

Understanding Why People Don't Ride Public Transit: A Multivariate Investigation of Transit Usage and Barriers

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ABSTRACT

Public transit ridership in the United States has declined over the past decade, and non- and low-frequency users cite barriers spanning personal safety, comfort and conditions, and service availability for staying off the system. Yet these barriers have typically been studied separately from one another and from actual usage. This study jointly models transit usage frequency and nine self-reported barriers to transit use using a nationally representative survey sample. A multivariate ordered probit model estimates usage frequency, specified as a five-level ordinal outcome, alongside nine binary barrier outcomes, yielding ten correlated outcomes. The model draws on the second wave of the Transportation Heartbeat of America Survey, conducted nationally in February and March 2026, with sociodemographic and built environment predictors including zip code-level vehicle ownership, density, and walkability. Average treatment effects translate coefficients into population-scale probability impacts.

Results show that the nine barriers separate into two largely independent families, an experiential safety and comfort cluster and a distinct service availability dimension. Women, older adults, and higher-income travelers show distinct barrier profiles, and racial and ethnic differences in safety and comfort barriers largely dissolve once income, location, and exposure are adequately controlled. This study is among the first to jointly model transit usage frequency alongside a comprehensive set of perceived barriers within a single multivariate framework using a recent national survey. Findings suggest agencies should pursue on-system safety improvements and service availability expansion strategically and separately, targeting interventions based on census and location data.

Keywords: Public Transit, Transit Usage Frequency, Barriers to Transit Use, Joint Modeling, Personal Safety, Built Environment

1. INTRODUCTION

Public transit is an essential component of the nation's mobility system, supporting economic activity and connecting riders to various destinations. In 2025, transit accounted for 8.07 billion trips nationwide, and 87 percent of those trips directly benefited local economies by connecting riders to workplaces, services, and other essential destinations (Dickens and Bonina, 2026). Beyond these direct economic benefits, public transit is an important mobility option for the roughly 8 percent of U.S. households that do not own a vehicle (U.S. Census Bureau, 2026). These carless households are disproportionately low-income (Brown, 2017; Wang et al., 2025), and more than 90 percent of those in large metropolitan areas live in neighborhoods with at least some transit service (Tomer, 2011). Even so, transit often falls short of providing carless households with the level of access to jobs and essential destinations that car ownership affords, and in a landscape built around driving, the absence of a car translates into unmet travel needs, forgone trips, and eroding economic standing (King et al., 2022; Wang et al., 2025). Public transit also delivers broader societal benefits. Transit exhibits a substantially lower fatality rate per passenger mile than automobile travel (National Safety Council, 2026), and, on average, produces lower greenhouse gas emissions per passenger mile than single-occupancy vehicle travel (McGraw et al., 2021).

Despite these benefits, public transit ridership in the U.S. has been in long-term decline. Bus ridership across 215 U.S. metropolitan areas fell by approximately 15 percent and rail ridership by 3 percent between 2012 and 2018 (Erhardt et al., 2022). Morris et al. (2025) find that the pandemic accelerated a broad, persistent shift toward staying home that reduced the time Americans spend traveling, with the decline falling disproportionately on transit. Automobile travel has substantially rebounded, whereas time spent traveling by public transit has not significantly recovered even to its already-declining pre-pandemic level. The growth of remote work arrangements since the pandemic has further eroded the commute trips that transit has traditionally relied upon, while the rapid growth of ride-hailing and delivery services has drawn travelers away from transit for many of the same trip purposes it once served (Diao et al., 2021). The proliferation of micromobility options, such as e-scooters and e-bikes, has introduced additional competition for the shorter trips that may have been served by transit in the past (Luo et al., 2021).

Persistent concerns about personal safety – on vehicles, at stops, and in the surrounding environment – have compounded these pressures, discouraging both current and prospective riders. The ridership decline also carries fiscal consequences. Falling farebox revenue combined with the expiration of federal pandemic relief funds has pushed many transit agencies toward operating budget shortfalls (Shrode, 2022). In response, some agencies have reduced service, risking a self-reinforcing cycle in which service cuts further suppress ridership and revenue, forcing still deeper reductions (Redelmeier and El-Geneidy, 2024). Explanations proposed in the literature for the pre-pandemic decline include rising vehicle ownership (Manville et al., 2023) and the growth of ride-hailing services (Diao et al., 2021). However, these aggregate, demand- and market-side explanations still leave open the question of what deters individual travelers from using transit in the first place.

A substantial body of research has examined the individual-level barriers that deter transit use – spanning concerns about personal safety, the comfort and conditions of the travel experience, and the level, quality, and reliability of service – with the magnitude of these barriers varying across sociodemographic groups and built environment contexts (see, for example, Yavuz et al., 2007; Fan et al., 2016; Mers et al., 2024; Asgharpour et al., 2025; Hosseini et al., 2025). Yet, despite this attention, a comprehensive understanding of the relative impacts of different barriers

in deterring transit use remains elusive. Transit usage and the barriers to transit usage have typically been examined separately, making it difficult to fully understand how specific barriers relate to one another and to an individual's frequency of use. Much of the evidence on barriers to transit use, moreover, is drawn from single cities or transit systems and from data pre-dating the pandemic-era restructuring of travel behavior. Changes in travel behavior have persisted in the post-pandemic era (Morris et al., 2025), limiting what the pre-pandemic era data sets can say about the national population today.

These gaps motivate the current study, which examines the relationship between transit usage and its barriers jointly rather than in isolation. The data are drawn from the second wave of the Transportation Heartbeat of America (THA) Survey, a nationwide survey of 8,273 respondents conducted in February and March 2026. The survey provides the ability to link self-reported transit usage and barriers to a rich set of sociodemographic attributes. Transit usage frequency is measured across six ordered categories. The barriers are elicited only from non- and low-frequency transit users, defined as respondents who report that public transportation is not available to them, that it is available but they never use it, or that they use it less than one day per month. These respondents indicate which of nine barriers affect their use of transit, organized into three thematic groups referenced throughout the paper: personal safety; comfort and conditions; and service (non-) availability.

Transit usage frequency and the nine barriers to transit use are modeled together, for a total of ten ordered outcomes, within a multivariate ordered probit framework. Estimating the outcomes simultaneously and allowing them to be correlated helps capture how usage and barriers are interrelated through shared observed and unobserved factors (rather than treating each barrier as an independent outcome). Because both usage frequency and the barriers are tied to a common set of sociodemographic and built environment attributes, and because the joint framework accounts for unobserved differences between those who report barriers and those who do not, the findings extend beyond the non- and low-frequency users who were asked about barriers to the population as a whole. This allows transit agencies and planners to identify the demographic and locational profiles most likely to face different types of barriers and to target interventions accordingly, regardless of an individual's current level of transit use.

The remainder of this paper is organized as follows. The next section presents a review of the literature on barriers to public transit use. This is followed by a description of the survey data and the modeling methodology. Model estimation results are then presented and discussed, followed by average treatment effects that quantify the magnitude of the estimated relationships. The final section discusses implications for transit agencies and planners and offers concluding remarks.

2. LITERATURE REVIEW

A comprehensive review of the literature on barriers to public transit use is beyond the scope of this paper. This section therefore offers a synthesis of the research conducted to date with citations to illustrative references – highlighting the substantive findings that have emerged, the gaps that remain, and the contribution this study seeks to make in addressing them. The barriers identified in prior research may be broadly grouped into three categories: personal safety, comfort and conditions, and service availability. The discussion below is organized accordingly.

Personal safety concerns are among the most consistently documented barriers to transit use. Using Chicago Transit Authority data linked to neighborhood-level characteristics, Yavuz et al. (2007) found that perceived insecurity varies systematically with individual demographics and

neighborhood disorder, poverty, and density. Physical stop design also shapes perceived safety; Abenoza et al. (2018) found that shelter characteristics, natural surveillance, and trustworthy real-time information were the most influential factors at Stockholm bus stops, with women reporting lower perceived safety than men. Fan et al. (2016) found that women waiting more than 10 minutes in perceived insecure surroundings in the Twin Cities region reported waits as dramatically longer than they actually were, and longer than what men reported under the same conditions. Harassment can compound these concerns for particular rider groups; Lubitow et al. (2020) found that routine harassment and discrimination from other passengers, staff, and members of the public led transgender and gender nonconforming riders in Portland, Oregon, to limit and alter their travel behavior. Concerns about interactions with law enforcement add a further dimension to personal safety, with He et al. (2022) finding Hispanic and Latinx riders more likely than others to cite such concerns as a reason for reducing transit use, and Aeschliman and Stathopoulos (2025) finding that 10 to 20 percent of Chicago-region riders felt less safe in the presence of enforcement personnel, even though enforcement was associated with higher rider satisfaction overall.

Comfort and conditions on board and at stops constitute a second recurring barrier, and one whose importance also varies across demographic groups. Asgharpour et al. (2025), analyzing a large Chicago Transit Authority satisfaction survey, found that cleanliness, comfort, safety, and reliability affected user segments unevenly, with higher-income and higher-education riders particularly sensitive to cleanliness and reliability, women more dissatisfied with current safety measures, and riders with disabilities and those facing intersecting vulnerabilities reporting the greatest dissatisfaction. Mers et al. (2024), pooling survey responses across nine U.S. transit agencies, similarly found that the attributes driving satisfaction differ by gender, income, and race, with reliability and comfort emerging as concerns that cut across multiple demographic groups. Sanitation-related fears proved especially consequential during the pandemic; Bian et al. (2022) found that perceived infection and sanitation risk led many choice riders in El Paso, Texas, to abandon transit, with awareness of operators' safety measures significantly lowering perceived risk. Physical comfort on board is a further concern; Silvano and Ohlin (2019), drawing on Swedish emergency department records, found that falls from acceleration and braking maneuvers disproportionately involved older riders, those using walking frames, and women across all age groups.

