Census (U.S. Census Bureau, 2020). These demographic characteristics represent those of the entire household (for instance, the education attainment refers to the highest level of education attained *across different members of the household*). The sample consists of 34.3% single adult households, with the remaining 65.7% being households with two or more adults. This distribution is quite close to the Census statistics. The sample has a slight underrepresentation of households with at least one child (aged 17 or younger) and a more significant underrepresentation of households with at least one retired adult. The underrepresentation of households with retired adults is unsurprising given that these individuals tend to have more stable long-term housing arrangements and households whose most recent relocations were more than five years prior to survey distribution were removed from consideration. Additionally, the majority of households had at least one working adult, while 18.4% were comprised only of adults who were all unemployed or retired. The sample includes a significant overrepresentation of households with high levels of educational attainment (30.8%) compared with Census data (2.9%), and underrepresentation of households with no bachelor's degrees, a finding in line with general survey response trends. In terms of annual household income, the sample is slightly skewed towards higher income levels, with 44.0% reporting an annual income higher than \$100,000 compared to 37.3% in the census data. There is also an overrepresentation of non-Hispanic individuals, making up 89.6% of the sample. Ethnicity was considered combined with race during the sample targeting, for the probability sample, so while the overall sample is fairly representative of non-Hispanic white individuals, ethnic representation was not fully captured with this approach. Finally, race was also reported at the household level, with a slight overrepresentation of households identifying as White only.

The observed skews in the exogenous variables relative to the US Census statistics imply that the unweighted descriptive statistics from this sample cannot be generalized to the entire population. For instance, because households with at least one retired adult are underrepresented in the sample and generally place a greater value (compared with households with no retired adults) on being close to friends and family (as we find in our model and discuss in the following section), it is likely that the aggregate descriptive statistics discussed in the previous section underestimate the overall importance of being close to friends and family (in relation to the other residential location factors) that may be present in the overall population. The implication is that policy decisions, planning, or interventions based on the sample's aggregate results might undervalue social proximity needs, especially for older or retired populations. However, the sample is reasonably representative of many of the exogenous variables (except for the presence of retired adults, educational attainment, and ethnicity), has substantial variation in each of the exogenous variables included, and is not derived from an endogenous sampling scheme. Therefore, there is no reason to believe that the individual-level causal relationships estimated in the current study would not apply to the population at large. Further, weighting is unnecessary for the individual-level analysis undertaken in this study; an unweighted approach is preferred due to its greater efficiency (see Wooldridge, 2001; Solon et al., 2015; Robbennolt et al., 2026).

2.2 Model Formulation

The framework adopted for this study is the Rank-Ordered Probit (ROP) model using a generalized likelihood function that accommodates multiple alternatives with the same rank (that is, tied rankings; see Nair et al., 2018). Consider an individual q $(q = 1, 2, ..., Q)$ who ascribes a utility U_{qi} to each alternative housing factor i $(i = 1, 2, ..., I)$. The individual-specific utility function for each alternative within the ROP model is written as follows:

$$U_{qi} = \boldsymbol{\beta}'\mathbf{x}_{qi} + \varepsilon_{qi} \tag{1}$$

where $\mathbf{x}_{qi}$ is a $(A \times 1)$ vector of exogenous attributes (including a constant for each alternative excluding a base alternative), and $\boldsymbol{\beta}$ is a corresponding $(A \times 1)$ vector of coefficients. We also assume that the error term ε_{qi} is independent and identically normally distributed across individuals q but allow a general covariance structure across alternatives for each individual. Specifically, let $\boldsymbol{\varepsilon}_q = (\varepsilon_{q1}, \varepsilon_{q2}, ..., \varepsilon_{qI})'$ $(I \times 1$ vector). Then, we assume $\boldsymbol{\varepsilon}_q \sim MVN_I(\mathbf{0}, \boldsymbol{\Lambda})$. Additionally, for identification of this specification (as in Multinomial Probit models), exclusion restrictions are needed for individual-specific covariates such that at least one individual characteristic is excluded from each alternative's utility in addition to being excluded from a base alternative. These exclusion restrictions are not needed for covariates whose values vary across alternatives (see Keane, 1992; Munkin and Trivedi, 2008).

Since the utility of all the alternatives can be multiplied by a positive constant and a constant can be added to all the utilities without changing the rank-ordering of the utilities, appropriate scale and level normalizations must be imposed on $\boldsymbol{\Lambda}$ for identifiability (Alvo and Yu, 2014). Taking the utility differentials with respect to the first alternative, only the elements of the covariance matrix $\mathbf{\Lambda}_1$ of $\tilde{\varepsilon}_{qi1} = \varepsilon_{qi} - \varepsilon_{q1}$ $(i \neq 1)$ are estimable. However, the approach used here takes the utility differences in a specific way as a function of the observed ranking (as discussed later). Thus, if individual q selects ranking r_q, the covariance matrix $\mathbf{\Lambda}_{r_q}$ is desired for the individual. But, even though different differenced covariance matrices are used for different individuals, they must originate from the same matrix $\mathbf{\Lambda}$. To achieve this consistency, $\mathbf{\Lambda}$ is constructed from $\mathbf{\Lambda}_1$ by adding an additional row on top and an additional column to the left. All elements of this additional row and column are assigned the value zero. Finally, since the scale of $\mathbf{\Lambda}$ is not identified, we normalize the element of $\mathbf{\Lambda}$ in the second row and second column to the value of one. These normalizations are innocuous and needed for identification, so this $\mathbf{\Lambda}$ matrix remains is fully general.

The model above may be written in a more compact form by defining the following vectors and matrices: $\mathbf{U}_q = (U_{q1}, U_{q2}, ..., U_{qI})'$ ($I \times 1$ vector) and $\mathbf{x}_q = (\mathbf{x}_{q1}, \mathbf{x}_{q2}, ..., \mathbf{x}_{qI})'$ $(I \times A)$ matrix. Then, we can write Equation (1) in matrix notation as:

$$\mathbf{U}_q = \mathbf{x}_q \boldsymbol{\beta} + \boldsymbol{\varepsilon}_q, \tag{2}$$

where $\mathbf{U}_q \sim MVN_I(\mathbf{x}_q \boldsymbol{\beta}, \mathbf{\Lambda})$.

