

Planning beyond the metro: Rural travel behavior and the built environment

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Abstract: Reducing greenhouse gas (GHG) emissions from transportation is particularly challenging in rural communities. People living in rural areas are more vehicle reliant and are also more likely to face barriers to meeting their mobility needs. One approach to reducing vehicle travel without exacerbating mobility challenges is through directing population growth into compact multimodal communities. Despite substantial differences in travel in rural versus urban contexts, very little prior research has evaluated the relationship between travel and the built environment (BE) in rural areas. We use spatially detailed travel behavior data to evaluate the relationships between BE factors and sustainable travel behaviors in rural communities in the United States. We find that the relationship between travel and the BE differs between rural and urban areas, with local access exhibiting a weaker association with travel behavior in rural communities when compared with urban communities. Conversely, regional access exhibits a larger association with travel behavior in rural communities. We also found that the association between personal characteristics and travel behavior was significantly smaller in rural communities. Furthermore, our results suggest that the relationships between travel and the BE may differ across different types of rural communities.

Transportation planners and researchers should take note of the different relationship between the BE and travel behavior in urban and rural areas. Our research suggests that while relationships between travel and the BE observed in urban-focused research may not hold in rural communities, there does appear to be some ability to influence travel behavior using the built environment.

Keywords: Built environment, travel behavior, VMT, mode choice, rural

Article history:

Received:
January 30, 2025
Received in revised form:
July 7, 2025
Accepted: July 15, 2025
Available online:
July 29, 2025

1 Introduction

Reducing greenhouse gas (GHG) emissions from transportation is particularly challenging in rural communities. Rural populations are more vehicle reliant; while over 30% of United States vehicle miles traveled (VMT) occur in rural areas (Federal Highway Administration, 2022), only 21% of the United States' population lives in rural areas (U.S. Census Bureau, 2020). People living in rural areas are also more likely to

experience unmet travel needs, particularly those who lack vehicle access (Espeland & Rowangould, 2024; Wang et al., 2023). It is important to ensure that policies that target GHG reductions do not exacerbate existing mobility challenges faced by many people living in rural areas.

Land-use planning presents an opportunity to both reduce GHGs and improve people's ability to meet their mobility needs. Both urban and rural communities have sought to influence travel choices through land use and planning strategies (Dalbey, 2008; Frank & Reiss, 2014; Stewart et al., 2016). However, the large body of research that evaluates the built environment's (BE's) impact on travel behavior is primarily focused on nonrural contexts (Ewing & Cervero, 2010; Stevens, 2017). Far less is known in rural areas (Frank & Reiss, 2014; Popovich et al., 2021; Stewart et al., 2016), which differ substantially in terms of the BE, transportation options, population demographics, and cultural and economic character. Prior rural-focused transportation research also points to distinct attributes of rural travel behavior, suggesting that the relationship between travel choices and the BE may differ in rural areas when compared to urban areas (Ao et al., 2022). Rural planners need clear insights about the relationship between the BE and travel behavior in rural contexts to inform land-use planning decisions in rural communities.

To address this gap, we answer two questions: First, how do BE factors used in contemporary planning literature relate to travel in rural communities in the United States? Second, is the relationship between travel and the BE different in urban and rural communities? We evaluate the relationship between the BE and travel choices (VMT and mode choice) in urban versus rural areas using spatially detailed data from the US-wide 2017 National Household Travel Survey (Federal Highway Administration, 2017) combined with BE data from the U.S. Environmental Protection Agency's (EPA) 2020 Smart Location Database (U.S. Environmental Protection Agency, 2020). We then use logistic regression and gamma generalized linear regression to model VMT, motorized reliance, and utilitarian active travel. We measure the relationship between travel behavior and built environment using marginal effects across all modeled outcomes. Our research suggests that relationships between travel and the BE observed in prior research conducted in urban areas may not hold in rural contexts.

2 Literature review

2.1 Travel and the built environment

A large body of literature has established that the BE impacts travel choices (Ewing & Cervero, 2010; Stevens, 2017). Many of these studies operationalize the BE using the "D-variables." Cervero and Kockelman (1997) first presented these variables as the "3 D's of the Built Environment": density, diversity and design. This list soon grew to include six (or more) D's, including destination accessibility, distance to transit, and demand management (Ewing & Cervero, 2010; Stevens, 2017). Studies that evaluate the impact of these measures on travel choices point to a modest but significant association between the BE and travel behavior, with compact development, multiple transportation options, and mixed land uses tied to less vehicle use and a greater share of pedestrian and transit trips (Cao et al., 2009; Cervero & Kockelman, 1997; Ewing & Cervero, 2010; Ralph et al., 2017; Stevens, 2017).

"Destination accessibility" and "distance to transit" are both accessibility measures. Accessibility refers to the ease of reaching desired destinations, typically integrating transportation and land-use characteristics into one metric. Handy (2018) argues that accessibility measures (rather than the D's) should be used to understand travel behavior,

as they combine relevant characteristics of the BE and better represent travelers' experiences. Accessibility is often measured in terms of distance or travel time to transportation infrastructure or specific destinations using a car, transit, or active travel (Handy, 1996; Karner et al., 2022; Levinson, 1998; Levinson & King, 2020). In the "D" literature, "destination accessibility" is most often measured in terms of proximity or access to jobs or a job center, and "distance to transit" is typically measured as the distance to a transit stop (Ewing & Cervero, 2010; Stevens, 2017).

A frequent challenge with accessibility measures is determining which destinations and travel options affect travelers' choices and how to measure accessibility to capture travelers' experiences (Handy & Niemeier, 1997; Hanson & Schwab, 1987; Karner et al., 2022). Prior research on accessibility and travel behavior finds that greater destination accessibility is associated with less personal vehicle use (Ewing & Cervero, 2010; Handy & Niemeier, 1997; Hanson & Schwab, 1987; Rasca & Saeed, 2022) while proximity to transit is associated with more transit use (Ewing & Cervero, 2010; Rasca & Saeed, 2022).

Two perennial and interrelated issues that arise in research on travel and the BE include residential self-selection and establishing causality. Because most studies on this topic are cross-sectional we cannot typically establish causal relationships between the BE and travel behavior (Handy, 2017; Ihlanfeldt, 2020). One phenomenon that limits our ability to draw causal inferences from most cross-sectional studies is residential self-selection, or the process in which residents choose to move to areas that allow them to travel as they desire. Reviews of this body of research is mixed on whether failing to control for residential self-selection overstates (Cao et al., 2009; Stevens, 2017) or diminishes (Ewing & Cervero, 2010) the relationship between the BE and travel behavior.

2.2 Rural travel behavior

Though there are several decades of research on travel and the BE, the vast majority of this literature focuses on urban and suburban areas (Ao et al., 2022; Ewing & Cervero, 2010; Popovich et al., 2021; Stevens, 2017). When travel behavior is observed across large areas it may include rural communities (e.g., nationwide or across a region), but because the majority of households modeled are nonrural the results largely reflect relationships in urban and suburban areas. A systematic literature review by Ao et al. (2022) found only 28 studies that explicitly examined rural travel and the built environment. They noted that a gap in existing research was a lack of comparative studies examining urban-rural differences.

In the few studies that explicitly examine differences in travel behavior across urban and rural contexts, distinct differences are observed. Compared with their urban counterparts, rural travelers are more likely to drive, less likely to use non-auto modes, and more likely to make fewer, longer trips (Pucher & Renne, 2005; Ralph et al., 2016; Voulgaris et al., 2017). However, most of our knowledge of urban-rural travel behavior differences stems from multivariate analyses that include a binary or categorical rural variable (Pickrell & Schimek, 1999; Schimek, 1996; Voulgaris et al., 2017). This model structure allows for static differences in travel behavior across urban and rural areas while assuming that the relationships between travel behavior and the BE and personal factors are similar in urban and rural areas. This may be obscure important differences in the relationship between BE and travel behavior urban versus rural contexts that may stem from substantial differences in the range of values for the D factors as well as potential interrelated or synergistic effects of these factors.