Service availability, encompassing both spatial coverage and temporal frequency, represents a third fundamental barrier to transit use. Hosseini et al. (2025) found that lower-income riders and residents of historically underserved Charlotte neighborhoods were especially sensitive to service availability, more often reporting limited routes, long wait times, and a lack of accessible stops as barriers to transit use, with Latino and Native American riders reporting the greatest difficulty. Using structural equation modeling across 152 U.S. urbanized regions, Lyons et al. (2025) found that both route density and service frequency substantially shape ridership, with frequency exerting a moderately larger effect than coverage. Consistent with this, Boisjoly et al. (2018) found that the volume of service supplied was among the strongest determinants of ridership across 25 North American transit agencies, suggesting that reductions in service supply may have exacerbated ridership declines observed in North American cities.

Taken together, this literature establishes that personal safety, comfort and conditions, and service availability each act as meaningful barriers to transit use, with their importance varying across sociodemographic groups and built environment contexts. However, existing studies have largely examined these barriers in isolation from one another and from actual transit usage frequency – leaving the relationships among barriers, and between barriers and use, not well

understood. Much of the evidence is also drawn from individual cities or transit systems and from data predating recent post-pandemic shifts in travel behavior, limiting its applicability to the national population today. Using a recent nationally representative survey sample, this study addresses these gaps by jointly modeling transit usage frequency alongside nine different barriers spanning all three thematic categories in order to characterize how these barriers collectively shape transit use across the U.S. population.

3. DATA DESCRIPTION

This section presents a detailed description of the data used in the study.

3.1 Survey Overview

The data analyzed in this paper are drawn from the second wave of the Transportation Heartbeat of America (THA) Survey, fielded across the United States between February and March 2026. The survey was administered to an online panel of participants assembled by a commercial firm, with quotas specified on an extensive set of socio-economic attributes to ensure that the respondent sample captured the variation in attributes that would be seen in the general population. This quota-based sampling approach ensured that reasonable sample sizes were obtained within multiple demographic subgroups defined by race, age, gender, educational attainment, household income, area type of residence (urban/rural), and census division of residence. Eligible participants included adults aged 18 years or older residing in the United States, and multiple attention checks and quality control questions were embedded in the survey to ensure robust response quality.

The dataset offers detailed coverage of attitudes regarding transportation, mobility, and urban living; current activity-travel behaviors and mode use; safety experiences across travel modes; commuting patterns and telework arrangements; online shopping and delivery behaviors; and knowledge and opinions about emerging transportation technologies and infrastructure investments. Additional built environment attributes were appended to the survey records, based on residential zip code, using information from the Environmental Protection Agency (EPA) Smart Location Database (Chapman et al., 2021). While the original survey dataset included a total of 8,567 responses, the final analysis dataset, cleaned of missing data and obviously erroneous records and inclusive of the appended built environment attributes, comprised 8,273 observations.

3.2 Endogenous Outcomes

The endogenous outcomes examined in this study consist of public transportation usage frequency and the nine self-reported barriers to public transportation use, each treated as a distinct outcome variable, for a total of ten endogenous outcomes modeled jointly. Although transit use was originally collected using six response categories, the usage frequency variable specified in the model retains only five ordered levels, as respondents who indicated that public transportation is not available to them were excluded from this outcome. The “This is not available to me” response reflects a lack of access rather than a level of use, and is therefore more appropriately treated as a separate consideration rather than the lowest level of a use-frequency scale.

The nine barrier outcomes were elicited only from non- and low-frequency users, defined as respondents who reported that public transportation is not available to them, that it is available to them but they never use it, or that they use it less than one day per month. These 6,279 respondents, representing 75.9 percent of the full sample, were asked the following question: “Do any of the following concerns contribute to your decision not to travel by public transportation more often? Please select all that apply.” Respondents could select as many of the nine barriers as

they deemed applicable, and the resulting percentages are therefore not mutually exclusive and do not sum to 100 percent.

Table 1 presents descriptive statistics for all ten endogenous outcomes, with the usage frequency outcome shown across its six original response categories and the nine barriers organized into the three thematic groups introduced earlier. Among the usage frequency categories, the largest single group of respondents, at 33.8 percent, reported that transit is available to them but that they never use it, while smaller shares reported using transit with increasing frequency, from 13.2 percent using it less than one day per month down to 6.1 percent using it three or more days per week. Notably, 28.9 percent of the full sample reported that public transportation is not available to them at all, underscoring that lack of access remains a first-order barrier for a substantial share of the population before considerations of comfort, safety, or habit even come into play.

Table 1. Descriptive Statistics of Transit Use Frequency and Self-Reported Transit Use Barriers

Outcome variable	Count	%
Transit use frequency (N = 8,273)		
<i>This is not available to me*</i>	2,388	28.9
This is available but I never use it	2,797	33.8
I use it less than one day per month	1,094	13.2
I use it 1-3 days per month	886	10.7
I use it 1-2 days per week	602	7.3
I use it 3 or more days per week	506	6.1
Self-reported transit barriers among non-transit users and infrequent users (N = 6,279)		
<i>Personal Safety Concerns</i>		
Unpredictable or threatening behavior of other passengers	1,229	19.6
Risk of theft	753	12.0
Concerns about interactions with law enforcement or security officers	261	4.2
Feeling unsafe walking to or from transit stops	802	12.8
Feeling unsafe while waiting at transit stops	964	15.4
<i>Comfort/Conditions On-Board</i>		
Dirty or unsanitary conditions on transit vehicles or at stops	1,212	19.3
Fear of falling due to rapid acceleration or lack of seating	422	6.7
<i>Service Availability</i>		
Public transportation is not available near where I live	1,931	30.8
Public transportation is not available to reach my destinations	1,597	25.4

Note. (*) Excluded from the transit use frequency variable used in the model estimation stage.

Among the nine self-reported barriers, the two service availability items are the most frequently cited, with 30.8 percent of non- and low-frequency users reporting that public transportation is not available near where they live and 25.4 percent reporting that it is not available to reach their destinations. Personal safety concerns are also widely reported, led by unpredictable or threatening behavior of other passengers at 19.6 percent, followed by feeling unsafe while waiting at transit stops at 15.4 percent, feeling unsafe walking to or from transit stops at 12.8 percent, and risk of theft at 12.0 percent. Concerns about interactions with law enforcement or security officers are cited least often, at just 4.2 percent, suggesting that this particular safety

concern, while real for a meaningful minority of riders, is considerably less pervasive than concerns rooted in the behavior of fellow passengers or the physical environment surrounding transit. Within the comfort and conditions category, dirty or unsanitary conditions on transit vehicles or at stops are cited by 19.3 percent of respondents, a share comparable to the leading personal safety concern, while fear of falling due to rapid acceleration or lack of seating is cited by 6.7 percent. Taken together, these patterns suggest that service availability constraints and passenger-behavior-related safety concerns are the most pervasive barriers to transit use in the sample, while concerns tied specifically to law enforcement presence and the physical hazard of falling are comparatively less prevalent, though still meaningful for the subgroups of riders who report them.

3.3 Sample Description and Comparison by Transit Access

This section profiles the analysis sample and examines whether systematic differences in socio-demographic and household characteristics distinguish respondents who report that public transit is unavailable to them from those who report that it is available to them. Table 2 compares these two groups, i.e., respondents reporting no access to transit (N = 2,388; 28.9 percent) and respondents reporting that transit is available to them (N = 5,885; 71.1 percent), across individual- and household-level attributes. In the remainder of this paper, the former group is referred to as the "*Without Access*" group and the latter as the "*With Access*" group. Because availability is self-reported, the *Without Access* designation reflects respondents' own perception of their transit environment rather than an objective service measure, and the *With Access* group encompasses both active transit users and respondents who indicate that transit is available to them but choose to never use it.

As shown in Table 2, the characteristics that distinguish the *Without Access* group point consistently to residential context and lifecycle stage rather than to any single demographic attribute considered in isolation. Respondents who report lacking access skew markedly older, with close to 39 percent aged 65 or older compared with just about a quarter among those with access, and they are considerably more likely to be retired or not employed. At the household level, this *Without Access* group is more concentrated in smaller households without children present and residing in owner-occupied, single-family homes, with apartment living comparatively rare. Taken together, these traits form the demographic profile of low-density residential settings, suggesting that perceived unavailability is associated with where people live and their lifecycle stage.

Perceived unavailability also carries a discernible equity dimension, falling more heavily on populations with fewer resources to offset it. Women make up nearly 63 percent of the *Without Access* group, a notably higher share than among those with access. Educational attainment and household income both follow a similar gradient, with lower educational attainment and lower income households reporting a lack of transit access at noticeably higher rates than their more educated and higher-income counterparts. Limited transit availability thus tends to coincide with the very groups for whom the burden of resulting automobile dependence is likely to weigh most heavily.

The racial and ethnic composition of the two groups reinforces the locational context narrative rather than pointing to a distinct racial disparity. Respondents in the *Without Access* group are more White and non-Hispanic, while Black and Hispanic respondents, populations that concentrate more heavily in the urban areas where transit service tends to exist, are less prevalent among those reporting no access (when compared with the group having access to transit). This pattern signals the suburban and rural footprint of perceived unavailability rather than a racial

disparity in access per se, a distinction worth bearing in mind when interpreting model estimation results presented later in the paper.