For estimation, we define a contrast matrix for each individual q based on their ranking r_q of alternatives. Specifically, let the first ranked alternative for individual q be r_q^1, the second r_q^2, and so on until the last-ranked alternative r_q^I. Then, the following $(I-1)$ inequalities should hold: $U_{qr_q^2} - U_{qr_q^1} < 0, U_{qr_q^3} - U_{qr_q^2} < 0, \ldots U_{qr_q^I} - U_{qr_q^{I-1}} < 0.$ In vector notation, we can write these inequalities using a contrast matrix $\mathbf{M}_q$ with $(I-1)$ rows for each inequality and I columns for each alternative. To start, fill all the elements of the contrast matrix with zeros. Then, in the first row (corresponding to the first inequality above), place a negative one in the column corresponding to the first-ranked alternative and a one in the column corresponding to the second-ranked alternative. In the second row (corresponding to the second inequality above), place a negative one in the column corresponding to the second-ranked alternative and a one in the column corresponding to the third-ranked alternative. Continue this process until placing a negative one in the column corresponding to the penultimate-ranked alternative, and a one in the column corresponding to the last-ranked alternative in the final row (corresponding to the last inequality above).

The contrast matrix $\mathbf{M}_q$, as defined above, does not accommodate tied rankings. In the context of converting a set of importance ratings to a set of rankings, it is necessary to accommodate tied rankings as participants may indicate the same level of importance for multiple factors (in fact, the survey design included more factors than importance levels, so every record in the sample includes tied rankings). To account for these scenarios where respondents reported multiple factors with the same level of importance, we adopt the framework proposed by Allison and Chrisktakis (1994) for the ROL model and generalized to the ROP model by Nair et al. (2018). Specifically, it is assumed that when respondents provide the same level of importance for multiple housing factors, there is still an underlying preference ordering among them. Since this underlying preference ordering is unobserved, the likelihood is calculated as the probability of any possible ordering consistent with the observed ranking, resulting in a greater number of inequality conditions, J_q. For example, if an individual q assigns the first rank to alternative 3, has a tie for second rank among alternatives 2 and 4, and assigns third rank to alternative 1, they have the following four conditions: $U_{q2} - U_{qr3} < 0, U_{q4} - U_{q3} < 0, U_{q1} - U_{q2} < 0, U_{q1} - U_{q4} < 0$. Thus, in this example, the contrast matrix $\mathbf{M}_q$ is structured as follows:

$$\mathbf{M}_q = \begin{bmatrix} 0 & 1 & -1 & 0 \\ 0 & 0 & -1 & 1 \\ 1 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}.$$

Note that the number of rows in $\mathbf{M}_q$ is now $(J_q - 1)$, which depends on the number of ties in each individual's responses. Once the contrast matrix has been defined, the inequalities for each individual can be rewritten in vector form as $\mathbf{u}_q = \mathbf{M}_q \mathbf{U}_q < \mathbf{0}_{J-1}$, and it can be seen that $\mathbf{u}_q \sim MVN_{(J_q-1)}(\mathbf{B}_q, \mathbf{\Sigma}_q)$, with $\mathbf{B}_q = \mathbf{M}_q \mathbf{x}_q \boldsymbol{\beta}$ and $\mathbf{\Sigma}_q = \mathbf{M}_q \mathbf{\Lambda} \mathbf{M}'_q$ The likelihood of each observation in the sample (i.e., individual 1 having the ranking r_1, individual 2 having the ranking r_2, ..., and individual Q having the ranking r_Q) may then be written succinctly as $\text{Prob}[\mathbf{u}_q < \mathbf{0}_{J-1}]$. The parameter vector to be estimated is $\boldsymbol{\theta} = (\boldsymbol{\beta}', \overline{\mathbf{\Lambda}}')'$, where $\overline{\mathbf{\Lambda}}$ is a column vector obtained by vertically stacking the unique elements of the matrix $\mathbf{\Lambda}$. Then, the likelihood function is:

$$L(\boldsymbol{\theta}) = \prod_{q=1}^{Q} \Phi_{(J_q-1)}(\mathbf{0}_{(J_q-1)}; \mathbf{B}_q; \mathbf{\Sigma}_q), \tag{3}$$

where $\Phi_{(J_q-1)}(\mathbf{0}_{(J_q-1)}; \boldsymbol{\mu}, \boldsymbol{\varsigma})$ is the $(J_q - 1)$ dimensional multivariate cumulative normal distribution function computed at the truncation point vector $\mathbf{0}_{(J_q-1)}$ with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\varsigma}$.

The likelihood function above entails the evaluation of a $(J_q - 1)$ dimensional integral. In this paper, we use Bhat's (2011) maximum approximate composite marginal likelihood (MACML) procedure, along with procedures to accurately estimate the MVN distribution based on Bhat (2018).

3. MODEL RESULTS

The final model specification was developed through an iterative process of including exogenous variables in various forms and testing the statistical fit of a multitude of combinations of exogenous variables. Categorical variables were initially included in their most disaggregate form and progressively combined based on statistical tests to yield a parsimonious specification. Additionally, in some cases, we have chosen to keep some variables in the specification even if they are statistically significant only at the 80% confidence level (that is, a t-statistic threshold of 1.28; admittedly, some caution needs to be exercised in making conclusions based on such variables). A low t-statistic threshold was chosen because of the moderate sample size in each of the before- and during-COVID periods, the relatively large number of factors, and the potential of marginally significant variables to inform future empirical investigations with larger sample sizes. The model results are shown in Table 3 (a "--" entry in the table indicates that the row exogenous variable does not have any statistically significant impact on the column outcome factor, even at the 80% confidence level).[6] Note that the constants for each factor (both in the before-COVID period and the during-COVID period) are included in the model regardless of the t-statistic significance, because these simply adjust for the range of exogenous variables in the model. In addition to the variables presented, several other household composition variables were initially considered but did not have significant statistical impacts on residential location utilities even at the 80% confidence level. In particular, the gender of single-adult households and the structure of multi-adult households (whether the adults were a couple, living with older parents, or living with unrelated roommates), other than the presence of retired adults, did not have a statistically significant impact on the prioritization of the housing factors.

3.1 Main Estimation Results

The main estimation results are presented in Table 3. The first two rows of the table show the set of overall constant effects and the set of COVID-effect variables on the utility of each factor. Each of these sets of variables are estimated to match the observed before-COVID and during-COVID ranking choice proportions and do not have any substantial interpretations. However, significant heterogeneity in the impact of the pandemic is revealed by the interactions between the COVID-effect variable and the remaining exogenous variables. The remainder of this section focuses on the effects of the exogenous variables (on the utilities of the different location factors). For streamlining purposes, the exogenous variables are grouped into "Household Composition" and "Household Sociodemographic" variables, with the first set of variables focusing on general lifecycle variables and the second on education, income, race/ethnicity, and vehicle ownership. To conserve space, we discuss the results selectively, with an emphasis on the pandemic effects.