Importantly, while BE metrics capture elements of the physical environment that correlate to rurality, another potential driver of differences in travel behavior in rural communities is their demographics and economies. Rural communities in the United States are often older, whiter, and more centered on agricultural, manufacturing, and extractive industries (Davis, 2022; Theis & Driscoll, 2023). At the same time, many rural economies have seen decreasing manufacturing employment and depopulation, with residents moving to metro areas to access better jobs and services (Davis, 2022; Slack & Jensen, 2020). Rural communities have also seen a growing Hispanic population (Davis, 2022), which has been a key factor in reversing chronic population decline in some areas in recent years (Lichter & Johnson, 2020).

Beyond BE and demographic differences, rural populations in the United States are more likely to identify with concepts like “rugged individualism” (Frank & Hibbard, 2017) and feel that they are more linked with their natural environment and local community (Frank & Hibbard, 2017; Frank & Reiss, 2014; Theis & Driscoll, 2023). These sentiments come together to produce a “rural consciousness” (Theis & Driscoll, 2023), whereby people in rural communities view themselves as fundamentally different from urban communities (Frank & Hibbard, 2017; Frank & Reiss, 2014; Theis & Driscoll, 2023). Demographic differences and rural consciousness impact how rural communities organize around environmental justice issues, perceive planning activities, and think about the role that external actors play in their communities (Frank & Hibbard, 2017; Frank & Reiss, 2014; Theis & Driscoll, 2023). These concepts may also influence rural communities’ travel behaviors.

In light of the BE, demographic, and cultural differences between urban and rural contexts, we posit that these elements of rurality may interact synergistically, with distinct effects on travel behavior. Detecting these distinct effects requires a modeling framework that separately evaluates the determinants of travel behavior in rural and urban contexts. There are a handful of studies that directly evaluate differences in the relationship between non-auto travel and personal and BE factors across urban and rural contexts. These studies support the notion that there are significant differences in the relationship between travel and the BE in rural areas. In a study that focused on small cities and towns, Rasca and Saeed (2022) found that longer trips were associated with the choice to use transit, in contrast to urban-focused research findings. However, their findings for other BE factors were largely consistent with relationships observed in urban areas. Similarly, research that evaluates the choice to walk in rural communities points to important differences from urban communities. Stewart et al. (2016) found that residents of nine small towns across the United States did not walk for utilitarian purposes, while residents in Seattle, Washington did. Additionally, the factors walkers considered differed across urban and rural contexts: small town residents valued safety while people living in Seattle residents were more likely to value the ease of walking.

The relationship between BE and vehicle travel choices also differs across rural and nonrural areas. In a panel study of counties in Florida, Ihlanfeldt (2020) evaluated how changes in land use affected VMT. Their findings differed across urban and rural contexts, with changes in a number of land uses exhibiting an effect in urban counties, while in rural counties only “industrial” and “institutional” land uses demonstrated a significant effect. Similarly, using the 2001 National Household Travel Survey, Brownstone and Golob (2009) found that residential density, which often has a small negative relationship with VMT (Ewing & Cervero, 2010; Stevens, 2017), had a much smaller association with VMT in rural and small town contexts compared to their suburban and urban counterparts. Both studies suggest the interrelated effect of rurality and the BE on vehicle travel; however, they do not evaluate BE measures typically used contemporary in planning literature (i.e., accessibility or the Ds).

Although evaluating urban and rural differences was not its purpose, Salon (2015) attends to these differences using BE measures that are more typical in planning research. Salon evaluated the impact of the BE on travel behavior while accounting for rurality in California, finding that the relationships differ across the urban-rural spectrum. Using these results to control for residential self-selection, Salon then evaluated the impact of BE differences on commuting behavior. This study's results suggest that regional and local job access may have a greater impact on commute miles in rural communities when compared with nonrural communities. However, the study defined rural using a clustering algorithm based on attributes of California communities rather than a commonly applied definition. This, combined with the study's California focus, prevent us from using this study to generalize to rural contexts across the United States.

Our study advances rural travel behavior knowledge by using national data to evaluate the relationship between travel behavior and the BE in rural contexts using BE measures that connect with contemporary planning literature and practice (i.e., the "D" variables). The measures evaluated in this study are designed to capture travelers' experiences and land use and transportation characteristics that can be targeted during the design of communities and the planning process. We also evaluate both VMT and mode choice in rural contexts.

3 Evaluating the relationship between travel and the built environment

Our analysis addresses two questions: how do BE factors used in contemporary literature relate to VMT and mode choice in rural communities and, is this relationship different in urban and rural communities? We address the first research question by modelling VMT and mode choice as a function of the BE in rural communities while controlling for personal characteristics. We address the second question by evaluating differences between rural models and the corresponding urban models for each travel behavior outcome. We also evaluate models of the full sample compared to both the rural and urban models to determine whether the insights provided by separate urban and rural models differ from a combined model of the general population that includes an urban/rural binary variable. The latter model represents the typical approach to modeling rural populations (Pickrell & Schimek, 1999; Schimek, 1996; Voulgaris et al., 2017).

3.1 Data

Our analysis combines spatially detailed individual-level travel behavior data with BE characteristics. We use travel behavior and personal characteristics from the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration (FHWA), 2017). The FHWA provided United States Census block group (CBG) information for NHTS respondents' home locations by request¹. We then joined the spatially detailed NHTS data to CBG-level BE data from the 2021 U.S. Environmental Protection Agency's (EPA) Smart Location Database (SLD) (U.S. EPA, 2020). While some studies of BE use finer grained estimates, because NHTS data is only available at the block group we use block-group level BE estimates. We did not use the 2022 NHTS because the rural sample was much smaller, and the spatial detail needed for this analysis are not available in the 2022 dataset.

¹ We acquired this data by contacting the NHTS program contacts; their contact information can be found here: <https://nhts.ornl.gov/contact-us>

The NHTS is a periodic survey of United States households that asks respondents to complete a detailed travel diary for a single day (the “travel day”), which provides trip-level information about travel mode, destination type, and distance traveled. The NHTS also includes person-level and household-level sociodemographic characteristics including age, gender, income, education, employment, race, and ethnicity, as well as detailed vehicle characteristics for a person’s household. To characterize vehicle access, we classified people based on the number of vehicles and adults in their household, where households with one or more vehicle per adult are “fully equipped” and those with fewer than one vehicle per adult are “non-fully equipped,” consistent with Blumenberg et al (2020). NHTS data includes sample weights derived from United States Census data that can be used to weight respondents so that they are more representative of the United States population.

To represent travel behavior outcomes, we model travel day mode and travel day VMT, both from the NHTS. We categorized each respondents’ travel day mode in three ways: “auto reliant” survey respondents are those who only used motorized modes for all of their utilitarian trips on the travel day, “auto user” respondents are those who used a motorized mode for at least one trip of any kind on the travel day as a passenger or driver, and “active traveler” respondents are those who use walk or bike for at least one utilitarian trip on the travel day. Motorized trips include car, pickup truck, SUV, van, motorcycle, and taxi or ride share trips. Utilitarian travel includes trips to work, school/daycare/religious activity, medical/dental services, shopping/errands, transporting someone, and meals. Travel day VMT is defined as the total of the respondent’s motorized trip distances on the travel day. While modeling transit users would provide additional insight, we lacked a sufficient rural sample of transit users ($n = 275$) to accurately model this mode.

The EPA SLD includes measures of the BE estimated based on 2014 to 2018 United States Census Bureau (USCB) population data, 2017 USCB jobs data, 2018 HERE Maps Infrastructure data, and publicly available transit service data (U.S. Environmental Protection Agency, 2021). We chose four BE measures that are understood to relate to travel behavior in urban (Ewing & Cervero, 2010; Stevens, 2017) and rural contexts (Ihlanfeldt, 2020; Rasca & Saeed, 2022; Salon, 2015) that are not highly correlated. The first BE measure, which we termed “local access,” captures community or neighborhood-level density, measured as the natural log of jobs and households per acre in the CBG. The second BE measure, we termed “regional access,” represents the spatial accessibility of the larger region, and is measured as the natural log of jobs accessible within a 45-minute drive. The third BE measure, “transit access,” represents transit access, measured as a binary variable that indicates whether there is a transit stop within $\frac{3}{4}$ mile of the CBG centroid. We used a large radius for the transit access variable to capture sufficient variation given the low share of rural population with transit access. The fourth measure represents “local job diversity” (often referred to as land-use mix) is an entropy measure of eight job types in the CBG.