Perhaps the most intriguing pattern to emerge from Table 2 concerns vehicle ownership, precisely because of how little it differs between the two groups. One might expect the *Without Access* group to show substantially higher vehicle ownership than the *With Access* group, simply because those with transit access are likely situated in residential environments where multimodal options are available. Yet the two groups look remarkably similar on the vehicle ownership attribute, with the *Without Access* group registering only a marginally lower zero-vehicle share (9.6 percent) than the *With Access* group (11.5 percent), and comparable distributions across one-vehicle and multi-vehicle households as well. The direction of the difference is consistent with the locational context reasoning mentioned above, but the very modest magnitude of the difference is the more notable finding. It suggests that vehicle ownership in the United States has become so nearly universal that locational context, at least as captured by a broad *Without Access/With Access* distinction, is no longer a strong differentiator of car ownership patterns; meaningful gaps in vehicle ownership may now be confined to very niche transit-intensive markets where owning and operating/parking an automobile is onerous.

Table 2. Socio-Demographic Characteristics by Reported Transit Access (%)

<i>Individual-level characteristics</i>			<i>Household-level attributes</i>		
Variable	<i>Without Access</i> (N = 2,388)	<i>With Access</i> (N = 5,885)	Variable	<i>Without Access</i> (N = 2,388)	<i>With Access</i> (N = 5,885)
Gender			Annual household income		
Female	62.8	48.9	Less than \$25,000	24.1	17.0
Male	37.2	51.1	\$25,000 to \$49,999	21.9	19.6
Age category			\$50,000 to \$99,999	27.9	26.1
18 to 24 years	8.2	11.0	\$100,000 to \$149,999	14.8	21.6
25 to 44 years	21.2	34.7	\$150,000 to \$199,999	6.9	10.4
45 to 64 years	32.0	29.8	\$200,000 or more	4.4	5.3
65 years or older	38.6	24.5	Household size		
Employment status			One	22.3	21.0
Full-time	27.4	45.9	Two	42.1	31.0
Part-time	8.5	9.7	Three or more	35.6	48.0
Retired or not employed	64.1	44.4	Housing unit type		
Educational attainment			Single-family	71.4	66.2
High school or less	38.4	29.9	Apartment	14.8	22.8
Some college/technical	36.0	31.2	Other	13.8	11.0
Bachelor's degree(s)	14.2	18.5	Homeownership status		
Graduate degree(s)	11.4	20.4	Own or other	70.7	63.8
Race			Rent	29.3	36.2
Asian or Pacific Islander	8.0	7.8	Presence of children		
Black	11.3	18.0	One or more	21.9	36.1
Other	11.5	13.3	None	78.1	63.9
White	69.2	60.9	Vehicle ownership		
Ethnicity			Zero	9.6	11.5
Hispanic	12.9	21.7	One	45.1	43.6
Non-Hispanic	87.1	78.3	Two or more	45.3	44.9

3.4 Comparison of Attitudes by Transit Access

This section presents a comparison of attitudes toward transportation, travel, the environment, and residential living between the *Without Access* and *With Access* groups. In addition to understanding the socio-economic characteristics that distinguish between the two groups, it is important to consider differences in attitudes, values, and preferences, as these differences shape where people choose to live, how they travel, and how they view different modal options. A deeper understanding of these attitudinal differences can help inform policies and campaigns aimed at fostering more multimodal travel patterns.

Figure 1 compares the attitudes of the *Without Access* and *With Access* groups across a range of statements touching on transportation, travel time use, environmental orientation, congestion, and residential preferences. Unless otherwise noted, the percentages reported in this comparison represent the share of respondents who agree with each statement, computed as the sum of the “strongly agree” and “somewhat agree” response categories.

The comparison is defined as much by where the two groups agree as by where they diverge. The importance of owning a car is essentially universal and virtually indistinguishable between the two groups, with 85.5 percent of those without access agreeing with this statement compared to 84.4 percent of those with access. Preferences for a spacious home even if farther from transit are similarly close, within two points of one another. On these two fronts at least, it appears that both groups place a similar premium on cars and on spacious living arrangements.

Where the groups diverge most is on transit itself and on the kinds of neighborhoods that support it. Under one-third of those without access like the idea of using public transit personally, compared with over one-half of those with access. Enthusiasm for mixed-use neighborhoods, where stores, restaurants, and homes sit close together, also shows a substantive difference of nearly 17 percentage points between the two groups. This suggests that those with transit access are far more likely to self-select into mixed-use neighborhoods. The one item in this cluster where the *Without Access* group actually scores higher is the view that apartment living does not provide enough privacy, which fits with this group’s greater concentration in single-family homes. Perceived unavailability of transit, in other words, seems to be associated with a more tepid interest in transit-supportive living more broadly, rather than just a more modest interest in using transit as a means of travel.

The environmental items are revealing because they separate stated conviction from actual behavior. Commitment to an environmentally friendly lifestyle differs only moderately between the two groups. But the behavioral items tell a different story. Only 24.4 percent of those without access report using less polluting modes of travel as much as possible, and just 19.9 percent try to walk or bicycle for their trips, compared with 44.8 percent and 40.0 percent among those with access. This suggests that people in both groups hold rather similar values regarding the environment and the importance of following an environmentally friendly lifestyle; however, they diverge in actual behavior because of the differences in built environment contexts, situational and personal circumstances, and multimodal option availability.

Attitudes toward congestion tell a similar story, with differences more likely rooted in where people live rather than what they believe. Those without access are considerably less likely to describe congestion as a major problem in their daily travel, less inclined to adjust their schedules around it, and less willing to pay more for a faster trip. This fits naturally with the low-density, more suburban and exurban residential profile of this *Without Access* group. For residents in these settings, the everyday travel problem is less about sitting in traffic and more about distance

and a lack of options, a distinction that matters for the kinds of improvements these residents are likely to value.

Finally, the mobility constraint items reveal interesting patterns of differences. A majority of those without access to transit agree that their situation makes using public transportation hard or nearly impossible, and 70.7 percent say they have no reasonable alternative to their usual way of getting around. Yet 71.8 percent of the Without Access group still describe themselves as satisfied with their transportation options overall. This pattern shows up alongside a more general pattern of lower engagement with the act of traveling itself, as those without access are also less likely to say they enjoy traveling or make good use of time spent traveling. Together, these patterns suggest a group that has adjusted its expectations to fit a more car-reliant environment and lifestyle, coming to treat travel as a necessary task rather than as an experience worth valuing in its own right.

Taken as a whole, the attitudinal comparison is helpful in discerning the values, perceptions, and preferences of those with and without access to transit. They place the same value on car ownership and living space, but those without transit access feel less drawn to transit-supportive ways of living, are largely unbothered by congestion, and appear largely content with a more limited car-oriented transportation context.

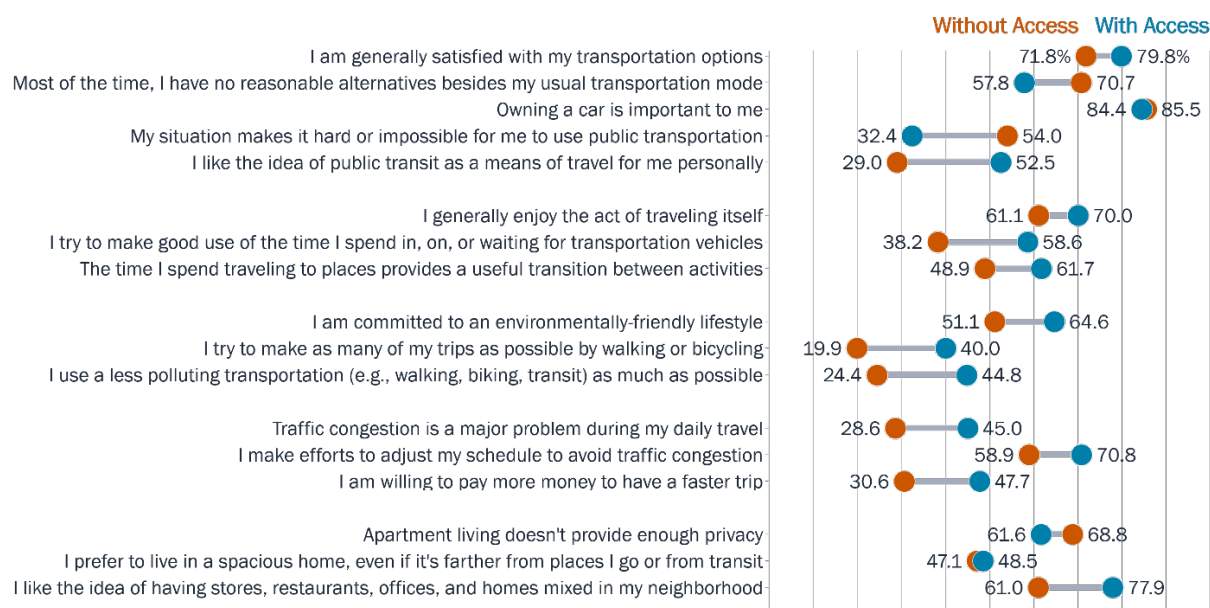


Figure 1. Transportation and Residential Attitudes by Reported Transit Access
(Percent Somewhat or Strongly Agreeing with Each Statement; Without Access = 2,388;
With Access = 5,885)

3.5 Travel Choices and Mode Use Patterns by Transit Access

This section compares how the *Without Access* and *With Access* groups differ in the use of various travel modes, specifically driving alone, riding in a carpool or vanpool (informal or formal), using a ride-hailing service, walking, and bicycling. Comparing mode use across the two groups helps establish the extent to which the absence of transit is offset by greater reliance on other modes, or whether it instead reflects a broader shortage of travel options in these residents' contexts. Figure 2 presents this comparison.