Household composition has several effects on location preferences. Households with children and retired adults tend to generally value being close to friends and family, a trend that has grown for retired adults since the pandemic. It appears that both groups have also begun prioritizing affordability after the onset of the pandemic (as reflected in the positive signs on these variables interacted with the "during-COVID" indicator in the "affordability" column). Those with children place a much higher valuation on access to high quality schools relative to households without children (especially, and expectedly, relative to single adult households), with this

[6] Regarding the use of an 80% confidence level, there is a tradeoff in model specifications between the chance of including variables incorrectly (Type I error) and of rejecting variables incorrectly (Type II error). Selecting a confidence level fundamentally influences the probability of making each of these types of errors, as choosing a higher confidence level (compared with a lower confidence level) mitigates the chance of incorrectly including unimportant variables but increases the chance of excluding variables that may actually have meaningful effects. In fact, as strongly endorsed and supported by the American Statistical Association (Wasserstein and Lazar, 2016; Wasserstein et al., 2019), there is a need to avoid the mindset of applying a blanket 95% level of confidence (or any other specific level of confidence) across all modeling contexts. In the current situation of a moderate sample size and an interest in distinguishing preferences in two periods (with only 617 households in the before-COVID group and 667 households in the during-COVID group), we prefer choose a slightly lower confidence level (allowing a slightly larger Type I error) if it means identifying variables that are suggestive and that may inform future specifications using larger samples. Additionally, we will note that few coefficients (only 16 of the 102 estimated coefficients) turned out to be statistically significant at the 80% level, but not at the 90% level. Also, these few variables saw little movement in their estimated effect sizes across a wide range of tested specifications. Finally, in model estimations that excluded variables with coefficients below a 90% confidence level (t-statistic of 1.645) and a 95% confidence level (t-statistic of 1.96), there was little impact on the sign or magnitude of the estimates of other variables reported in Table 2. As indicated by Lu and White (2014), Srivastava et al. (2018), and Brennan et al. (2021), such stability of estimates through robustness testing at different confidence levels lends additional credibility to the results.

valuation for high quality schools only increasing further in the during-COVID period (this shift effect is, however, statistically significant only at the 86% confidence level). Households with children also ascribe lower utility to being close to public transit relative to households without children, consistent with previous literature suggesting that households with children have complex trip-chaining patterns that are not easily pursued on public transit (Brown et al., 2016; Kersting et al., 2021). Additionally, since the pandemic, households with children reveal a growing preference for local accessibility through neighborhood walkability (significant only at the 88% level) and access to cultural centers and activities, likely reflecting the tendency of parents to return their children to social activities (Szpunar et al., 2021). Further, households with retired adults have also begun prioritizing space and separation from others since the pandemic (significant at the 85% confidence level), while placing less value on commute distance. As retired adults are more susceptible to the impacts of COVID-19, this increased attention given to space and separation from others is not surprising. Finally, in the group of household composition variables, the valuation (utility) that households with no workers place on commute distance and living in areas with access to cultural centers is generally lesser than for households with workers, though there is no change in this valuation (utility) because of the pandemic.

Among the household sociodemographic characteristics, those with a graduate degree tend to ascribe (both before- and during-COVID) less utility to affordability and closeness to friends and family, likely because they are more willing to move to areas with better employment opportunities (Clark and Wang, 2005; Kortum et al., 2012). Also, households with higher levels of educational attainment (bachelor's degree or higher) do not place much value on quality of schools when children are not present (relative to their childless peers of lower formal education). But, beyond the existing preference for school quality among those with children (discussed in the previous paragraph), households with one or more adult members with a bachelor's degree or higher place a higher utility on quality of schools when children are present than households with children and adult members with lower than a bachelor's degree. This latter result is consistent with existing findings suggesting that parents with high educational attainment are more likely to prioritize school quality (see Zhan, 2015). Some caution needs to be exercised in these interpretations, given that many of these effects are statistically significant at only about the 85% confidence level. Continuing with education effects, households with high levels of formal educational attainment (bachelor's degree or higher) have a heightened valuation (relative to households with lower formal education levels) for "Having a walkable neighborhood and being near local activities" in the during-COVID period (compared to the before-COVID period), likely because they are more aware of the physical and psychological benefits of outdoor physical activities and were more likely to partake in physical activities during the pandemic (see Setiowati et al., 2023; Hwang et al., 2023).

The income effects in Table 3 also reveal significant impacts on residential location valuations, with high-income (\$100K+) households placing greater utility than low-income households (<100K) to "Being close to the highway" and "Quality of schools," and clearly placing a greater emphasis on being close to family and friends in the during-COVID period. Further, households with an annual income of 50K or more place less valuation (less utility) on short commutes compared to households with an annual income less than 50K, and this is especially so in the during-COVID period. The latter result is consistent with the notion that those with higher incomes maximize their earnings by searching a wider area for suitable jobs, leading to longer commute distances (Clark and Wang, 2005; Bhat, 2015; He and Hu, 2015; Xue et al., 2020).

Although race and ethnicity play a role in housing choices, the effects of the pandemic on the different valuations of location factors by racial groups seem rather marginal. One key difference before the pandemic, which has not changed since the pandemic, is that households identifying as Black tend to prioritize, relative to their peers, access to public transit, both in the before- and during-COVID periods. This finding aligns with existing research showing that Black families tend to concentrate in neighborhoods with high levels of transit accessibility, likely compensating in part for significant racial disparities in income and vehicle ownership (see, for example, Yan et al., 2022). Since the pandemic, households identifying as Black also tend to place less value on space and separation from others, consistent with evidence that Black families are less likely to have access to technology and online resources that prevent social isolation and may therefore prefer continued in-person interactions (Finucane et al., 2022). Asian households also place less utility on space and separation from others in general, as well as being less likely to prioritize walkability and access to cultural centers. Households identifying as Hispanic tend to place less utility than non-Hispanic ethnicities on walkability in the during-COVID period, while also placing high value on being close to friends and family compared with non-Hispanic households.

Finally, households with more vehicles generally place greater importance on being close to highways and less on walkability and access to public transit, intuitive results since they have more vehicles available for personal travel rather than needing to use these active modes. Additionally, the desire for space and separation from others since the pandemic is heightened among vehicle owners, perhaps because they have been better able to prioritize additional space because of being less constrained by mobility considerations (this effect though is statistically significant only at the 80% confidence level).

Overall, the above model results suggest that proximity to friends and family emerged as increasingly important in the during-COVID period, particularly for retired adults and high-income households. Families with children showed growing preferences for neighborhood walkability and access to cultural activities as parents sought to restore children's social engagement. Similarly, while the importance of schools dropped for all population groups, this decline in importance was smaller for families with children. Retired adults and households with many vehicles increasingly prioritized space and separation from others, likely driven by health concerns and increasing availability of work-from-home arrangements. Meanwhile, the importance of accessibility seems to have increased overall (in terms of access to friends and family, being close to a highway, having neighborhood walkability, and having a relatively short commute to work) except in the case of access to public transit, which has been prioritized much less in the during-COVID period, particularly among single adults.