We defined urban and rural based on the 2010 Urban Area Criteria (UAC) developed by the USCB. This variable is included in the 2017 NHTS based on respondents’ home addresses (FHWA, 2020). The 2010 UAC classifies Census Blocks as “Urbanized Areas” (population $> 50,000$), “Urban Clusters” ($50,000 > \text{population} > 2,500$), or “Rural” (population $< 2,500$) by grouping Census Blocks together algorithmically based on measures of density and development (Federal Register, 2011). We opted for the 2010 UAC over other rural definitions as it is the most spatially detailed classification scheme we had access to, and is a publicly available and widely accepted rural definition in the United States (Bennett et al., 2019; Childs et al., 2022; Hart et al., 2005; Isserman, 2005).

Urbanized Areas are usually considered “urban” and previous studies have treated Urban Clusters as either urban and rural as they represent micropolitan and small town centers (Childs et al., 2022; Quallen & Rowangould, 2022). We evaluate our models using two definitions of rural. The “expansive” rural definition counts Urban Clusters as rural, while the “restrictive” rural definition treats Urban Clusters as urban. Table 1 summarizes the BE measures and person characteristics for survey respondents living in urban and rural areas (using the restrictive rural definition). It also includes information about both the weighted and unweighted samples. Additionally, Figure 1 shows the distribution of the BE variables for urban and rural areas in the NHTS sample.

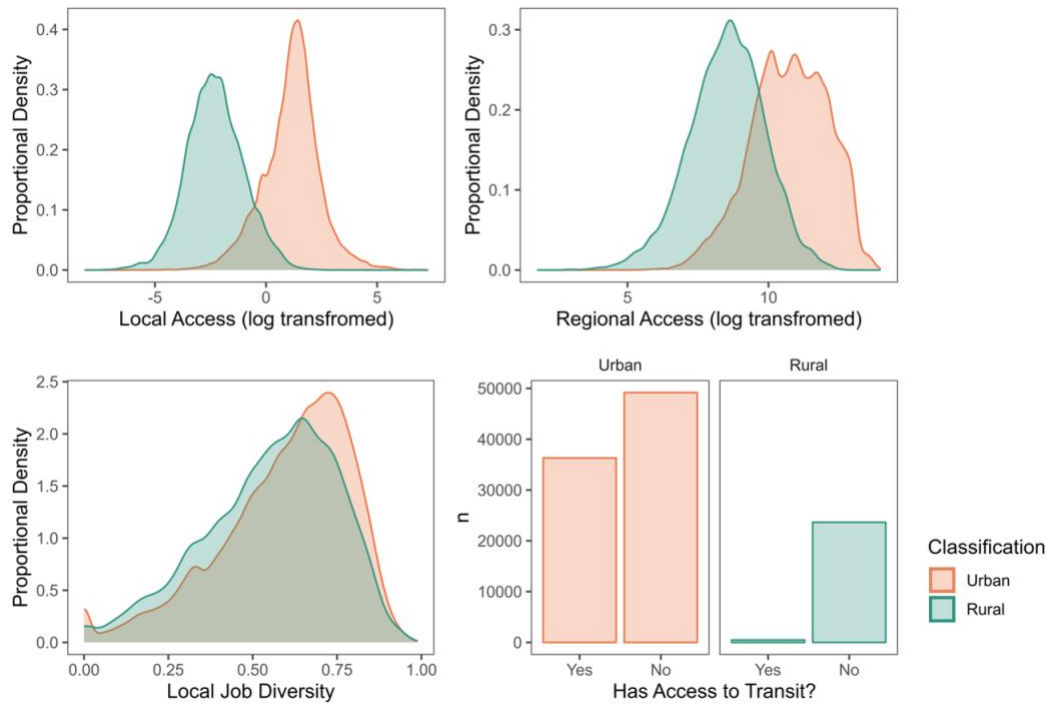


Figure 1. Distribution of built environment variables in urban and rural contexts using the restrictive rural definition

3.2 Methods

To answer each research question, we evaluated person-level data in multivariate statistical models. Our analysis included adults over the age of 21 who took at least one trip to or from their home (for which we have BE data) or worked at home for pay on the travel day (indicating a utilitarian out of home or virtual activity.) We also excluded people with travel day VMT that exceeded 300 miles to ensure that the analysis reflects routine travel behaviors. We evaluated Cook’s Distances to confirm that vehicle travelers at the high end of the included range did not adversely affect our models (see Appendix A). The relatively high distance cutoff ensured that “super-commuters” (Moss & Qing, 2012) were included in the study. We also omitted any respondents that were missing any of the variables used in this analysis. We randomly sampled one person per household to ensure that the analysis uses independent observations. Our analysis included 109,612 people out of 264,235 people in the full NHTS sample. We applied respondent weights to infer United States population characteristics in the summary statistics shown in Table 1. We did not use weights in our regression analysis as many of the variables included in the regression were also used to weigh the data.

Table 1. Summary of study sample living in urban and rural contexts using the restrictive rural definition

Categorical variables	Urban N = 85,470		Rural N = 24,121	
	Sample %	Weighted %	Sample %	Weighted %
Race and Ethnicity				
Non-Hispanic White	75	59	88	85
Non-Hispanic Black	8	15	5	6
Hispanic (all races)	9	17	3	6
Other race, multiple, or unknown	8	9	4	3
Age				
22-35	18	27	11	18
36-50	22	28	18	26
51-69	41	34	49	42
70+	19	11	22	14
Employed ¹	61	69	55	64
Education				
High school or less	19	23	30	34
Some college	29	30	33	33
Bachelor's or more	52	47	37	33
Household Income				
<\$35,000	27	32	29	30
\$35,000 - \$74,999	30	29	33	33
\$75,000 - \$125,000	24	22	24	24
>\$125,000	19	17	14	13
Two or more adults ²	65	68	75	81
Children in home ²	24	36	22	38
Vehicle access: fully equipped ²	83	72	91	86
Female ²	54	54	52	50
Transit access ²	42	53	2	1
Auto user (≥ 1 motorized trip) ²	92	88	96	96
Auto reliant (all utilitarian trips are motorized) ²	75	71	84	87
Active traveler (≥ 1 bike/ped utilitarian trip) ²	21	24	13	10
Continuous variables	Sample Mean (SD)	Weighted Mean (SD)	Sample Mean (SD)	Weighted Mean (SD)
Regional access (Jobs within 45 min. drive)	99,644 (127,804)	130,299 (163,809)	11,465 (19,527)	11,943 (18,697)
Local access ((Households + jobs) / acres)	7.8 (28)	13 (46)	0.3 (1.6)	0.3 (2.3)
Local job diversity (8-job entropy measure)	0.6 (0.2)	0.6 (0.2)	0.6 (0.2)	0.5 (0.2)
VMT on travel day	31 (39)	30 (37)	44 (45)	45 (44)

² Variable is binary.

The summary statistics in Table 1 are consistent with prior literature, with people living in rural areas exhibiting higher VMT, greater vehicle reliance, and lower rates of active travel than their non-rural counterparts (Pucher & Renne, 2005; Stewart et al., 2016). We also observe that people living in rural areas are more likely to be lower income, white, and older, also consistent with prior estimates (Davis, 2022). The expansive rural definition summary statistics (see Table B1 in the Technical Appendix) also reflect these observations. As expected, Figure 1 shows that rural areas have much lower local access, regional access, and transit access. Interestingly, we observe similar distributions for local job diversity.

To model travel day VMT we used a gamma model with a log-link function. We chose this model as it captures the skewed VMT distribution and it handles heteroskedastic data with a single bound at zero (Smithson & Shou, 2020). The VMT data is also “boundary inflated,” meaning that it includes a large number ($n = 7634$) of people who did not produce VMT on the travel day. As gamma models cannot include zero values we employed a two-stage “hurdle model,” which combines a logistic (logit) regression with a continuous regression (the gamma model) to handle cases at the boundary (Smithson & Shou, 2020). The first stage of our hurdle model is the “auto user” model. Beyond the auto user model, we modeled the odds that a respondent was auto reliant and the odds that a respondent was an active traveler using logit models. Additional detail on model specifications and outlier testing is provided in Technical Appendix A.