Driving alone looks quite similar across the two groups, and this similarity is worth noting at the outset, since it shows that perceived transit unavailability does not necessarily separate drivers from non-drivers. About 70 percent of both groups drive alone at least once a week, and the shares reporting less frequent solo driving are quite similar as well. It does not appear that the use of the private automobile distinguishes the *Without Access* group from the *With Access* group.

Carpooling and vanpooling show a modest gap favoring the *With Access* group. Fifty-seven percent of those with access ride in a carpool or vanpool at least once a week, compared with 52.1 percent of those without access, and a somewhat larger share of the *Without Access* group, 16.8 percent, reports that carpooling is not available to them at all (versus 9.1 percent among those with access).

The starkest difference in the figure emerges for ride-hailing. More than half of those without access, 57.4 percent, report that a ride-hailing service is not available to them, compared with only 9.7 percent of those with access. Frequent use, at least once a week, is uncommon in both groups but especially rare among those without access, at roughly 2 percent, compared with 11.9 percent among those with access. Considering frequent and infrequent use together, only about 18 percent of the *Without Access* group uses ride-hailing at all, compared with over half of the *With Access* group. This finding is noteworthy since ride-hailing is sometimes proposed as a private-sector substitute for transit in areas where transit service is limited. The results here point in the opposite direction; ride-hailing services tend to be available in the same places where transit operates, rather than filling a void where transit is absent.

This pattern is consistent with the residential context established earlier for the *Without Access* group, one of lower-density suburban and exurban settings where automobile ownership and use already run quite high. Ride-hailing services tend to concentrate in denser settings, where travel demand is high enough to sustain them and residents are more inclined to seek multimodal alternatives to the automobile. In the lower-density settings that characterize the *Without Access* group, demand for ride-hailing is simply less likely to exist. Hence, its limited availability there may reflect market realities as much as any gap in service provision. This suggests that ride-hailing does not fill the void left by the absence of transit, not because providers have overlooked these areas, but because the travel patterns typical of these settings do not generate the demand ride-hailing needs to be economically viable.

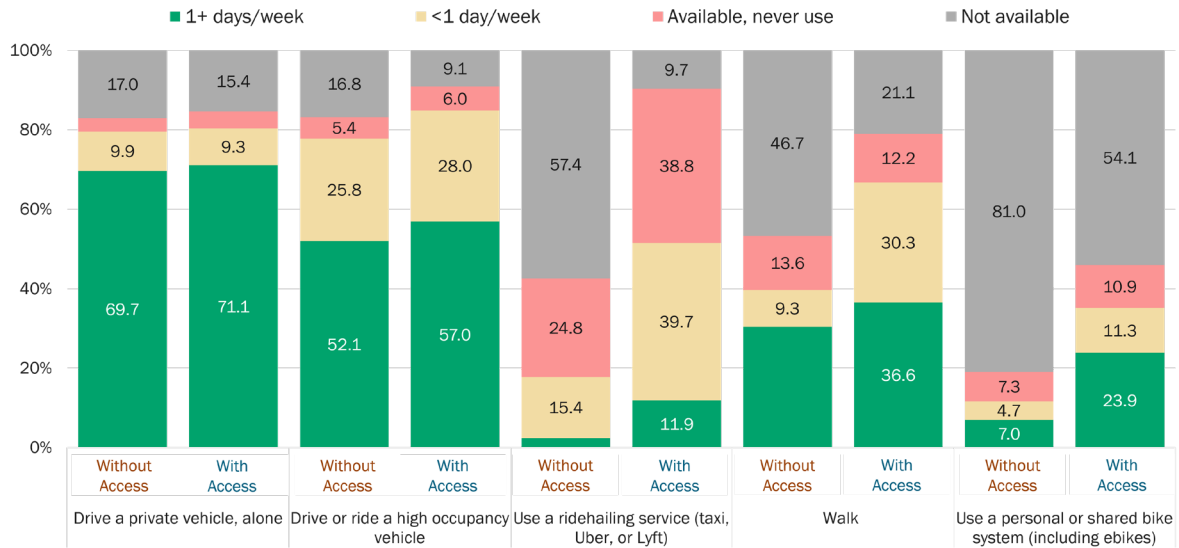


Figure 2. Travel Mode Use Frequency by Reported Transit Access
(Percent of Respondents; Without Access = 2,388; With Access = 5,885)

Walking and bicycling exhibit a broadly similar pattern, though somewhat less pronounced. Those without access walk less frequently, with 30.4 percent walking at least once a week compared with 36.6 percent among those with access. They are considerably more likely to report that walking is simply not a viable option in their area (46.7 percent among the Without Access group versus 21.1 percent in the With Access group). Bicycling shows the widest availability gap of the five modes examined. It is found that 81.0 percent of those without access report that bicycling is not available to them, compared with 54.1 percent of those with access, although actual bicycling frequency remains relatively modest in both groups (but higher among those with transit access, suggesting that a multimodal transit-oriented environment sees more bicycling – likely due to both built environment effects and self-selection effects).

These results point to a broader conclusion. The Without Access group does not compensate for the lack of transit through greater use of the private automobile; driving alone occurs at nearly the same rate in both groups. Rather, every alternative to the automobile, i.e., ride-hailing, walking, bicycling, and to a lesser degree carpooling, becomes considerably less available (and used) once transit itself is unavailable – most likely due to the nature of the built environment context. Perceived transit unavailability is greater in built environments where the private automobile ends up serving as close to the only viable mode choice.

4. ANALYTIC FRAMEWORK

The modeling framework consists of a multivariate ordered-response probit model with ten outcome dimensions. The first dimension is the transit usage frequency outcome, an ordered-response variable spanning five categories, ranging from having transit available but never using it to using it three or more days per week (as listed in Table 1). Respondents who report that transit is not available to them are not assigned a usage frequency, since their response reflects the absence of service rather than a frequency of use. Besides, the differences between those with and without service available have been descriptively examined in the previous section. Therefore, in our analytic framework, we focus on the usage frequency outcome only for the 5,885 (=8,273-2,388)

respondents who report transit being available to them. Of these 5,885 respondents, 3,891 are non-users (transit never used) or low-frequency users (transit used less than once a month). These 3,891 respondents provide information on the nine barrier outcomes, while the other 1,994 higher-frequency respondents contribute only the usage frequency outcome. Because the 3,891 respondents were able to select any combination of the nine barrier reasons, each barrier is modeled as a separate binary outcome rather than as a single multinomial choice. The ten dimensions for these 3,891 respondents are estimated jointly to accommodate two distinct sets of unobserved correlation. The first set contains nine correlations between the usage frequency outcome and each of the nine barriers, and the second contains 36 correlations among the barriers themselves. The full formulation of this joint model is presented in Appendix A. In brief, each of the ten outcomes arises from a latent propensity that is a linear function of exogenous variables and a standard normal error term, and the ten error terms are allowed to be correlated through a general correlation matrix. The model is estimated by maximum likelihood, using the matrix-based analytic approximation of the multivariate normal cumulative distribution function described in Bhat (2018).

5. MODEL ESTIMATION RESULTS

This section presents the model estimation results in detail. The discussion begins with the effects of individual, household, and geographic and built-environment attributes on transit use frequency and the nine self-reported barriers to transit use, organized by variable category. This is followed by a discussion of the correlations among the ten outcomes and an assessment of overall model fit. Throughout the discussion of model estimation results, it is important to keep in mind that the coefficients discussed reflect effects on the underlying propensity, or likelihood, of each outcome rather than a direct effect on the observed ordinal or binary variable itself. The average treatment effects presented in the next section help quantify the magnitude of the effects of different variables on the outcome variables. Detailed model estimation results are shown in Table 3.