3.2 Implied Correlations between the Housing Factors

The implied error covariance matrix showing the estimated variances and covariances among the different housing factors in the model is shown in Table 4. In the estimation of the ROP model, only the matrix of error differences is estimable and multiple undifferenced error covariance matrices can be consistent with a single differenced covariance matrix. Therefore, the covariances between the factors shown in Table 4 are for the error differenced terms with the commute distance factor. Examining these effects reveals a statistically significant positive relationship between all the housing factors in the model (all covariance terms are statistically significant at the 90% confidence level or higher), as differenced with commute distance. Assuming that the variance of commute distance is relatively small compared to the variances of the other factors, and there is little correlation between commute distance and other location factors in the unobserved component, the differenced correlation matrix in Table 4 may be informally interpreted as the covariations among the non-commute distance factors. With this assumption, we observe relatively low variances for the first four factors in Table 4 (on the order of 1.0) and relatively high variances for the last four factors (ranging from 2.18 to 6.67). This implies more uniformity in the valuation (given exogenous variables) of affordability and broad social/activity access factors (the first four factors in Table 4), and less uniformity in the valuation (again, given exogenous variables) of more specific quality of schools, public transit access, and walkable neighborhood factors (the last four factors in Table 4). The covariances among the many non-commute location factors also seem plausible. For instance, an underlying unobserved trait of sociability across all members of a household would likely cause that household to value being near friends and family, being near cultural activities, and being close to families highly, as each of these residential location factors facilitates opportunities for greater social interaction near the home. The strong correlations in Table 4 highlight the importance of considering all location factors jointly, rather than considering the importance of each factor alone.

3.3 Model Fit

The performance of the full ROP model may be compared with that of an IID ROP model, which assumes that the errors between the many location factors are independent and identically distributed. That is, the IID model maintains a correlation structure with zeros for all off-diagonal terms rather than estimating the correlations shown for the full model in Table 4. The highly significant correlations discussed in the previous section already imply the superiority of the full ROP model and the need to account for these error correlations. The relative performance of the two models can also be assessed by comparing a series of goodness-of-fit metrics. These metrics are computed for each of the two models and shown in Table 5. First, the adjusted likelihood ratio index for the full model is significantly larger than that of the independent model, suggesting that the full model offers a significantly better fit. Second, since the independent model is a nested form of the full model, the two can be compared with a likelihood ratio test. The likelihood ratio test statistic is 3037.9, which is much higher than the chi-squared value with 35 degrees of freedom at any reasonable level of significance, indicating a superior fit for the proposed model. Third, the proposed model can be compared with the independent model using a Bayesian Information Criterion (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. The BIC for the full model is 13562.73 while that of the independent model is 15027.30. once again indicating the superiority of the full model. Finally, the two models can be compared at an aggregate level based on the predicted shares selecting the highest and lowest rank for each factor, compared with the observed shares. The bottom section of Table 5 shows observed and predicted shares selecting each factor as the highest or lowest ranked. Then, in each case, the absolute percentage error is calculated based on the difference between the observed and predicted shares, and an average of the absolute percentage errors for each factor is taken, weighted by the observed share. This weighted average percent error (WAPE) is lower for the proposed joint model for both the highest and lowest ranked factors, demonstrating the higher predictive power of the proposed model.

Finally, in addition to the comparison with the IID ROP model, and to further justify the use of the ROP model compared with a multivariate ordered probit (MORP) model estimated using the actual Likert scale ratings, we estimate a MORP model using the chosen Likert ratings for each respondent. Then, to compare with the ROP model, we calculate the probability of each individual choosing any combination of Likert scale ratings that would lead to the same rank-ordered set of outcomes used in the ROP model. The predictive likelihood for the MORP model computed in this way is -13750.14 (compared with the convergent (and predictive) likelihood for the ROP model of -13404.19). Further, the Bayesian Information Criterion (BIC) for the MORP model is 13953.75 (less than the value of 13562.73 for the ROP model). These fit measures demonstrate that the ROP model is better able to capture the overall priority rankings of the location factors than the MORP model that predicts the actual scale-point outcomes for each factor.

4. IMPLICATIONS

While the estimation results discussed in Section 3 offer important insights into the effects of the exogenous variables on the utilities for each of the location factors, they do not provide an intuitive representation of the true magnitude of these effects or the tradeoffs that occur between these location factors. From a policy perspective it may be helpful to understand how the prioritization of these location factors changes with each of the exogenous variables, and specifically how the pandemic has impacted this prioritization differently for distinct groups. To do so, we compute the Average Treatment Effect (ATE), which is the impact on a downstream posterior variable of interest due to a treatment that alters the state of an antecedent variable from A to B. In this case, the intent is to compute the effect of the COVID-19 pandemic on the prioritization of housing attributes. To quantify this effect, we set all individuals in the dataset to a particular category of an exogenous variable and to the base before-COVID state. Then, using the model estimates presented in Table 3, we compute the probability of each individual ranking each outcome first (with any combination of ordering for the other outcomes). Taking the average across individuals provides the average share that would rank each outcome first for a set level of the exogenous variable in the before-COVID period. We use the same procedure to compute the shares for the during-COVID period. Finally, the percent change in these shares between the two time periods represents the overall effect of the pandemic on the prioritization of these housing factors for each exogenous variable group.[7]

The ATE results are presented in Table 6. Each row in the table corresponds to a single exogenous variable. Then, the values in each column show the percent change in the share of respondents ranking that housing factor first during the pandemic compared with the share ranking the same factor first before the pandemic. For instance, the third numeric value of "-7.03" in the "Affordability" column indicates that households without children are 7.03% less likely to rank affordability as their most important factor during the pandemic than they were before the pandemic. The fourth numeric value of "5.38" indicates that households with children are 5.38%

[7]We should note that the use of in-sample ATEs calculated in this manner will not be completely unbiased. While the relationships between the exogenous variables and outcomes are estimated consistently using the unweighted approach, the skews present in the exogenous variables (see the discussion in Section 2.1.3) imply that the aggregate ATE calculations will not be unbiased. For instance, the underrepresentation of households with retired adults, along with the relatively stronger shift among retired adults towards prioritizing living near friends and family, implies that the real overall effect of the pandemic on this factor may have been higher in magnitude than the overall ATE displayed in the final row of Table 6. Such biases are mitigated somewhat in our ATE analysis because we are fixing each exogenous variable and only altering the time period for each ATE calculation, which should provide a good approximation of the change in preference over time within a single demographic group, even if that group is over- or under-represented in the dataset. Still, because the preferences of some groups are overrepresented in the ATE calculations, these ATE values should be treated with some caution and not be overgeneralized beyond the current context.

more likely to rank affordability as their top factor during the pandemic relative to before the pandemic. The final row of the table shows the overall percent change in the first ranked factors over the pandemic with no other changes to exogenous variables.