We present model results that evaluate the relationship between BE predictors and the modeled outcomes using average marginal effects (AMEs) for continuous variables and average conditional effects (ACEs) for categorical variables, as described in Technical Appendix A. As both the logit and gamma models have non-linear and conditional effects, AMEs and ACEs are a more accurate representation of effect sizes (Arel-Bundock et al., 2024). AMEs are interpreted as semi-elasticities for continuous predictors, while ACEs represent the estimated effect of categorical predictors when the condition is met. In the VMT models these are interpreted as the expected increase in VMT when the condition is met, whereas for the mode choice models these represent the proportional increase in the odds of making that choice when the condition is met. All AMEs and ACEs for BE variables are reported in this manuscript while AMEs and ACEs for all predictors modeled are shown.

With four modeled outcomes (VMT, Auto User, Auto Reliant, Active Travel), four separate models per outcome (full sample with an urban/rural variable, full sample with BE variables, rural sample, urban sample), and two urban/rural classification schemes (expansive, restrictive), we have 28 separate models. For the sake of brevity, we primarily discuss a subset of results, focusing on the models created by the restrictive definition of rural, as most users of the UAC apply it in this way (Bennett et al., 2019; Childs et al., 2022). Our discussion also focuses primarily on two models that capture driving and bicycle and pedestrian behaviors, the VMT and Active Travel models (Tables 2 and 3) because the findings of the Auto Reliant and Auto User models overlap and do not provide additional insights. We supplement the discussion of the VMT and Active travel models that use the restrictive rural definition with insights from other models where merited. Results for the Auto User and Auto Reliant models that use the restrictive rural definition and for models of all four outcomes (VMT, auto user, auto reliant, and active travel) using the expansive rural definitions can be found in the Technical Appendix (Tables B2 – B7).

For all four outcomes we evaluated separate models for the urban sample, rural sample, and the full sample. All models include personal and household characteristics as

predictors. The urban and rural models and one of the full models include BE characteristics as predictors.

We evaluated urban and rural models separately to ascertain differences in the relationship between travel and the BE across urban and rural contexts. While interaction terms are often used to evaluate these types of differences, the separate urban and rural models evaluated are equivalent to creating a single model with interaction terms representing all predictor variables interacted with an urban/rural binary variable. Another option would have been to include interaction terms for just the BE variables, but this would not have controlled for urban/rural variation in the relationships between travel outcomes and person characteristics. Because prior literature indicates that rural populations differ meaningfully from urban populations, we chose to use separate urban and rural models to allow for these differences. Separate urban and rural models achieve the same result as a single model with interaction terms for all predictors, but the outputs are more easily interpreted. Our approach to modeling urban and rural areas separately is analogous to prior research that evaluates differences in the effects of the built environment on travel behavior across geographic contexts (Espeland & Rowangould, 2024; Ihlanfeldt, 2020; Salon, 2015; Wang et al., 2023).

We also separately modeled the full sample in two ways. One model includes BE characteristics as predictors, while the other includes only an urban/rural predictor (and not BE characteristics). The full models were designed to reflect the two most common ways travel modeling is done at a national scale. The full models are included to validate that our modeling approach is consistent with prior literature. The second model column in Tables 2 and 3 establishes that evaluating the full sample with a simple urban/rural binary variable and personal characteristic controls (full model without BE controls) produces observations consistent with prior literature: rural populations drive farther, are more likely to drive, are more likely to be reliant on automobiles, and are less likely to participate in utilitarian active travel compared to urban populations. The first model column (full model with BE terms) verifies that our modeling approach can produce observations that are relatively consistent with prior literature that aggregates urban and rural data (including Ewing and Cervero (2010) and Stevens (2017)) in terms of the estimated magnitude and direction of BE relationships.

We compared the effects of BE on all travel outcomes in the urban and rural models using the 95% confidence intervals of the AMEs and ACEs for each variable. Non-overlapping confidence intervals indicate significantly different associations between the corresponding variable and travel outcome in urban versus rural communities.

For all models we report the Akaike Information Criterion (AIC) scores, with a lower AIC score indicating better fit (Smithson & Shou, 2020). One important note on AIC scores is that they are affected by sample size, with larger samples exhibiting higher AIC scores. We additionally report $T_{jur} R^2$ values for the logit models. We use $T_{jur} R^2$ values as they can be interpreted like R^2 values in linear models, where $T_{jur} R^2 = 1$ indicates full explanatory power and $T_{jur} R^2 = 0$ indicates no explanatory power. Gamma models do not have a widely accepted fit measure that serves as an equivalent to R^2 to compare relative fit between models. We report Null and Residual Deviance as well as the Gamma Model dispersion parameters in the model result tables (Table 1 and Table B4 in the Technical Appendix).

Table 2. Estimated average marginal effects (AMEs) and average conditional effects (ACEs) for gamma model of VMT, restrictive definition

Term/Model Info	Full Model (BE) Estimate (95% CI)	Full Model (No BE) Estimate (95% CI)	Urban Model Estimate (95% CI)	Rural Model Estimate (95% CI)
Personal Characteristics				
2+ Adults	0.166 (-0.447 – 0.779)	1.424 (0.826 – 2.023)***	0.128 (-0.533 – 0.789)	0.304 (-1.152 – 1.76)
Race and Ethnicity (Base: Non-Hispanic White)				
Hispanic (all races)	2.477 (1.444 – 3.510)***	1.215 (0.216 – 2.214)*	2.315 (1.268 – 3.363)***	3.442 (-0.168 – 7.052)
Non-Hispanic Black	2.604 (1.571 – 3.637)***	2.240 (1.218 – 3.262)***	2.323 (1.252 – 3.393)***	3.766 (0.808 – 6.725)*
Other race, multiple, or unknown	0.362 (-0.611 – 1.335)	-0.726 (-1.672 – 0.220)	0.031 (-0.957 – 1.019)	2.461 (-0.689 – 5.610)
Has Child in Home	0.987 (0.287 – 1.686)**	1.764 (1.058 – 2.470)***	0.849 (0.098 – 1.600)*	2.393 (0.664 – 4.121)**
Education (Base: Less Than HS)				
College or More	3.239 (2.548 – 3.930)***	2.331 (1.639 – 3.022)***	3.116 (2.354 – 3.878)***	3.307 (1.800 – 4.813)***
Some College	2.283 (1.598 – 2.968)***	2.100 (1.407 – 2.794)***	2.240 (1.472 – 3.007)***	2.871 (1.437 – 4.305)***
Income (Base: Less than \$35,000)				
\$35,000-\$74,999	5.623 (4.990 – 6.257)***	5.556 (4.919 – 6.193)***	5.633 (4.943 – 6.323)***	5.438 (4.001 – 6.875)***
\$75,000-\$125,000	7.994 (7.223 – 8.764)***	7.635 (6.867 – 8.403)***	7.672 (6.837 – 8.506)***	8.804 (7.032 – 10.576)***
\$125,000+	9.687 (8.751 – 10.624)***	8.739 (7.824 – 9.654)***	8.878 (7.885 – 9.872)***	12.047 (9.736 – 14.358)***
Age (Base (22-35))				
36-50	0.097 (-0.763 – 0.957)	0.849 (0.004 – 1.693)*	0.100 (-0.804 – 1.004)	0.676 (-1.567 – 2.921)
51-69	-0.620 (-1.416 – 0.176)	0.579 (-0.201 – 1.359)	-0.458 (-1.296 – 0.379)	-0.216 (-2.324 – 1.893)
70+	-4.209 (-5.155 – -3.263)***	-2.969 (-3.903 – -2.035)***	-4.090 (-5.095 – -3.086)***	-3.603 (-6.014 – -1.192)**
Female	-3.094 (-3.600 – -2.589)***	-3.094 (-3.600 – -2.588)***	-3.182 (-3.734 – -2.630)***	-2.373 (-3.517 – -1.23)***
Non-Fully Vehicle Equipped	7.300 (6.668 – 7.933)***	8.727 (8.122 – 9.332)***	7.044 (6.381 – 7.708)***	6.282 (4.480 – 8.085)***
Employed	4.758 (4.170 – 5.346)***	4.453 (3.865 – 5.042)***	4.998 (4.360 – 5.635)***	3.123 (1.789 – 4.458)***
Built Environment and Rural Classification				
Is Rural		13.980 (13.213 – 14.748)***		
Local Access	-0.095 (-0.101 – -0.089)***		-0.093 (-0.102 – -0.085)***	-0.049 (-0.061 – -0.037)***
Regional Access	-0.010 (-0.016 – -0.003)**		0.002 (-0.006 – 0.010)	-0.038 (-0.049 – -0.027)***
Local Job Diversity	-0.032 (-0.069 – 0.006)		-0.011 (-0.055 – 0.033)	-0.119 (-0.187 – -0.051)***
Has Access to Transit	-0.897 (-1.531 – -0.264)**		-0.864 (-1.509 – -0.218)**	-5.021 (-8.729 – -1.313)**
Model Fit Info				
N	108462	108462	84658	23804
AIC	976118	977572	748282	227368
Null/Residual Deviance	131410/122478	131410/123893	104797/98714	24283/23515
Gamma Dispersion Parameter	1.465	1.465	1.607	1.006