Table 3. Model Estimation Results (N=5,885)

Explanatory Variables (base category)	Transit Use Frequency <i>Ordinal (5-level)</i>	Personal Safety Concerns						Comfort / Conditions On-Board		Service Availability	
		Threatening Passengers	Theft Risk	Law Enforcement	Unsafe Walking	Unsafe Waiting	Unsanitary Conditions	Fall Risk	No Service (Org.)	No Service (Dest.)	
											<i>Binary variables (reported, not reported [base])</i>
Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat		
<i>Individual-level characteristics</i>											
Female (not female)	-0.15 -4.88	0.23 5.35	— —	— —	0.28 5.39	0.32 6.79	0.20 4.36	0.17 2.62	— —	-0.11 -2.46	
Age (18–24 years)											
25–44 years	— —	— —	— —	— —	— —	— —	— —	— —	-0.15 -2.55	-0.23 -4.00	
45–64 years	-0.17 -4.81	-0.24 -4.34	-0.34 -5.33	-0.32 -3.56	-0.23 -3.75	-0.23 -3.94	-0.31 -5.57	— —	— —	— —	
65 years or older	-0.69 -13.70	-0.50 -8.86	-0.70 -9.95	-0.67 -3.80	-0.49 -7.46	-0.40 -6.57	-0.57 -9.98	-0.25 -3.02	— —	— —	
Employment status (retired or not employed)											
Full-time	0.36 8.88	— —	— —	0.52 6.33	— —	— —	— —	— —	— —	0.16 3.05	
Part-time	0.28 5.25	— —	— —	— —	— —	— —	— —	— —	— —	0.14 1.78	
Educational attainment (high school or less)											
Some college/technical	— —	0.11 2.63	— —	— —	— —	— —	— —	— —	0.20 3.10	0.17 2.71	
Bachelor's degree(s)	0.17 3.78	— —	— —	— —	— —	— —	— —	— —	0.47 6.36	0.52 7.41	
Graduate degree(s)	0.41 8.07	— —	— —	0.22 2.35	0.32 4.30	0.16 2.49	— —	0.29 2.91	0.67 8.58	0.40 5.12	
Race (White)											
Black	0.08 2.04	— —	— —	— —	— —	— —	— —	— —	-0.28 -3.70	-0.30 -4.19	
Other races	— —	— —	— —	— —	— —	— —	— —	— —	-0.17 -2.19	— —	
Hispanic (not Hispanic)	0.11 2.79	— —	0.23 3.95	— —	— —	— —	— —	— —	— —	— —	
<i>Household-level attributes</i>											
Annual household income (less than \$25,000)											
\$25,000 – \$49,999	-0.22 -4.37	— —	— —	— —	— —	— —	— —	— —	— —	— —	
\$50,000 – \$99,999	-0.30 -5.84	— —	— —	— —	-0.18 -3.09	— —	— —	-0.15 -2.03	— —	— —	
\$100,000 – \$149,999	-0.23 -3.94	— —	-0.09 -1.69	— —	-0.18 -2.49	-0.12 -2.15	0.10 2.34	-0.27 -2.87	— —	— —	
\$150,000 or more	-0.23 -3.94	— —	-0.09 -1.69	— —	-0.26 -2.90	-0.12 -2.15	0.10 2.34	-0.22 -1.92	— —	0.21 3.17	
HH size 2 or more (1)	— —	— —	— —	— —	0.20 3.13	— —	— —	— —	0.12 2.40	— —	
Child present (none)	— —	— —	— —	— —	— —	— —	— —	0.25 3.51	— —	— —	
Housing unit type (other)											
Single-family home	-0.14 -2.81	— —	— —	— —	— —	— —	— —	— —	— —	-0.10 -1.94	
Apartment	0.08 1.67	— —	— —	— —	— —	— —	— —	— —	— —	— —	
Renter (owner or other)	0.09 2.31	— —	-0.11 -2.12	— —	— —	— —	— —	— —	-0.18 -2.97	— —	
Vehicle deficient (Sufficient)	0.58 14.23	— —	— —	— —	-0.13 -1.82	— —	— —	— —	— —	-0.26 -3.24	

Table 3. Model Estimation Results (N=5,885) (Continued)

Explanatory Variables (base category)	Transit Use Frequency Ordinal (5-level)	Personal Safety Concerns					Comfort / Conditions On-Board		Service Availability	
		Threatening Passengers	Theft Risk	Law Enforcement	Unsafe Walking	Unsafe Waiting	Unsanitary Conditions	Fall Risk	No Service (Org.)	No Service (Dest.)
		Binary variables (reported, not reported [base])								
	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat	Coef. t-stat
Geographic and built-environment attributes										
Census division of respondent's residence (New England)										
Middle Atlantic	— —	— —	— —	— —	— —	— —	0.18 2.68	— —	— —	— —
East North Central	— —	0.14 2.09	— —	— —	— —	— —	0.16 2.40	— —	-0.23 -3.21	— —
West North Central	— —	0.20 2.38	— —	— —	— —	0.16 2.02	— —	— —	— —	— —
East South Central	— —	— —	— —	0.25 1.84	— —	— —	— —	— —	— —	— —
West South Central	— —	0.16 2.35	— —	0.19 1.96	— —	0.15 2.56	0.19 2.86	— —	— —	— —
South Atlantic	— —	0.10 1.66	— —	— —	— —	— —	— —	— —	— —	— —
Mountain	— —	0.33 4.06	— —	— —	— —	0.21 2.95	0.23 2.74	— —	— —	— —
Pacific	— —	0.22 3.37	— —	— —	— —	— —	0.19 2.93	0.21 2.66	-0.21 -2.60	— —
Vehicle-ownership rates in respondent's zip code										
No-vehicle homes	1.02 8.19	— —	— —	— —	— —	— —	— —	— —	— —	— —
2+ vehicle homes	— —	— —	— —	— —	— —	— —	— —	— —	0.43 2.34	0.39 2.33
Population density per acre of respondent's zip code (low, < 5 people)										
Medium (5–10 people)	0.16 4.05	0.20 3.96	— —	— —	0.26 4.95	0.26 5.40	0.14 2.94	— —	-0.23 -3.54	-0.16 -3.13
High (>10 people)	0.40 9.10	0.32 6.04	0.20 3.77	0.21 2.65	0.26 4.95	0.26 5.40	0.14 2.94	— —	-0.23 -3.54	-0.16 -3.13
Walkability Index in respondent's zip code (low, ≤ 5.75)										
Medium (>5.75, ≤10.5)	-0.14 -2.40	— —	— —	— —	— —	— —	— —	— —	-0.25 -3.27	— —
High (> 10.5)	-0.14 -2.40	— —	— —	— —	— —	— —	— —	— —	-0.52 -5.10	— —
Thresholds	1 2	0.01 0.07	0.95 15.41	0.86 15.34	1.90 23.29	1.21 14.14	1.07 18.02	0.81 13.45	1.49 19.89	0.77 5.06
	2 3	0.59 7.10	— —	— —	— —	— —	— —	— —	— —	— —
	3 4	1.15 13.76	— —	— —	— —	— —	— —	— —	— —	— —
	4 5	1.70 20.15	— —	— —	— —	— —	— —	— —	— —	— —
Correlations (only top diagonal shown)										
Usage	1.00	— —	— —	— —	— —	— —	— —	— —	— —	— —
Threatening Passengers	—	1.00	0.66 26.77	0.33 6.70	0.56 21.47	0.68 31.31	0.71 35.48	0.41 11.68	-0.06 -2.08	-0.05 -1.82
Theft Risk	—	—	1.00	0.40 8.27	0.53 17.62	0.59 21.77	0.56 20.29	0.43 11.46	-0.09 -2.35	-0.09 -2.34
Law Enforcement	—	—	—	1.00	0.25 4.93	0.41 9.10	0.33 6.74	0.41 8.24	0.16 3.30	-0.11 -2.12
Unsafe Walking	—	—	—	—	1.00	0.77 39.24	0.50 17.82	0.46 12.14	— —	— —
Unsafe Waiting	—	—	—	—	—	1.00	0.61 25.26	0.43 11.69	— —	— —
Unsanitary Conditions	—	—	—	—	—	—	1.00	0.38 10.06	— —	— —
Fall Risk	—	—	—	—	—	—	—	1.00	— —	— —
No Service at Origin	—	—	—	—	—	—	—	—	1.00	0.41 14.53
No Service at Destination	—	—	—	—	—	—	—	—	—	1.00

Note. Coef. = coefficient; t-stat = t-statistic. A "—" indicates that the variable was not statistically significant at the 90% confidence level and was not retained.

5.1 Effects of Individual-level Demographic Characteristics

Women show a lower underlying propensity for frequent transit use than men, and this lower usage comes together with a distinctly higher propensity to report most of the on-system barriers. Women are more likely than men to cite the threatening behavior of other passengers, feeling unsafe walking to or from stops, feeling unsafe while waiting at stops, unsanitary conditions, and fear of falling. Two barriers stand out as exceptions with risk of theft and concerns about law enforcement showing no significant gender difference. This pattern suggests that it is the fear of harassment and the exposure of walk-access routes and waiting areas, rather than property crime or encounters with enforcement, that most distinctly discourages women from using transit. This is consistent with prior evidence that personal safety concerns weigh more heavily than pro-environmental attitudes in shaping women's transit use, marking safety as a central factor behind lower ridership among women (Hsu et al., 2019). At the same time, women are less likely than men to report that transit fails to reach their destinations, which suggests that the gender gap in transit use has more to do with the safety and quality of the travel experience than with where transit service operates.

The underlying propensity of transit use generally declines with age, with propensity of usage dropping significantly for the 45-to-64 and 65-or-older age groups. What is notable is that these older age groups are also less likely to report nearly every barrier, including personal safety concerns and unsanitary conditions. Interestingly, those 65 and older exhibit a lower propensity for fear of falling, a hazard to which older travelers are generally more vulnerable (Silvano and Ohlin, 2019). Rather than suggesting that older travelers face fewer real obstacles, this pattern more likely reflects a lifestyle that has moved away from transit altogether (Yang, 2025). Older individuals have long since built their daily travel around the private vehicle and may not view transit conditions as barriers relevant to their own lives. On the other hand, younger adults, who use transit the most, are also the ones most exposed to its downsides and therefore more likely to identify barriers to usage. The 25-to-44 age group stands out in a different way. This group shows no broad pattern across the safety and comfort barriers, but it is less likely to report that transit is unavailable near home or unavailable to reach their destinations. This reflects the more transit-served locations where early- and mid-career adults tend to live (Shin and Tilahun, 2022).