In the remainder of this section, we combine the insights from Table 3 and Table 6 to draw implications for transportation planning and urban development. In certain instances, it may seem that the estimates from Table 3 and Table 6 are inconsistent, but this is because Table 3 provides the effect of each exogenous variable on the before-COVID and during-COVID utilities for the different factors, while Table 6 provides the ATEs for the magnitude of the shift effects corresponding to each exogenous variable on the top-rank share changes between the before-COVID and during-COVID periods. For instance, consider the effect of children on the "Being close to family and friends" column in Table 3. Based on the entry of "0.16," the implication is that households with children attribute a higher utility to this factor in both the before-COVID and during-COVID periods, relative to households without children. However, the ATE effect shows an entry of "33.07" for households with no children as the COVID-shift effect for this factor and the entry of "-8.74" for children. This is because there is a positive COVID shift effect for "Presence of Children" on the utility of other factors such as "Affordability" and "Access to cultural centers and activities" in Table 3, which translates to positive ATE effects for these other factors in Table 6. But, as the utilities for these other factors rise in the post-COVID period for households with children, they swamp the generic utility of "presence of children" in the post-COVID period for "Being close to family and friends," leading to the "-8.74" ATE effect.

4.1 Changing Valuations for Space and Access to Friends and Family

The COVID-19 pandemic had broad implications for our conceptualization of space and separation. Fears of infection and lockdowns that kept people in their homes for extended periods of time, sometimes in overcrowded conditions for daily activities, appear to have changed the way many people prioritize their own personal space. The results in Table 6 reveal that retired adults, White and Asian households, and households with three or more vehicles have all begun to place a much greater emphasis on having space and separation from others since the pandemic. This changing space prioritization suggests a growing preference for suburban/rural residential type areas among these population subgroups, which can have the result of increasing trip distances for both work and nonwork trips and greater reliance on private vehicles. While some of these individuals may have more options to telework and may make fewer commute trips, they will generally have longer commutes as well as generate new travel patterns for leisure trips (see Zenkteler et al., 2022; Caldarola and Sorrell, 2022; Robbennolt et al., 2024).

At the same time, lockdowns prevented many individuals from visiting friends and families for extended periods of time, particularly for those living far away from relatives. Therefore, it is unsurprising that we see an overall shift in preference toward being close to friends and family since the pandemic (20.02%; see the second numeric entry in the last row of Table 6). The shift is particularly apparent for those without children, retired adults, high-income families, and Hispanic households. This bi-directional push-pull dichotomy for more space and separation on the one hand, and greater access to friends and family on the other, highlights the challenges families face to maintain social connections and also stay safe from sickness contagions. Especially in the context of meeting the needs of aging and retired individuals, our results underscore the significance of urban design and housing policies that keep older adults connected to activities in their local communities to prevent social isolation. Such policies could include "aging in place" efforts that help keep older adults in their homes and communities where they have existing connections to the space (both their home and neighborhood) as well as close friends and family (see Pani-Harreman et al., 2021). A key barrier, however, is cost. Early in the pandemic, many governments implemented a wide range of policies to reduce the economic shock, including income support, eviction bans, and support for renters and mortgage holders. However, many of these programs expired soon after lockdowns ended, and our results suggest that the importance placed on affordability increased significantly for retired individuals during the pandemic. Therefore, additional measures to help keep retired adults in their homes and communities would provide security against other potential shocks to the housing market.

Finally, in contrast to most other population subgroups, those with children and Black families place less emphasis on having space and separation than they did before the pandemic. Families with children have tended to return to in-person activities more quickly, prioritizing returns to in-person school and socialization for children. Black families were also more likely to return to in-person interactions quickly (Eboigbe et al., 2023; Franco et al., 2024), in part due to social isolation during lockdowns, less access to technology for online activity participation (particularly at the start of the pandemic), and less access to safe public outdoor spaces for activities. Therefore, it is unsurprising that these families give less importance to space and separation from others, and more importance to neighborhood features such as walkability, commute distance, access to museums and cultural activities, and access to friends and family. These results suggest the need to broaden access to online opportunities, so that Black communities can maintain close connections and high levels of activity participation in the event of other future disruptions. The prioritization of investments in public infrastructure in disadvantaged communities to promote walkability and access to local opportunities should also be beneficial, as discussed next.

4.2 Growing Preference for Walkability and Being Near Local Activities

Although the overall growth in preference for walkability in Table 6 is small (a 1.15% increase), there is growing prioritization for walkability among several population groups. This is evident, for example, among families with children who are 17.87% more likely to rank walkability first after the onset of pandemic, presumably due to a desire for outdoor spaces and social/recreational activities for young children. Additionally, households with at least one member holding a bachelor's degree or higher show a stronger shift toward walkable neighborhoods, while the opposite is the case for households with individuals with lower formal education. This trend may, in part, reflect the changing preferences of teleworkers, who are known to prioritize outdoor spaces and leisure activities closer to their homes to better match their new work habits and lifestyles (see Caldarola and Sorrell, 2022; Robbennolt et al., 2024). At the same time, most population groups continue to value closeness to the workplace too, particularly non-retired individuals and individuals from low-mid income households who may still be making daily commutes. This result is consistent with the findings of Rajabi et al. (2024).

Overall, the above results reflect a growing preference for (work and nonwork) activities close to the home. For urban planners, these results point to a greater need for mixed-use developments that put shopping, restaurants, and recreation centers, as well as workplaces, closer to the homes of their end users. For transportation planners, the results emphasize the importance of paying careful attention to the design of pedestrian and active transportation environments, particularly at a time when pedestrian crashes and fatalities have been on the rise. In particular, adopting universal design principles when planning for walkable neighborhoods is especially important given the shift towards walkability among families with children. Including footpath connectivity rather than street connectivity as well as the presence of playgrounds and parks in walkability measures has been shown to more appropriately address the needs of families with children, and considering the differing abilities of these populations when planning walking environments is critical for addressing actual and perceived safety concerns (see Ellis et al., 2016; Stafford and Baldwin, 2018).