Note. *** p < 0.001, ** p < 0.01, * p < 0.05

Table 3. Estimated average marginal effects (AMEs) and average conditional effects (ACEs) for auto user logit model, restrictive definition

Term/Model Info	Full Model (BE) Estimate (95% CI)	Full Model (No BE) Estimate (95% CI)	Urban Model Estimate (95% CI)	Rural Model Estimate (95% CI)
Personal Characteristics				
2+ Adults	-0.060 (-0.065 – -0.055)***	-0.079 (-0.084 – -0.074)***	-0.066 (-0.072 – -0.060)***	-0.027 (-0.036 – -0.018)***
Race and Ethnicity (Base: Non-Hispanic White)				
Hispanic (all races)	-0.013 (-0.019 – -0.006)***	-0.006 (-0.012 – 0.001)	-0.016 (-0.023 – -0.009)***	0.004 (-0.014 – 0.022)
Non-Hispanic Black	-0.015 (-0.021 – -0.009)***	-0.019 (-0.025 – -0.013)***	-0.016 (-0.023 – -0.009)***	-0.013 (-0.025 – -0.002)*
Other race, multiple, or unknown	-0.003 (-0.009 – 0.004)	0.005 (-0.002 – 0.011)	-0.005 (-0.012 – 0.002)	0.006 (-0.009 – 0.022)
Has Child in Home	-0.011 (-0.016 – -0.007)***	-0.011 (-0.016 – -0.007)***	-0.020 (-0.024 – -0.015)***	-0.009 (-0.015 – -0.004)***
Education (Base: Less Than HS)				
College or More	0.039 (0.034 – 0.044)***	0.048 (0.043 – 0.052)***	0.039 (0.033 – 0.045)***	0.034 (0.026 – 0.041)***
Some College	0.004 (-0.001 – 0.008)	0.007 (0.002 – 0.011)**	0.002 (-0.004 – 0.007)	0.010 (0.003 – 0.016)**
Income (Base: Less than \$35,000)				
\$35,000-\$74,999	-0.019 (-0.024 – -0.014)***	-0.020 (-0.025 – -0.015)***	-0.023 (-0.028 – -0.017)***	-0.005 (-0.013 – 0.003)
\$75,000-\$125,000	-0.003 (-0.008 – 0.003)	-0.003 (-0.009 – 0.003)	-0.004 (-0.011 – 0.002)	0.001 (-0.009 – 0.010)
\$125,000+	0.021 (0.014 – 0.028)***	0.024 (0.017 – 0.032)***	0.023 (0.015 – 0.031)***	0.008 (-0.004 – 0.020)
Age (Base (22-35))				
36-50	-0.012 (-0.018 – -0.006)***	-0.021 (-0.027 – -0.014)***	-0.013 (-0.020 – -0.006)***	-0.002 (-0.013 – 0.009)
51-69	-0.024 (-0.030 – -0.018)***	-0.037 (-0.043 – -0.031)***	-0.029 (-0.035 – -0.022)***	0.003 (-0.008 – 0.014)
70+	-0.055 (-0.061 – -0.049)***	-0.069 (-0.075 – -0.062)***	-0.062 (-0.069 – -0.054)***	-0.015 (-0.027 – -0.004)**
Female	-0.005 (-0.009 – -0.002)**	-0.005 (-0.009 – -0.002)**	-0.005 (-0.009 – -0.002)**	-0.007 (-0.011 – -0.003)**
Non-Fully Vehicle Equipped	-0.141 (-0.149 – -0.133)***	-0.141 (-0.149 – -0.133)***	-0.181 (-0.189 – -0.173)***	-0.152 (-0.161 – -0.144)***
Employed	-0.009 (-0.014 – -0.005)***	-0.009 (-0.014 – -0.005)***	-0.007 (-0.011 – -0.002)**	-0.014 (-0.019 – -0.009)***
Built Environment and Rural Classification				
Is Rural		-0.039 (-0.043 – -0.035)***		
Local Access	0.024 (0.022 – 0.025)***		0.036 (0.034 – 0.038)***	0.005 (0.003 – 0.008)***
Regional Access	-0.012 (-0.014 – -0.011)***		-0.012 (-0.014 – -0.011)***	-0.007 (-0.010 – -0.005)***
Local Job Diversity	0.016 (0.007 – 0.025)***		0.021 (0.011 – 0.032)***	0.019 (0.004 – 0.035)*
Has Access to Transit	0.031 (0.027 – 0.036)***		0.028 (0.023 – 0.033)***	-0.001 (-0.019 – 0.018)
Model Fit Info				
N	99403	99403	77843	N
AIC	55693	57329	47361	8060
Tjur R2	0.102	0.077	0.114	0.016

Note. *** p < 0.001, ** p < 0.01, * p < 0.05

4 Results and discussion

Our results offer insights and new questions to explore about how the relationship between travel and the BE differ between rural and urban contexts. In the following sections, we demonstrate that the typical approach of aggregating urban and rural data obscures important differences between urban and rural contexts that are revealed when we evaluate them separately. Our discussion and results are based on the ACEs and AMEs shown in Figure 2, which visually represents the relationships between BE variables and the four modeled travel behavior outcomes, for the full, urban, and rural models. Figure 2 shows the AMEs and ACEs for the restrictive rural definition. The corresponding plot for the expansive definition (Figure C1) can be found in Technical Appendix C.

4.1 Local access matters more in urban areas while regional access matters more in rural areas

First, we find that in rural communities local and regional access are inversely related to VMT, and these associations are similar in magnitude (Figure 2, bottom left.) Importantly, local access exhibits a weaker association with VMT in rural communities compared to urban communities, while regional access exhibits a stronger association with VMT in rural compared to urban contexts. This local access finding is in line with the findings of Brownstone and Golob (2009), who found that residential density had a smaller impact on distances traveled in rural areas when compared to urban areas. Consistent with this result, we observe in our analysis more modest associations between local access and mode choice (likelihood of utilitarian active travel, auto reliance, and auto use) in rural contexts when compared with urban contexts (Figure 2, second column).

Overall, our findings and those of Brownstone and Golob (2009) suggest the primacy of vehicle use in rural contexts in comparison to urban contexts. In rural areas, the level of local access has a weaker relationship with mode choice, and the distances driven are more strongly related to how far one must travel to reach destinations. However, these findings are at odds with Salon (2015), who found the marginal effect of local access to be larger in rural areas. It is possible that these differences are due to Salon (2015) only examining California versus the national scale study undertaken here and by Brownstone and Golob (2009). Further, our analysis and the studies being discussed here all applied differing definitions of rural, Salon (2015) created a novel classification scheme for California, Brownstone and Golob (2009) used a proprietary nationwide classification scheme (Claritas, 2018), and we applied the USCB's 2010 UAC.