Both full-time and part-time workers exhibit a higher propensity for transit use than those who are retired or not employed, in keeping with the regular, fixed-destination travel that characterizes commuting. At the same time, both groups are more likely to report that transit does not reach their destinations, which suggests that even among those most inclined to use transit regularly, a mismatch between transit networks and job locations remains a key concern (Maharjan et al., 2024). Full-time workers additionally show a higher propensity to cite concerns about interactions with law enforcement or security officers, which may reflect greater exposure to enforcement presence during peak commuting periods, though this interpretation should be treated with some caution given the demographic heterogeneity of the full-time workforce.

The underlying propensity to use transit rises with educational attainment. Compared with those with a high school education or less, propensity for transit use is not significantly different for respondents with some college, but it is higher for those with a bachelor's degree and still higher for those with a graduate degree. Higher education also comes with a greater propensity to report barriers. The propensity to report two service availability barriers, no service near home and no service to destinations, is elevated at every education level relative to high school or less, which may reflect both the more suburban locations where highly educated professionals often live and a greater underlying interest in transit that makes its absence register as a real barrier rather than simply a non-issue. Graduate degree holders, specifically, are also more prone to report higher

concern about law enforcement interactions, unsafe walking and waiting environments, and fear of falling, concerns that do not show up for other education levels. Rather than pointing to objectively worse transit conditions for this group, this more likely reflects higher expectations and a more critical eye toward the transit experience among riders who have more resources and more high-end modal alternatives at their disposal (Asgharpour et al., 2025).

Race and ethnicity show a more targeted set of effects. Black respondents exhibit a greater propensity to use transit more often than White respondents and are less likely to report that transit is unavailable, whether near home or to reach their destinations – a pattern consistent with Black populations being more concentrated in the urban areas where transit service tends to exist. Notably, after accounting for other demographic and built environment factors, no significant racial differences show up on any of the personal safety or comfort barriers. This suggests that racial differences in perceived barriers that often appear in simple descriptive comparisons likely reflect differences in income, residential location, and exposure to transit rather than race itself. Hispanic respondents likewise depict a propensity to use transit more often than non-Hispanic respondents, but stand out in one specific respect – a higher propensity to cite risk of theft as a barrier, a pattern that does not extend to any of the other barriers to transit use.

5.2 Effects of Household-level Attributes

Household income shows a rather uniform influence on propensity for transit use. Each successively higher income bracket is associated with about the same level of lower propensity to use transit relative to the lowest income group earning less than \$25,000 a year. The two highest income brackets, \$100,000-149,999 and \$150,000 or more, show a very similar pattern of effects across several of the barrier outcomes – suggesting that once household income climbs above the \$100,000 threshold, further increases in income do not meaningfully change how these barriers are perceived. Where the two highest income brackets do differ is on the destination-side service availability barrier. Only the very highest income households earning \$150,000 or more show a distinct, elevated propensity to report that transit does not reach their destinations. Higher income households are also somewhat less likely to cite risk of theft, feeling unsafe walking to or from stops, feeling unsafe while waiting at stops, and fear of falling, a pattern that likely reflects the premium quality and nature of transit modes serving locales inhabited by high income residents. The exception is unsanitary conditions, which the two highest income brackets are somewhat more likely to report, consistent with heightened expectations for cleanliness among higher income travelers.

Household size and the presence of children have a rather modest impact on propensity to report transit use barriers. Individuals in households of two or more people show a higher propensity to report both feeling unsafe walking to or from transit stops and transit not being available near their homes. Both effects are consistent with the presence of other household members shaping how the trip is evaluated: walk access is judged not only for oneself but also for companions who travel together or are escorted to and from stops, and a single nearby stop is less likely to serve several people with different destinations and schedules. Households with children present, meanwhile, show a distinctly higher propensity to cite fear of falling as a barrier, a pattern that likely reflects heightened caution when traveling with children on transit vehicles (rather than any greater personal risk to the respondent per se).

Housing type and homeownership status point to differences in suburban versus urban contexts. Respondents living in single-family homes show a lower propensity for frequent transit use and a lower propensity to report that transit fails to reach their destinations, relative to those in

other housing types. In contrast, apartment residents show a higher propensity for frequent transit use, consistent with apartments being more common in denser, better-served locations. Renters are likely to use transit somewhat more frequently than homeowners, and are less likely to report risk of theft or the absence of transit service near their homes as barriers – findings that are generally consistent with the notion that renters tend to be located in denser locations better served by transit.

A very significant effect within the household-level attributes is depicted by vehicle deficiency, defined as households with no vehicle or with fewer vehicles than drivers; all remaining households, with at least as many vehicles as drivers, are considered vehicle-sufficient and serve as the base category. Vehicle-deficient households show a substantially higher propensity to use transit frequently, underscoring that the lack of access to an automobile may be among the strongest drivers of transit use. These same households are somewhat less likely to cite feeling unsafe walking to or from transit stops and less likely to report that transit fails to reach their destinations, a pattern consistent with vehicle-deficient households more often being located in, or having sorted themselves into, areas where transit is a viable and reasonably well-connected option (Toy et al., 2025).

5.3 Effects of Geographic Context and Built Environment

Model estimation results show that census division has no significant influence on the propensity to use transit. There are, however, significant differences among census divisions in the propensity to report barriers to transit use. This indicates that macro-level regional differences shape how transit is experienced much more than they shape the underlying inclination to use transit.

Regional differences are concentrated mainly in the personal safety and comfort barriers. Compared to New England, respondents in most other census divisions show a higher propensity to report threatening behavior from other passengers (as a barrier), with the effect strongest in the Mountain division. The Middle Atlantic, East North Central, West North Central, West South Central, Mountain, and Pacific divisions all show a higher propensity to report unsafe waiting conditions or unsanitary conditions. Concerns about law enforcement interactions are significant only in the East South Central and West South Central divisions, and fear of falling is significant only in the Pacific division. It is likely that New England's older and more established transit systems may set a relatively favorable reference point for the quality and safety of the transit experience – one that other regions do not fully match. The East North Central and Pacific divisions also show a lower propensity to report that transit is unavailable near home, a result consistent with the extensive and long-standing transit networks these regions have built over time.

The share of no-vehicle homes in a respondent's zip code proves to be a strong indicator of transit use frequency, but shows no significant influence on the propensity to report barriers to transit use. This variable may be reflecting the nature of transit-oriented places, where daily travel is organized around transit as much as it is around the private automobile. Zip codes with a high share of two-or-more-vehicle households show the opposite pattern, with residents of these areas showing a higher propensity to report that transit is unavailable both near home and near their destinations, a result consistent with these being more car-oriented areas with relatively low transit service.

Population density (number of people per acre) of the respondents' zip code shows a dual effect on transit use and barriers. Propensity for frequent transit use rises with density, and the propensity to report the two service availability barriers declines, confirming that denser areas are better served by transit. At the same time, most of the personal safety and comfort barriers also exhibit a higher propensity of being reported with increasing density. Threatening passenger

behavior, unsafe walking, unsafe waiting, and unsanitary conditions all show a higher propensity in denser areas, while theft and law enforcement concerns are significant at the highest density level. This pattern suggests that density improves transit availability while simultaneously increasing exposure to crowding, disorder, poor cleanliness, and enforcement presence that tend to accompany higher ridership.

The walkability index is computed in the EPA Smart Location Database as a composite score summarizing the extent to which the built environment supports walking, formed as a weighted sum of the ranked values of employment mix, land-use mix, intersection density, and proximity to the nearest transit stop. It ranges in value from 1 (least walkable) to 20 (most walkable), which the EPA groups into four tiers, namely least walkable (1.0–5.75), below average (5.76–10.50), above average (10.51–15.25), and most walkable (15.26–20.0) (Chapman et al., 2021), with the top two tiers combined into the High category here. The results from Table 3 run counter to the expectations of prior research, which has generally found that walkable environments support transit use (Cervero, 2001; Ryan and Frank, 2009; Ewing and Cervero, 2010). After controlling for density and other covariates, residents of more walkable zip codes show a lower propensity to use transit than residents of the least walkable areas, even though they also show a lower propensity to report that transit is unavailable near home. This combination points toward mode substitution as the likely explanation, since short trips that might otherwise be made by transit can instead be made on foot or emerging micromobility modes in these walkable settings.

5.4 Correlations Among Endogenous Outcomes

The correlation parameters among the unobserved components of the ten outcomes are reported in the final section of Table 3. Many of these correlations are statistically significant and retained in the model. The correlation matrix is quite informative as it reveals how the barriers group together and how they relate to usage after accounting for observed characteristics.

The correlation between usage frequency and every one of the nine barriers is statistically insignificant. This is a notable result. It indicates that the relationship between frequency of transit use and perceived barriers largely operates through the observed sociodemographic and built environment characteristics already included in the model, rather than through any additional shared unobserved factors. Usage and barriers are linked largely based on who people are and where they live, and not through some common underlying disposition that the model has not captured.

The nine barriers separate into two largely distinct groups. The five Personal Safety items and the two Comfort and Conditions items are strongly and positively correlated with one another, pointing to a general underlying sensitivity in which a respondent who perceives one on-system barrier tends to perceive the others as well. The two Service Availability items are also strongly correlated with each other at 0.41 ($t = 14.53$), but they show only weak, and mostly negative, correlations with the experiential barriers described above. Service availability, in other words, appears to represent a separate dimension of concern from the safety and comfort barriers. This separation makes intuitive sense. Perceiving that transit is physically unavailable is a fundamentally different concern than perceiving the on-system experience as unsafe or unpleasant. A respondent without transit service nearby has little basis for forming opinions about crowding, theft, or conditions on a system they do not see or use, which is consistent with the mildly negative correlations observed between these two barrier groups.