4.3 Reduced Valuation of Public Transit Access

Related to the changing preference for local accessibility discussed in the previous section, we find a substantial reduction in the prioritization of public transit access during the pandemic (a 19.79% decrease in public transit being ranked as the most important factor in residential choice decisions during the pandemic compared with before the pandemic; see the last row of Table 6). This dramatic shift in neighborhood preferences, as well as the overall shift toward more private modes (see the substantial 23.02% increase in those prioritizing being close to the highway in the during-COVID period), implies a need to prioritize transit recovery in the wake of the pandemic, encouraging riders who left transit during the pandemic to return, and aligning transit services with the changing needs of potential riders. This is particularly so because, before the pandemic, being close to public transit was important for Black families and those with zero household vehicles, as reflected in the results in Table 3 as well as in many other studies (see Neff and Pham, 2007; Yang and Cherry, 2017; Lee and Lee, 2022). For instance, Black families were 21.61% more likely than white families to rank public transit as their first priority in neighborhood residential selection before the pandemic, based on our ATE computations for the before-COVID period (not shown in Table 6). Clearly, then, such families are likely to be more impacted by transit service changes than other families; transportation service provision, therefore, should be viewed as much from the standpoint of social justice and equity as the more traditional objectives of reducing traffic congestion and mobile-source emissions. For instance, improving connectivity to grocery stores and facilitating travel for those with packages or shopping bags could help with trip chaining patterns that are more prevalent among those who are traditionally reliant on transit for their trips. Improving accessibility, in terms of ease of access to transit stops and boarding/alighting of vehicles, as well as maintaining safety measures, are also critical concerns for these disadvantaged groups. These changes in prioritization of transit access may also reflect changing employment and remote work trends, as declines in transit found in other studies have been associated with fewer workers commuting to dense downtown office locations during the pandemic and after (Paul and Taylor, 2024). Therefore, a more detailed understanding of the future of remote work, and the consequent emerging land use patterns in urban core areas and attitudes towards shared modes, is warranted to predict future transit demands more accurately. A reevaluation of fixed transit route locations and better matching between routes and travel patterns may be necessary to align these services with changing travel needs.

4.4 Reduced Importance of School Quality

Finally, another notable implication regards the overall reduction in prioritization of neighborhoods with high quality schools (a 18.51% overall reduction in those ranking it first after the onset of pandemic compared to before the pandemic). While school quality is ranked relatively low overall, parents before the pandemic were 102.84% more likely to rank school quality first than those without children and this gap has only grown during the pandemic. However, the reduced valuation of school quality during the pandemic is present even for parents, who experienced a 6.56% reduction in the likelihood of ranking school quality first. This reduction in the prioritization of school quality likely relates to the disruptions in schools and remote learning that took place during the pandemic as well as growing opportunities for online learning. Other recent studies (see Jabbari et al., 2022) have found that families with access to online learning tools generally have lower perceptions of the quality of their local schools, indicating that these online tools may be substituting for the perceived quality of physical learning opportunities. This reduction in the valuation of proximity to quality physical schools underscores the need to better understand the efficacy of online and remote learning options, the perceived value of schools and learning opportunities, and the broader impacts of the pandemic on educational outcomes.

The changing valuation of school quality also has important implications for land use and transportation patterns. There is evidence that, consistent with our results, parents are generally becoming more willing to have their children travel longer distances to get to school and are more willing to explore private schooling or homeschooling, reducing the need to prioritize school quality in the housing decision (Cuddy et al., 2020; Musaddiq et al., 2022). Instead, other neighborhood attributes such as walkability and access to museums and cultural centers seem to be important draws for families with children. Beyond this shift toward preferences for different neighborhood features, the reduced emphasis on school quality has implications for transportation outcomes. Existing results show that mode choice is significantly impacted by the distance of the trip to school, with children living farther from school being more likely to take the bus than being dropped off by a parent and being much less likely to use active modes (He, 2011). This could indicate a growing reliance on school buses for longer-distance trips to and from school, and a greater reliance on local activity participation for other activities outside of school hours.

5. CONCLUSIONS

Residential location decisions involve the careful consideration of tradeoffs between a wide range of location factors. In the current study, using data from the 2021 Puget Sound Household Travel Survey and a rank-based modeling approach, we investigate how households value different location factors and how this valuation has changed due to the pandemic. Our results reveal significant heterogeneity across households in residential location preferences as well as important changes in these preferences between the before-COVID and during-COVID periods. Overall, our results indicate higher priority placed on "living near friends and family" during the pandemic, particularly for retired adults, high income groups, and Hispanic individuals. Having space and separation from others is simultaneously important for retired adults. Walkable environments appear to be particularly important in the during-COVID residential location choices of families with children, while access to highways has become more important for almost all population subgroups and quality of schools has come down in priority even for households with children. These evolving preferences for (residential location) factors have important implications for urban planning and transportation service provision, as well as in forecasting future land-use patterns and travel demand. First, given the slowly changing nature of the housing market, it is likely that changing preferences, such as those documented between the before-COVID and during-COVID periods, will lead to mismatches between housing supply and demand for specific location types. For instance, the reduced prioritization for school quality among parents (as discussed in the previous section) may lead to demand reduction in neighborhoods with high-quality schools. While we cannot determine whether these preference changes will persist in the post-pandemic period, the residential location decisions made during this period will have lasting implications due to the long-term nature of residential commitments. Further, given the supply constraints and high costs of relocation, any of these shifts that do persist over time may not necessarily be revealed in home purchase data for many years, creating mismatches between evolving preferences and housing stock provision. Thus, understanding these changing preferences in advance (even if they are temporary) is critical to help planners prepare for, rather than merely react to, periods of preference volatility. Second, these residential location preferences demonstrate a strong connection between residential location decisions and downstream transportation outcomes, providing insights into self-selection effects that are critical for transportation planning. The model reveals ways in which priorities are established in the residential location decision process among transportation factors (including walkability, public transit access, and access to highways), economic factors (such as affordability), and social factors (such as being close to friends and family), demonstrating the need to understand these dynamics when modeling downstream transportation decisions. Therefore, integrated transportation-land use models must continue to recognize and accommodate the evolving valuations for different residential location factors. This can include (a) ensuring that transportation-related considerations (such as lifestyle preferences aligning with the use of specific modes, accessibility considerations, and travel needs) are adequately represented as they influence residential location preferences (that is, explicitly accommodating the self-selection effects mentioned above), (b) incorporating dynamic parameters (and varied scenario forecasting that addresses potential shocks to these preferences such as that caused by the pandemic) to predict how residential location preferences may change over time and how these changes will influence overall travel demand patterns, and (c) incorporating these elements in a demographic-specific way, to ensure that heterogeneity in these preferences is addressed. Of course, policy responses should also be sensitive to the uncertainty inherent to these shifting preferences and priorities. Given the strong preferences shifts caused by the onset of the COVID-19 pandemic and the ongoing uncertainty about the persistence of these shifts, long-term planning strategies should be designed that are flexible enough to handle such uncertainties and capable of adapting to both these ongoing effects as well as future preference shocks caused by similar extreme events.

Future research studies should examine the evolving patterns of preferences for residential locations in other metropolitan areas and over a broader geographic scale, given evidence of significant differences in housing preferences and outcomes across regions of the U.S. (see Yan, 2020; Robbennolt et al., 2024). Additionally, jointly analyzing residential location choices with dwelling unit attributes and other household decisions (such as vehicle ownership, employment, and telework decisions) would be a fruitful avenue to extend the current study. Finally, while the current study employs a household-level analysis using the responses from a single reference adult, future research should examine the preferences and priorities of all members of the household to explicitly incorporate intra-household bargaining and joint decision-making processes. Such an approach would ensure that the priorities of all household members are brought into play, while also shedding light on the ways that such negotiation processes shape the resulting household-level decision.