Our results for regional access and mode choice are, not surprisingly, less straightforward, indicating that regional access has an inverse association with utilitarian active travel and a positive association with motorized vehicle reliance and use (Figure 2, left column). We included regional access in our mode choice models to ensure that our models were consistent for all travel outcomes, although it was not our first choice conceptually. Other research has found the choice to use non-auto modes is related more strongly to more local conditions (Ewing & Cervero, 2010; Handy & Niemeier, 1997; Sugiyama et al., 2012). Consequently, regional access (jobs accessible by car) is generally not used for predicting mode. Ewing and Cervero (2010) only list two studies in their meta-analysis that use a jobs accessible by car metric to assess non-auto modes (see Ewing & Cervero (2010) Table A-10). These two studies found job accessibility by auto to be non-significant or inversely associated to active travel respectively, consistent with our analysis. It is possible that in our analysis regional access is associated with unobserved features such as bicycle and pedestrian infrastructure quality, transit system

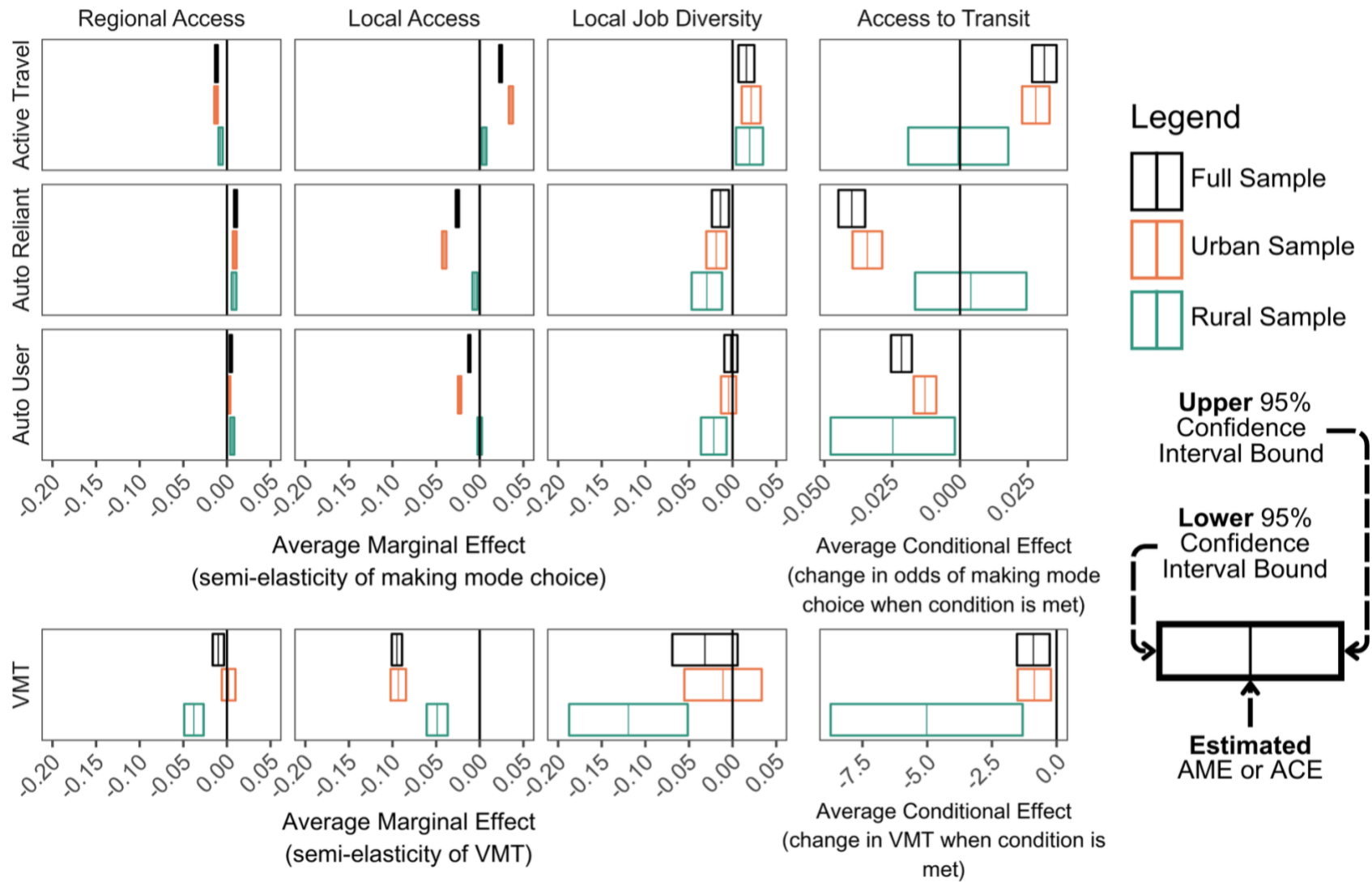


Figure 2. Model results for BE variables; plots illustrate 95% confidence intervals of AMEs (for regional access, local access, and local job diversity) and ACEs (for access to transit) using the restrictive definition of rural

quality, or the presence of on-demand transit service (i.e., paratransit), which could muddle the relationship between regional access and mode choice.

On the topic of transit access, we note that the lack of fixed route transit services in rural areas makes it possible that in our rural models transit access is a proxy for proximity to a town center or a major transportation corridor. Access to dense centers has been shown to be one of the strongest predictors of urban travel behavior (Ewing & Cervero, 2010; Stevens, 2017). Additionally, the transit access variable does not include on-demand services such as paratransit, which may be the primary transit option for eligible populations in rural contexts. Future research on this topic would be better served by a more meaningful representation of rural transit access.

We do not observe statistically significant differences in the relationships between rural and urban local job diversity regardless of modeled outcome or definition (VMT or mode). This conclusion is based on the overlapping range of the 95% confidence intervals of the urban and rural AMEs, which indicate that the urban and rural AMEs are not significantly different from each other. Although local job diversity is statistically significant in the rural VMT model but not the urban model, this reflects differences in whether each AME is statistically different from zero rather than reflecting an evaluation of the significance of the difference between the urban and rural AMEs. The lack of a significant difference between the urban and rural local job diversity AMEs may occur because the association is truly the same or it may be due to the relatively large confidence intervals of the estimated effects of local job diversity in our models.

4.2 Travel behavior is less related to personal attributes in rural contexts

Our results with respect to personal characteristics are relatively consistent between models (see Table 2 and Table 3). In most cases where differences are observed, we observe that the magnitude of the relationships between personal characteristics and travel outcomes are smaller in rural communities. The difference is greatest when looking at vehicle access, where the relationship between being fully vehicle equipped and travel behavior is much smaller in rural communities. Our results suggest that rural populations are more vehicle dependent in general, with less variation in travel outcomes related to their personal circumstances and vehicle access. This finding is consistent with Salon (2015) and prior literature on rural travel behavior (Pucher & Renne, 2005; Ralph et al., 2016; Voulgaris et al., 2017), rural unmet need (Espeland & Rowangould, 2024; Wang et al., 2023) and household vehicle access (Blumenberg et al., 2020).

4.3 “Rural” is not a monolith, suggesting potential intra-rural travel differences

An important caveat to these findings is that many differences in associations between travel behavior and the BE across urban and rural contexts we observed in our analysis (described above) are not all replicated when the definition of rural is changed from the restrictive definition to the expansive definition (which includes urban clusters). Additionally, the direction of some of the built environment results, particularly regional access (see Figure C1 in technical appendix), are not in line with previous literature and do not have a clear explanation when using the expansive definition. For this reason, we focus our discussion on the restrictive rural definition, which draws a clearer line between urban and very rural and seems to reflect and deepen what we know about urban and rural travel behavior differences.

Regardless, the incongruity of our results using the expansive definition suggests that travel behaviors differ across the urban-rural continuum. This non-homogeneity between definitions has been noted both in transportation research (Quallen & Rowangould, 2022) and in other fields (Wineman et al., 2020), suggesting there is also a need to better

understand how acknowledging the heterogeneity of rural contexts impacts our understanding of rural travel behaviors. However, such a discussion is beyond the scope of this paper.