Within the experience-related barriers, the Personal Safety items form the tightest cluster. Feeling unsafe walking to a stop and feeling unsafe waiting at a stop show the strongest correlation of any pair in the table at 0.77 ($t = 39.24$). This is followed closely by strong correlations among threatening passenger behavior, unsafe waiting, and unsanitary conditions. The Comfort and Conditions items connect naturally to this cluster in addition to forming a separate group of their own, suggesting that riders perceive safety concerns and discomfort as part of a unified broader negative experience rather than as distinct problems.

Two additional patterns are worth noting in the correlation matrix. Concerns about law enforcement interactions are positively correlated with the other safety and comfort items, but more moderately than the correlations among those items themselves. This suggests that concern about law enforcement interactions represents a somewhat distinct dimension of the transit experience rather than a core part of the general safety and comfort-conditions clusters. Law enforcement concern is also the only barrier that correlates positively with reporting no service near home.

5.5 Model Fit

The proposed joint model, which allows the ten outcomes to be correlated with one another, is compared against an independent model that estimates the same ten outcomes separately, without accounting for the correlation terms discussed above.

The proposed model achieves a log-likelihood of -19,998.88 at convergence, compared to -21,656.33 for the independent model, a clear improvement in fit. This advantage holds up against both a constants-only benchmark and an equal-probability benchmark. The adjusted likelihood ratio index relative to the constants-only model is 0.136 for the proposed model, compared to 0.066 for the independent model, and the adjusted likelihood ratio index relative to the equal-probability model is 0.403 for the proposed model, compared to 0.355 for the independent model. Both comparisons favor the proposed joint model.

The proposed model also achieves a lower Bayesian Information Criterion, at 41,299.78, compared to 44,371.64 for the independent model. This result is notable because the Bayesian Information Criterion penalizes models for additional parameters, and the proposed model includes 150 parameters compared to 122 parameters for the independent model. Even after accounting for this larger number of parameters, the proposed model is found to offer a superior statistical fit.

A formal likelihood ratio test comparing the two models yields a test statistic of 3,314.9, evaluated against a chi-square distribution with 28 degrees of freedom, corresponding to the difference in the number of parameters between the two models. This test statistic is significant at any conventional confidence level, confirming that modeling the ten outcomes jointly, with their underlying correlations, fits the data significantly better than treating them as independent uncorrelated outcomes. Taken together, these fit statistics consistently favor the proposed joint model over the independent specification, and they support the use of the multivariate framework adopted in this study.

6. AVERAGE TREATMENT EFFECTS

Table 4 reports average treatment effects (ATEs), expressed as the percentage change in the probability of each outcome when an explanatory variable shifts from its base category to the indicated level, across the 5,885-respondent analysis sample. For a detailed explanation of average treatment effects and how they are computed, please see Hwang et al. (2025). Because the ten

outcomes are estimated jointly, these effects capture the total impact of each shift, including effects transmitted indirectly through the correlated outcomes, which is something the coefficients alone cannot capture. For variables with more than two categories, the effect of each category is reported relative to its base category. A positive value means more individuals report the outcome, and a negative value means fewer do. The effects across different outcomes are not mutually exclusive, and they do not add up in any straightforward way.

Most of the treatment effects are rather modest in size, though a few stand out as quite large. Taken together, they place the coefficient results discussed earlier on a scale that is easier to interpret. The largest positive effects on usage frequency come from vehicle deficiency, high residential density, graduate education, and full-time employment. The largest negative effect on usage comes from advanced age.

Age produces the broadest set of effects on barrier perceptions in the entire table. Shifting from the youngest age group to the oldest reduces the incidence of nearly every barrier by a substantial margin, with the largest reductions occurring for concerns about law enforcement, theft, and unsafe walking, alongside the largest reduction in usage found anywhere in the table. This result quantifies and further elucidates the transit disengagement pattern discussed earlier. Older individuals report far fewer barriers not because transit conditions are better for them, but because many have largely stopped using transit altogether (and hence do not perceive barriers as strongly as groups who experience transit firsthand).

Shifting from male to female raises the incidence of the on-system safety and comfort barriers, most strongly for feeling unsafe while waiting and feeling unsafe while walking. This same shift lowers both transit usage and the likelihood of reporting that transit fails to reach one's destination. The effect of gender is concentrated in the quality and safety of the transit experience rather than whether service exists at all.

Rising household income produces a fairly steady pattern of reductions, lowering usage as well as the incidence of theft, unsafe walking, unsafe waiting, and fear of falling. This pattern reverses at the top of the income distribution. The two highest income groups show a rise in the incidence of reporting unsanitary conditions, giving the heightened-expectations explanation offered earlier greater credence. The highest income group additionally shows a rise in the incidence of reporting that transit fails to reach destinations, consistent with high-income households living in areas that are only nominally served by transit.

Educational attainment produces some of the largest barrier increases in the table, although the two service availability barriers peak at different education levels. Graduate degree holders show the largest increase in reporting no service near home, while bachelor's degree holders show the largest increase in reporting that transit fails to reach their destinations – with graduate degree holders also elevated on this second barrier. Combined with a strong propensity for increased usage and moderate increases across several of the experiential barriers, this pattern describes a group that is more inclined to use transit and, for that reason, presumably more attuned to where transit falls short.

Among other attributes, vehicle deficiency produces the largest single effect on usage found anywhere in the table. High population density raises the incidence of every on-system barrier except fear of falling. At the same time, it lowers both service availability concerns. This exemplifies the density tradeoff. Density comes with improved transit availability, but also comes at the cost of a less pleasant user experience. Greater walkability, by contrast, modestly lowers usage while also reducing the perception that service at the origin end is lacking, with this second effect even larger at the highest walkability level.

Table 4. Average Treatment Effects (ATEs) of Exogenous Variables

Variable (Base)	Treatment	Transit Use Frequency	Personal Safety Concerns					Comfort / Conditions On-Board		Service Availability	
			Threatening Passengers	Theft Risk	Law Enforcement	Unsafe Walking	Unsafe Waiting	Unsanitary Conditions	Fall Risk	No Service (Org.)	No Service (Dest.)
Individual-level demographic characteristics											
Gender (male)	Female	-20.73	33.38	—	—	49.42	55.18	27.20	35.72	—	-13.27
Age (18–24 years)	25 to 44	—	—	—	—	—	—	—	—	-17.85	-25.57
	45 to 64	-23.14	-25.13	-39.27	-45.88	-28.09	-26.71	-31.18	—	—	—
	65 or older	-69.44	-48.12	-68.38	-74.50	-52.35	-42.94	-52.28	-37.06	—	—
Employment status (retired or not employed)	Full-time	77.74	—	—	176.70	—	—	—	—	—	23.28
	Part-time	55.82	—	—	—	—	—	—	—	—	19.60
Educational attainment (high school or less)	Some college/technical	—	13.68	—	—	—	—	—	—	35.00	26.98
	Bachelor's degree(s)	31.03	—	—	—	—	—	—	—	92.13	95.88
	Graduate degree(s)	86.18	—	—	50.27	54.56	24.27	—	65.28	141.43	71.80
Race (White)	Black	13.12	—	—	—	—	—	—	—	-31.87	-33.36
	Other races	—	—	—	—	—	—	—	—	-19.86	—
Ethnicity (not Hispanic)	Hispanic	17.45	—	38.61	—	—	—	—	—	—	—
Household-level attributes											
Annual income (less than \$25,000)	\$25,000 – \$49,999	-27.35	—	—	—	—	—	—	—	—	—
	\$50,000 – \$99,999	-36.34	—	—	—	-22.42	—	—	-23.24	—	—
	\$100,000 – \$149,999	-29.05	—	-12.56	—	-21.67	-14.67	12.83	-37.95	—	—
	\$150,000 or more	-29.05	—	-12.56	—	-30.62	-14.67	12.83	-31.92	—	28.69
Household size (one person)	Two or more	—	—	—	—	34.74	—	—	—	17.02	—
Presence of children (none)	One or more	—	—	—	—	—	—	—	56.83	—	—
Housing unit type (other)	Single-family	-19.50	—	—	—	—	—	—	—	—	-11.70
	Apartment	12.75	—	—	—	—	—	—	—	—	—
Ownership status (own or other)	Rent	15.10	—	-15.36	—	—	—	—	—	-20.83	—
Vehicle sufficiency (sufficient)	Deficient	135.98	—	—	—	-17.65	—	—	—	—	-29.89
Residential built environment characteristics of respondent zip code											
No-vehicle homes (25 th Percentile)	75 th Percentile	13.89	—	—	—	—	—	—	—	—	—
2+ vehicle homes (25 th Percentile)	75 th Percentile	—	—	—	—	—	—	—	—	13.50	11.78
Population density (low, <5 people per acre)	Medium (5-10 people)	32.27	29.04	—	—	45.81	42.85	18.80	—	-26.36	-17.89
	High (>10 people)	92.38	49.66	34.34	47.53	45.81	42.85	18.80	—	-26.36	-17.89
Walkability Index (low, ≤ 5.75)	Medium (>5.75, ≤10.5)	-19.05	—	—	—	—	—	—	—	-25.77	—
	High (> 10.5)	-19.05	—	—	—	—	—	—	—	-48.35	—

Overall, these treatment effects provide quantitative insights above and beyond what may be inferred from model estimation results. Age, employment, and vehicle access stand out as the strongest levers on transit usage, while income, education, and the built environment shape a more varied set of barriers that together describe distinct populations, and distinct sets of concerns, that transit agencies and planners may need to address in customized ways. For example, a low-income, vehicle-deficient rider's use of transit hinges chiefly on whether service exists nearby, with few complaints about the on-system experience, while a higher-income, highly educated traveler is the most likely to report that transit does not reach the desired destinations and to hold the system to higher standards of cleanliness and comfort where service does exist.