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Table 1: Ranked Importance of Housing Factors

Factor in choosing current home	Rankings before COVID (617 participants)						Rankings during COVID (667 participants)					
	Top-ranked	Top 2 ranks	Top 3 ranks	Last 3 ranks	Last 2 ranks	Last-ranked	Top-ranked	Top 2 ranks	Top 3 ranks	Last 3 ranks	Last 2 ranks	Last-ranked
Affordability	27.8	47.4	61.0	13.3	8.4	4.2	27.2	47.8	62.1	10.9	6.3	3.0
Being close to family and friends	8.3	17.4	27.1	38.2	24.8	11.0	10.1	19.8	29.4	34.4	21.6	9.8
Access to cultural centers and activities	5.9	13.8	23.1	36.5	22.5	10.0	5.7	13.1	22.7	37.8	21.9	8.5
Being close to the highway	4.3	9.8	17.5	46.7	31.2	15.7	4.9	11.1	19.5	44.5	29.5	13.3
Quality of schools (K-12)	9.0	16.0	23.0	53.6	42.2	25.2	7.1	12.9	18.5	61.3	49.4	31.4
Having space and separation from others	9.4	20.5	33.4	28.7	17.5	8.0	10.3	21.7	33.4	29.3	18.1	8.7
Being close to public transit	10.2	21.1	31.8	39.2	28.1	15.4	9.1	18.4	28.5	40.2	28.7	14.4
Having a walkable neighborhood and being near local activities	12.1	25.4	40.7	20.2	11.2	4.4	12.0	26.7	42.9	18.1	10.0	4.1
Being within a reasonably short commute to work	13.0	28.6	42.4	23.6	14.1	6.1	13.6	28.5	43.0	23.5	14.5	6.8

Table 2: Descriptive Statistics of Exogenous Variables

Variable	Number	Percent in Sample	Percent in Census
Number of adults (18 or older)			
1	440	34.3	34.4
2+	844	65.7	65.6
Presence of children (17 or younger)			
Yes	360	28.0	30.4
No	924	72.0	69.6
Presence of retired adult			
No	1105	86.1	69.2
Yes	179	13.9	30.8
Number of workers			
0	236	18.4	29.2
1+	1048	81.6	70.8
Highest level of education achieved by any household member			
Less than bachelor's degree	446	34.7	75.6
Bachelor's degree	443	34.5	15.5
Graduate degree	395	30.8	2.9
Household income			
<$50,000	343	26.0	33.8
$50,000-$99,999	385	30.0	28.9
≥$100,000	556	44.0	37.3
Race			
White	846	65.9	61.6
Asian	152	11.8	12.4
Black or other	286	22.3	26.0
Ethnicity			
Hispanic	133	10.4	18.7
Not Hispanic	1151	89.6	81.3
Number of vehicles			
0	165	12.9	8.3
1	622	48.4	32.6
2	376	29.3	37.0
3+	121	9.4	22.1

Table 3: Model Estimation Results

Variables (base)	Affordability		Being close to family and friends		Access to cultural centers and activities		Being close to the highway		Quality of schools (K-12)		Having space and separation from others		Being close to public transit		Having a walkable neighborhood and being near local activities		Being within a reasonably short commute to work	
	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
Constant	-0.06	-0.60	-0.88	-8.17	-1.13	-9.77	-1.63	-10.28	-3.00	-8.50	-1.67	-7.88	-3.05	-2.77	-1.87	-2.68	--	
Constant * During-COVID Effect	-0.35	-2.63	-0.50	-4.00	-0.33	-2.40	-0.12	-0.85	-0.90	-2.84	-0.32	-1.34	-0.68	-0.65	-0.60	-0.89	--	
Household Composition																		
Household Size (2+ adults)																		
Single Adult	--		--		--		--		-0.45	-2.68	--		--		--		--	
Single Adult * During-COVID Effect	--		--		--		--		--		--		-0.78	-1.49	--		--	
Presence of Children (no children)																		
Children	--		0.16	2.98	--		--		0.95	2.79	--		-0.80	-1.69	--		--	
Children * During-COVID Effect	0.17	1.94	--		0.22	2.54	--		0.48	1.47	--		--		0.64	1.55	--	
Presence of Retired Adults (none)																		
Retired Adults	--		0.29	3.00	--		--		--		--		--		--		--	
Retired Adults * During-COVID Effect	0.26	1.82	0.29	1.85	--		--		--		0.36	1.45	--		--		-0.44	-2.93
Employment (at least one worker)																		
No Workers	--		--		0.14	2.33	--		--		--		--		--		-0.38	-5.58
Household Sociodemographic Characteristics																		
Education (less than bachelor's degree)																		
Bachelor's degree	--		--		--		--		-0.24	-1.33	--		--		--		--	
Bachelor's degree * Children	--		--		--		--		0.48	1.50	--		--		--		--	
Bachelor's degree * During-COVID Effect	--		--		--		--		--		--				0.41	1.47	--	
Graduate degree	-0.28	-4.51	-0.17	-3.50	--		-0.13	-2.42	-0.32	-1.49	--		--		--		--	
Graduate degree * Children	--		--		--		--		0.56	1.74	--		--		--		--	
Graduate degree * During-COVID Effect	--		--		--		--		--		--				0.41	1.47	--	
Income (<$50,000)																		
$50,000 - $99,999	--		--		--		--		--		--		--		--		-0.18	-1.95
$50,000 - $99,999 * During-COVID Effect	--		--		--		--		--		--		--		--		-0.23	-1.78
$100,000+	--		--		--		0.15	2.71	1.21	4.99	--		--		--		-0.22	-2.38
$100,000+ * During-COVID Effect	--		0.34	5.44	--		--		0.38	1.29	--		--		--		-0.26	-2.10

Table 3: Model Estimation Results (cont.)