5 Conclusions

Our analysis suggests that the built environment (BE) and travel behavior relationship is distinct in rural contexts. This difference is especially pronounced when evaluating the association between local access and mode choice and vehicle travel. In rural areas, regional and local access exhibit similar relationships. In contrast, in urban areas local access is more strongly associated with mode choice and vehicle travel than regional access. Furthermore, we found the association between local access and travel behavior is weaker in rural areas when compared with urban areas. Though local access is positively related to sustainable travel behaviors regardless of context, our results suggest that rural planners may not get the same returns as their urban counterparts. Additionally, in our analysis the relationship between travel behavior and personal characteristics is weaker in rural contexts, underscoring people's greater vehicle reliance in these contexts.

Overall, when seeking to use BE changes to meet transportation goals in rural areas, planners may see a smaller impact than they might expect, especially when altering local access. Importantly, these differences were only detected when we modeled rural travel behavior separately. When we evaluated the same data using a more traditional modeling approach that combines urban and rural contexts and controls for rurality, our results confirm the findings of prior literature, and the unique relationship between travel and the BE in rural contexts is obscured.

An addendum to these findings is they are sensitive to how we define rural. The transportation literature has noted that travel varies across the rural-urban spectrum (Millward & Spinney, 2011) and also within rural areas (Espeland & Rowangould, 2024; Quallen & Rowangould, 2022). Our findings and the existing literature (Brownstone & Golob, 2009; Espeland & Rowangould, 2024; Quallen & Rowangould, 2022) support this conclusion. This strengthens the case of scholars like Hoggart (1990), who argue that before we draw strict lines between urban and rural we need to better understand intra-rural differences.

An important caveat to this study is that it describes associations, not causal relationships. We attempted to control for residential self-selection by including a wide range of personal characteristics, but we were unable to explicitly control for it, weakening our results (Cao et al., 2009; Stevens, 2017). If our findings are an indication of causal relationships, it would point to shortcomings of existing research on the effects of the BE on travel behavior, namely that it would be unlikely to apply in rural contexts. At present we can only suggest this as a possibility. Future research is needed to establish whether causal relationships differ across urban and rural contexts.

Despite these limitations, this study has prescient insights into differences in associations between travel and the BE in rural contexts, highlighting considerations for future transportation and planning academic research, policy, and practice. Planning professionals that seek to reduce VMT and auto reliance through BE changes in rural contexts should proceed cautiously when following recommendations of prior research conducted in urban areas, although there may still be potential pathways to reducing emissions in rural communities through transportation and land-planning.

Our results indicate that while the BE affects travel choices in rural communities its effect is much smaller in rural contexts. This smaller effect underscores the challenges that rural communities face when seeking to reduce VMT and GHG emissions, highlighting the possibility of undershooting GHG or VMT reduction targets. These

findings are valuable to decision-makers in rural communities, who are already implementing policies that target smart growth (Dalbey, 2008; Frank & Reiss, 2014) without clear information on the impacts they may have on travel behavior.

Acknowledgments

This study was partially funded by a grant from the National Center for Sustainable Transportation (NCST), supported by the U.S. Department of Transportation's University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange and does not necessarily reflect the official views or policies of the U.S. Government. The U.S. Government assumes no liability for the contents or use thereof.

Author contribution

The authors confirm contribution to the paper as follows: study conception and design: H. Schukei, D. Rowangould; data collection and programming: H. Schukei; analysis and interpretation of results: H. Schukei, D. Rowangould; draft manuscript preparation: H. Schukei, D. Rowangould. All authors reviewed the results and approved the final version of the manuscript.

Appendix

Appendix available as a supplementary file at <https://doi.org/10.5198/jtlu.2025.2671>.

References

- Ao, Y., Li, M., Ding, X., Zheng, J., Xiao, S., Deng, S., . . . , & Martek, I. (2022). Built environment and travel behavior in rural areas: A scientometric literature review. *Frontiers in Ecology and Evolution, 10*. <https://doi.org/10.3389/fevo.2022.1018581>
- Arel-Bundock, V., Greifer, N., & Heiss, A. (2024). How to interpret statistical models using marginal effects for R and Python. *Journal of Statistical Software, 111*, 1–32. <https://doi.org/10.18637/jss.v111.i09>
- Bennett, K. J., Borders, T. F., Holmes, G. M., Kozhimannil, K. B., & Ziller, E. (2019). What Is rural? Challenges and implications of definitions that inadequately encompass rural people and places. *Health Affairs, 38*(12), 1985–1992. <https://doi.org/10.1377/hlthaff.2019.00910>
- Blumenberg, E., Brown, A., & Schouten, A. (2020). Car-deficit households: Determinants and implications for household travel in the U.S. *Transportation, 47*(3), 1103–1125. <https://doi.org/10.1007/s11116-018-9956-6>
- Brownstone, D., & Golob, T. F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics, 65*(1), 91–98. <https://doi.org/10.1016/j.jue.2008.09.002>
- Cao, X., Mokhtarian, P. L., & Handy, S. L. (2009). Examining the impacts of residential self-selection on travel behavior: A focus on empirical findings. *Transport Reviews, 29*(3), 359–395. <https://doi.org/10.1080/01441640802539195>
- Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment, 2*(3), 199–219. [https://doi.org/10.1016/S1361-9209\(97\)00009-6](https://doi.org/10.1016/S1361-9209(97)00009-6)
- Childs, E. M., Boyas, J. F., & Blackburn, J. R. (2022). Off the beaten path: A scoping review of how ‘rural’ is defined by the U.S. government for rural health promotion. *Health Promotion Perspectives, 12*(1), Article 1. <https://doi.org/10.34172/hpp.2022.02>
- Claritas. (2018). *Assessing the role of urbanicity*. Cincinnati, OH: Claritas, LLC. https://nhts.ornl.gov/assets/Assessing_the_Role_of_Urbanicity.pdf
- Dalbey, M. (2008). Implementing smart growth strategies in rural America: Development patterns that support public health goals. *Journal of Public Health Management and Practice, 14*(3), 238–243. <https://doi.org/10.1097/01.PHH.0000316482.65135.e8>
- Davis, J. C. (2022, November). *Rural America at a glance: 2022 Edition*. Washington, DC: United States Department of Agriculture Economic Research Service. <https://www.ers.usda.gov/webdocs/publications/105155/eib-246.pdf?v=2341.8>
- Espeland, S., & Rowangould, D. (2024). Rural travel burdens in the United States: Unmet need and travel costs. *Journal of Transport Geography, 121*, 12. <https://doi.org/10.1016/j.jtrangeo.2024.104016>
- Ewing, R., & Cervero, R. (2010). Travel and the built environment. *Journal of the American Planning Association, 76*(3), 265–294. <https://doi.org/10.1080/01944361003766766>
- Federal Highway Administration. (2017). *2017 National Household Travel Survey* (Dataset). U.S. Department of Transportation. <https://nhts.ornl.gov>
- Federal Highway Administration. (2020, August). *Derived variables*. U.S. Department of Transportation. https://nhts.ornl.gov/assets/DerivedVariables_V1.2.pdf
- Federal Highway Administration. (2022, September 24). *Highway Statistics 2020*. U.S. Department of Transportation. <https://www.fhwa.dot.gov/policyinformation/statistics/2020/>

- Federal Register. (2011). Urban Area Criteria for the 2010 Census. Retrieved from <https://www.federalregister.gov/documents/2011/08/24/2011-21647/urban-area-criteria-for-the-2010-census>
- Frank, K. I., & Hibbard, M. (2017). Rural planning in the twenty-first century: Context-appropriate practices in a connected world. *Journal of Planning Education and Research*, 37(3), 299–308. <https://doi.org/10.1177/0739456X16655599>
- Frank, K. I., & Reiss, S. A. (2014). The rural planning perspective at an opportune time. *Journal of Planning Literature*, 29(4), 386–402. <https://doi.org/10.1177/0885412214542050>
- Handy, S. (1996). Understanding the link between urban form and nonwork travel behavior. *Journal of Planning Education and Research*, 15(3), 183–198. <https://doi.org/10.1177/0739456X9601500303>
- Handy, S. (2017). Thoughts on the meaning of Mark Stevens’s meta-analysis. *Journal of the American Planning Association*, 83(1), 26–28. <https://doi.org/10.1080/01944363.2016.1246379>
- Handy, S. (2018, May). Enough with the “D’s” already—Let’s get back to “A.” *Transfers Magazine*, 1. Retrieved from <https://transfersmagazine.org/wp-content/uploads/sites/13/2018/05/Susan-Handy--Enough-with-the-Ds.pdf>
- Handy, S., & Niemeier, D. A. (1997). Measuring accessibility: An exploration of issues and alternatives. *Environment and Planning A: Economy and Space*, 29(7), 1175–1194. <https://doi.org/10.1068/a291175>
- Hanson, S., & Schwab, M. (1987). Accessibility and intraurban travel. *Environment and Planning A: Economy and Space*, 19(6), 735–748. <https://doi.org/10.1068/a190735>
- Hart, L. G., Larson, E. H., & Lishner, D. M. (2005). Rural definitions for health policy and research. *American Journal of Public Health*, 95(7), 1149–1155. <https://doi.org/10.2105/AJPH.2004.042432>
- Hoggart, K. (1990). Let’s do away with rural. *Journal of Rural Studies*, 6(3), 245–257. [https://doi.org/10.1016/0743-0167\(90\)90079-N](https://doi.org/10.1016/0743-0167(90)90079-N)
- Ihlanfeldt, K. (2020). Vehicle miles traveled and the built environment: New evidence from panel data. *Journal of Transport and Land Use*, 13(1), 23–48. <https://doi.org/10.5198/jtlu.2020.1647>
- Isserman, A. M. (2005). In the national interest: Defining rural and urban correctly in research and public policy. *International Regional Science Review*, 28(4), 465–499. <https://doi.org/10.1177/0160017605279000>
- Karner, A., Levine, K., Alcorn, L., Situ, M., Rowangould, D., Kim, K., ..., & National Academies of Sciences, Engineering, and Medicine. (2022). *Accessibility measures in practice: A guide for transportation agencies* (p. 26793). Washington, DC: Transportation Research Board. <https://doi.org/10.17226/26793>
- Levinson, D., & King, D. (2020). *Transport access manual: A guide for measuring connection between people and places*. Sydney, Australia: Committee of the Transport Access Manual, University of Sydney. <https://ses.library.usyd.edu.au/handle/2123/23733>
- Levinson, D. M. (1998). Accessibility and the journey to work. *Journal of Transport Geography*, 6(1), 11–21. [https://doi.org/10.1016/S0966-6923\(97\)00036-7](https://doi.org/10.1016/S0966-6923(97)00036-7)
- Lichter, D. T., & Johnson, K. M. (2020). A demographic lifeline? Immigration and Hispanic population growth in rural America. *Population Research and Policy Review*, 39(5), 785–803. <https://doi.org/10.1007/s11113-020-09605-8>
- Millward, H., & Spinney, J. (2011). Time use, travel behavior, and the rural–urban continuum: Results from the Halifax STAR project. *Journal of Transport Geography*, 19(1), 51–58. <https://doi.org/10.1016/j.jtrangeo.2009.12.005>

- Moss, M., & Qing, C. (2012). *The emergence of the “super-commuter”* (p. 24). New York: New York University.
https://www.researchgate.net/publication/254609835_The_Emergence_of_the_Super-Commuter
- Pickrell, D., & Schimek, P. (1999). Trends in personal motor vehicle ownership and use: Evidence from the nationwide personal transportation survey. *Journal of Transportation and Statistics*, 2. <https://doi.org/10.21949/1404567>
- Popovich, N., Spurlock, C. A., Needell, Z., Jin, L., Wenzel, T., Sheppard, C., & Asudegi, M. (2021). A methodology to develop a geospatial transportation typology. *Journal of Transport Geography*, 93, 103061. <https://doi.org/10.1016/j.jtrangeo.2021.103061>
- Pucher, J., & Renne, J. L. (2005). Rural mobility and mode choice: Evidence from the 2001 National Household Travel Survey. *Transportation*, 32(2), 165–186.
<https://doi.org/10.1007/s11116-004-5508-3>
- Quallen, E. L., & Rowangould, G. (2022, January). Consistently inconsistent: An assessment of definitions of rural and travel behavior outcomes in Vermont. Paper presented at the Transportation Research Board Annual Meeting, January 9–13, Washington, D.C.
- Ralph, K., Voulgaris, C. T., & Brown, A. (2017). Travel and the built environment: Insights using activity densities, the sprawl index, and neighborhood types. *Transportation Research Record*, 2653(1), 1–9. <https://doi.org/10.3141/2653-01>
- Ralph, K., Voulgaris, C. T., Taylor, B. D., Blumenberg, E., & Brown, A. E. (2016). Millennials, built form, and travel insights from a nationwide typology of U.S. neighborhoods. *Journal of Transport Geography*, 57, 218–226.
<https://doi.org/10.1016/j.jtrangeo.2016.10.007>
- Rasca, S., & Saeed, N. (2022). Exploring the factors influencing the use of public transport by commuters living in networks of small cities and towns. *Travel Behavior and Society*, 28, 249–263. <https://doi.org/10.1016/j.tbs.2022.03.007>
- Salon, D. (2015). Heterogeneity in the relationship between the built environment and driving: Focus on neighborhood type and travel purpose. *Research in Transportation Economics*, 52, 34–45. <https://doi.org/10.1016/j.retrec.2015.10.008>
- Schimek, P. (1996). Household motor vehicle ownership and use: How much does residential density matter? *Transportation Research Record*, 1552(1), 120–125.
<https://doi.org/10.1177/0361198196155200117>
- Slack, T., & Jensen, L. (2020). The changing demography of rural and small-town America. *Population Research and Policy Review*, 39(5), 775–783.
<https://doi.org/10.1007/s11113-020-09608-5>
- Smithson, M., & Shou, Y. (2020). *Generalized linear models for bounded and limited quantitative variables*. Retrieved from <https://doi.org/10.4135/9781544318523>.
- Stevens, M. R. (2017). Does compact development make people drive less? *Journal of the American Planning Association*, 83(1), 7–18.
<https://doi.org/10.1080/01944363.2016.1240044>
- Stewart, O. T., Vernez Moudon, A., Saelens, B. E., Lee, C., Kang, B., & Doescher, M. P. (2016). Comparing associations between the built environment and walking in rural small towns and a large metropolitan area. *Environment and Behavior*, 48(1), 13–36.
<https://doi.org/10.1177/0013916515612253>
- Sugiyama, T., Neuhaus, M., Cole, R., Giles-Corti, B., & Owen, N. (2012). Destination and route attributes associated with adults’ walking: A review. *Medicine and Science in Sports and Exercise*, 44(7), 1275–1286.
<https://doi.org/10.1249/MSS.0b013e318247d286>

- Theis, N., & Driscoll, A. (2023). Rural consciousness and framing environmental (in)justice. *Environmental Justice*, 16(2), 118–125. <https://doi.org/10.1089/env.2021.0080>
- U.S. Census Bureau. (2020). 2020 Decennial Census [Dataset]. <https://www.census.gov/data/developers/data-sets/decennial-census.html>
- U.S. Environmental Protection Agency. (2020). *Smart location database* (Dataset). Retrieved from <https://www.epa.gov/smartgrowth/smart-location-mapping#SLD>
- U.S. Environmental Protection Agency. (2021, June). *Smart location database technical documentation and user guide version 3.0*. Retrieved from https://www.epa.gov/sites/default/files/2021-06/documents/epa_sld_3.0_technicaldocumentationuserguide_may2021.pdf
- Voulgaris, C. T., Taylor, B. D., Blumenberg, E., Brown, A., & Ralph, K. (2017). Synergistic neighborhood relationships with travel behavior: An analysis of travel in 30,000 US neighborhoods. *Journal of Transport and Land Use*, 10(1), 437–461. <https://doi.org/10.5198/jtlu.2016.840>
- Wang, W., Espeland, S., Barajas, J. M., & Rowangould, D. (2023). Rural–nonrural divide in car access and unmet travel need in the United States. *Transportation*, 52, 507–536. <https://doi.org/10.1007/s11116-023-10429-6>
- Wineman, A., Alia, D. Y., & Anderson, C. L. (2020). Definitions of “rural” and “urban” and understandings of economic transformation: Evidence from Tanzania. *Journal of Rural Studies*, 79, 254–268. <https://doi.org/10.1016/j.jrurstud.2020.08.014>