Variables (base)	Affordability		Being close to family and friends		Access to cultural centers and activities		Being close to the highway		Quality of schools (K-12)		Having space and separation from others		Being close to public transit		Having a walkable neighborhood and being near local activities		Being within a reasonably short commute to work	
	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
Household Sociodemographic Characteristics (cont.)																		
Race (White)																		
Asian	--		--		-0.14	-2.02	--		--		-0.29	-1.54	--		-0.52	-1.57	--	
Black or other	--		--		--		--		--		--		0.68	1.78	--		--	
Black or other * During-COVID Effect	--		--		--		--		--		-0.57	-1.74	--		--		--	
Ethnicity (not Hispanic)																		
Hispanic	--		0.27	2.45	--		--		-0.33	-1.34	--		--		--		--	
Hispanic * During-COVID Effect	--		0.31	2.22	--		--		--		--		--		-0.62	-1.48	--	
Transportation Characteristics																		
Number of household vehicles (none)																		
1 vehicle	--		--		--		0.19	2.56	--		--		-1.51	-1.79	-0.83	-1.51	--	
2 vehicles	--		--		--		0.36	4.41	--		0.30	2.00	-1.77	-1.83	-0.93	-1.55	--	
3+ vehicles	--		--		--		0.36	4.41	--		0.45	1.36	-1.97	-1.81	-0.93	-1.55	--	
3+ vehicles * During-COVID Effect	--		--		--		--		--		0.41	1.28	--		--		--	

Table 4: Implied Error Covariance Matrix

Housing Factors	Affordability	Being close to family and friends	Access to cultural centers and activities	Being close to the highway	Quality of schools (K-12)	Having space and separation from others	Being close to public transit	Having a walkable neighborhood and being near local activities
Affordability	1.00	0.70	0.50	0.41	0.18	0.48	0.14	0.17
Being close to family and friends		0.98	0.71	0.64	0.35	0.46	0.13	0.19
Access to cultural centers and activities			1.10	0.74	0.46	0.44	0.40	0.42
Being close to the highway				1.17	0.58	0.51	0.37	0.36
Quality of schools (K-12)					2.48	0.39	0.25	0.24
Having space and separation from others						2.18	0.31	0.35
Being close to public transit							6.67	0.71
Having a walkable neighborhood and being near local activities								4.37

Table 5: Data Fit Measures

Disaggregate Fit Measures					
Metric		**Joint Model**		**Independent Model**	
LL Convergence		-13404.19		-14923.16	
LL Constants		-15292.70		-15292.70	
Parameters		102		67	
Adjusted Likelihood Ratio Index		0.117		0.021	
BIC		13562.73		15027.30	
Likelihood Ratio Test		3037.9			
Aggregate Fit Measures					
First Ranked Outcome	**Observed**	**Joint Model**		**Independent Model**	
	Share (%)	Share (%)	APE	Share (%)	APE
Affordability	27.5	24.6	10.5	31.2	13.5
Being close to family and friends	9.2	8.7	5.4	12.5	35.9
Access to cultural centers and activities	5.8	5.5	5.2	11.1	91.4
Being close to the highway	4.6	4.1	10.9	7.8	69.6
Quality of schools (K-12)	8.0	8.2	2.5	5.8	27.5
Having space and separation from others	9.9	10.1	2.0	9.9	0.0
Being close to public transit	9.6	11.1	15.6	6.8	29.2
Having a walkable neighborhood and being near local activities	12.1	13.6	12.4	10.1	16.5
Being within a reasonably short commute to work	13.3	14.1	6.0	4.8	63.9
Weighted Average Percent Error (WAPE)		**8.4**		**31.0**	
Last Ranked Outcome	**Observed**	**Joint Model**		**Independent Model**	
	Share (%)	Share (%)	APE	Share (%)	APE
Affordability	3.6	2.2	38.9	1.8	50.0
Being close to family and friends	10.4	6.9	33.7	5.4	48.1
Access to cultural centers and activities	9.2	7.5	18.5	6.8	26.1
Being close to the highway	14.4	12.3	14.6	11.5	20.1
Quality of schools (K-12)	28.4	27.5	3.2	28.1	1.1
Having space and separation from others	8.4	5.3	36.9	9.5	13.1
Being close to public transit	14.9	25.8	73.2	27.7	85.9
Having a walkable neighborhood and being near local activities	4.2	8.4	100.0	9.2	119.0
Being within a reasonably short commute to work	6.5	4.1	36.9	0.0	100.0
Weighted Average Percent Error (WAPE)		**30.2**		**37.8**	

Table 6: Average Treatment Effects

Variable	Levels	Affordability	Being close to family and friends	Access to cultural centers and activities	Being close to the highway	Quality of schools (K-12)	Having space and separation from others	Being close to public transit	Having a walkable neighborhood and being near local activities	Being within a reasonably short commute to work
Household Size	2+ Adults	-3.96	19.47	-1.40	22.34	-19.02	3.52	-12.62	-1.26	13.00
	Single Adult	-3.40	20.29	1.03	23.30	-17.94	5.09	-31.78	5.27	13.49
Presence of Children	No Children	-7.03	33.07	-8.01	31.43	-30.31	8.32	-17.33	-5.48	19.31
	Children Present	5.38	-8.74	23.60	-3.72	-6.56	-7.96	-27.23	17.87	-1.59
Presence of Retired Adults	No Retired Adults	-6.06	10.91	4.57	28.24	-17.04	1.44	-19.29	2.05	21.02
	Retired Adults	17.37	47.61	-25.22	-3.85	-27.62	22.68	-22.01	-3.40	-58.76
Employment	No Workers	-2.65	18.97	2.03	24.63	-18.72	4.68	-19.63	1.45	15.46
	Workers Present	-3.35	20.95	0.87	23.47	-18.29	4.31	-19.71	1.28	10.05
Education	Less than Bachelor's	-1.97	20.93	2.59	26.76	-17.34	6.85	-17.43	-10.28	16.13
	Bachelor's Degree	-4.28	18.31	-2.08	21.35	-19.44	3.21	-21.10	7.35	13.41
	Graduate Degree	-5.02	20.16	-2.58	21.33	-19.28	2.65	-21.09	7.18	10.46
Household Income	Income < \$50,000	-2.09	-24.82	3.41	26.08	-34.27	4.68	-20.08	0.72	28.67
	\$50,000 - \$99,999	-0.78	-24.53	5.09	27.92	-33.87	5.31	-19.88	1.07	33.25
	\$100,000+	-6.20	79.53	-7.55	18.51	-8.90	3.21	-19.51	1.48	-17.11
Household Race	White	-5.26	18.76	-1.84	20.48	-19.51	14.50	-20.38	0.58	12.27
	Asian	-4.98	17.46	-1.51	20.40	-19.23	15.78	-19.86	1.27	12.45
	Black or Other	1.60	26.06	4.33	32.44	-15.45	-33.47	-18.60	3.54	16.36
Ethnicity	Not Hispanic	-2.24	7.41	1.22	25.16	-18.05	4.42	-20.26	3.95	14.18
	Hispanic	-19.53	78.78	-19.59	1.33	-21.39	0.88	-15.94	-23.22	4.28
Vehicle Ownership	No Vehicles	-2.47	21.21	1.69	26.07	-17.39	0.95	-17.63	2.87	14.46
	1 Vehicle	-3.40	20.36	-0.61	21.44	-18.24	-0.44	-19.33	1.33	13.39
	2 Vehicles	-3.10	20.73	0.03	24.50	-18.18	-0.55	-20.37	0.24	13.61
	3+ Vehicles	-10.24	12.87	-6.38	12.81	-22.25	38.85	-21.58	-2.14	9.06
Overall		-3.74	20.02	-0.57	23.02	-18.51	4.15	-19.79	1.15	13.22