7. DISCUSSION AND CONCLUSIONS

This paper aims to understand why non- and low-frequency transit users do not use transit. The study utilized data from the second wave of the Transportation Heartbeat of America survey and involved the estimation of a multivariate ordered probit model that jointly estimates transit usage frequency alongside nine self-reported barriers spanning personal safety, comfort and conditions, and service availability. Because the model includes a host of sociodemographic and built environment predictors, the study findings extend beyond the barrier-reporting subsample to the broader population, offering transit agencies and planners insights on those who are likely to face different types of barriers to transit usage.

The results point to a clear structural finding that should guide how agencies think about transit improvement efforts. The nine barriers separate into two internally cohesive but largely independent groups. One group covers the on-system experience including personal safety and comfort and conditions. These barriers are found to be strongly correlated with one another, and so a rider who perceives one tends to perceive several of the barriers within this grouping. The other group covers service availability, denoting whether transit reaches a rider's home or destination at all. These two groups are only loosely related to each other, and improving one is unlikely to move the other in any appreciable way. This means transit agencies are, in effect, working with two separate levers. Making the on-system experience safer and more pleasant will do little to address riders who lack service altogether, and expanding service will do little to reassure potential riders who perceive transit as unsafe or uncomfortable. Because the on-system barriers cluster so tightly together, packaged improvements that address safety and cleanliness at the same time are likely to work better than addressing each concern in isolation.

The specific barriers that hold different groups back also differ sharply, and this has direct implications for how interventions should be designed. Women report elevated concern across the on-system safety and comfort barriers rather than service coverage gaps, pointing to investments in lighting, staffing, and the walking and waiting environment around stops as the more effective lever for this group. Older adults show the largest usage decline of any group in the model – yet they report the fewest barriers – a pattern that reflects disengagement rather than genuinely better conditions. Removing barriers alone is unlikely to bring this group back, since they no longer interact with the system enough to name what troubles it. Reaching them would likely call for proactive outreach, travel training, and awareness programs delivered through channels older adults already trust – framed around independence and continued mobility rather than around fixing problems they do not report experiencing. Employed and highly educated travelers, by contrast, use transit more and expect more from it; yet they, along with the highest-income households, are the ones most likely to say transit cannot get them where they need to go. This suggests a recoverable segment of ridership among suburban professionals and commuters.

Further investment in frequency, reliability, and direct connections to employment centers could plausibly draw these population segments toward transit. Hispanic travelers stand out for an elevated concern about theft that persists even after accounting for other characteristics, pointing to a more targeted role for visible security measures and community-based safety messaging in these communities.

An encouraging pattern in the results concerns equity. After accounting for income, residential location, and exposure to transit, racial and ethnic differences in safety and comfort barriers largely disappear. This indicates that the disparities visible in simple descriptive comparisons are largely attributable to circumstances, i.e., where people live and how much they use transit, rather than race itself. The practical implication is that equity-focused strategies may be best delivered through place-based and income-based instruments, such as protecting service in transit-reliant urban cores and offering income-qualified fare programs, rather than through interventions targeted narrowly by race or ethnicity.

The built environment plays an important role with results pointing toward two distinct kinds of intervention. The share of no-vehicle homes in a neighborhood is a strong predictor of transit usage, but carries no association with any barrier at all. This makes it a clean and reliable indicator of where transit investment will do the most good. Population density tells a more complicated story. Denser areas see higher transit usage and fewer service availability concerns, confirming that density delivers service; but they also see a rise in nearly every on-system barrier, since denser areas put more riders on more heavily used systems and expose them to more crowding, unsanitary conditions, and disorder in the process. Managing this trade-off means agencies should scale management of conditions, cleaning, safety staffing, and crowding relief, to ridership levels rather than treating it as a fixed cost. Walkability, meanwhile, appears to substitute for transit on short trips rather than complement it, suggesting that transit investment in highly walkable areas should focus on regional connectivity for longer trips rather than on short-hop coverage that walking and micromobility already serves well.

Two further points are worth emphasizing for how agencies act on these findings. First, because usage and barrier perceptions are linked almost entirely through observed demographic and built environment characteristics rather than through any hidden shared covariates, agencies can identify the populations most likely to face each barrier directly from census and location data, without the need for specialized attitudinal research. This makes many of the targeted interventions discussed above immediately actionable. Second, reported satisfaction should not be mistaken for an absence of unmet need. A large majority of the Without Access group report no reasonable alternative to their usual way of getting around, yet a similarly large majority describe themselves as satisfied with their transportation options overall, a pattern consistent with individuals adjusting their expectations to fit a car-reliant environment. Investment decisions grounded in satisfaction surveys risk systematically favoring the status quo, and should additionally consider objective accessibility and availability measures.

A caveat on the practical scope of this paper is warranted. Transit service is planned and delivered at aggregate scales. Routes traverse corridors serving diverse travelers, and Title VI requirements direct agencies to distribute service and amenities equitably across their service areas (FTA, 2012), leaving little room to customize service for narrow market segments. The individual-level modeling pursued in this paper is consistent with, rather than in tension with, that reality. Estimating behavioral relationships at the individual level avoids the biases that arise when heterogeneous travelers are pooled, and the ATEs reported earlier translate those estimates into the population-scale terms in which agencies plan. Indeed, the finding that usage and barriers are

linked only through observable characteristics implies that agencies can identify where barrier-removal investments will yield the greatest response using census and location data alone, which is precisely the aggregate, geography-based targeting that agencies already practice. Moreover, the levers implied by these findings fit within these constraints. Improvements provided uniformly across a system still disproportionately relieve the groups that report the corresponding barriers the most, other measures can legitimately be tailored to specific groups, and individual-level understanding becomes directly actionable as demand-responsive services expand.

Overall, these findings point toward a potential set of priorities for transit agencies and planners. Mitigating on-system barriers through better lighting, visible guardianship, cleanliness, and safer vehicle operation will help retain and attract riders who already have access but feel unsafe or uncomfortable using it. Expanding and better targeting service availability, particularly toward job access and the neighborhoods with the highest shares of no-vehicle homes, will help reach travelers for whom transit would be an appealing option. Shaping the built environment in transit-supportive ways, and recognizing that density brings both more riders and more exposure, will help ensure that growth in usage does not come at the cost of a worse experience for riders. Raising awareness through outreach tailored to disengaged groups, particularly older adults and residents of low-density areas who may not be aware of services that exist or how to use them, will help close the gap between who could use transit and who currently does.

This study has several limitations that point toward useful directions for future research. The barriers examined here are based on self-reported perceptions rather than objective measures of safety, service, or conditions. Combining subjective and objective measures may help in further informing the design of interventions and policies that enhance transit futures. The data also come from a single cross-sectional survey wave, and longitudinal or panel data would show more directly how barriers and usage evolve in concert over time, and whether relieving a given barrier brings about a shift in ridership propensity. The model was also deliberately estimated using only sociodemographic and built environment predictors, excluding attitudes and residential self-selection, and future work could incorporate these factors within a framework formulated to account for the resulting complex endogeneity. Finally, this study utilizes data derived from a national sample, whereas transit usage patterns and interventions tend to be more localized and context specific. Conducting targeted surveys of this nature within metropolitan areas may help better inform transit policy and investments in local contexts.

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DISCLOSURE STATEMENT

The authors report there are no competing interests to declare.

DECLARATION OF GENERATIVE AI USE

Artificial intelligence tools – ChatGPT and Claude – were used to support the preparation of this manuscript, assisting with formatting content and refining language. All AI-assisted output was critically reviewed, revised, and validated by the authors. The study design, analysis, interpretation of results, and conclusions reflect the authors’ academic and professional judgment. AI tools

improved efficiency and communication but did not substitute for engineering judgment, technical review, or responsibility for the final content. The authors are solely responsible for all content, including any errors or omissions.

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APPENDIX A: METHODOLOGICAL FORMULATION

The presentation below develops the likelihood contribution for a single respondent, and the index for the individual is suppressed throughout for readability. Also, as noted in Section 4, the specific barrier outcomes are only available for the non- and low-frequency users. Individuals who are higher-frequency users contribute only to the first ordinal outcome, and the multivariate ordered-response probit model described below collapses to a single univariate ordered probit model. Thus, we describe the formulation for an individual with a full set of ten ordinal outcomes, and the system is simply marginalized to the univariate level for these higher-frequency transit users.

Label the ordered outcomes using the index i ($i = 1, 2, \dots, I$, with $I = 10$), and let the index for the ordered levels for each outcome be k_i ($k_i = 1, 2, \dots, K_i$) where K_i is the number of ordered levels of outcome i . The first outcome is transit usage frequency, for which $K_1 = 5$, and the remaining nine outcomes are the perceived barriers to public transit use, each of which is binary so that $K_2 = K_3 = \dots = K_{10} = 2$. Each outcome i arises from a latent propensity y_i^* that is linear in a set of covariates and is mapped to the observed level through an outcome-specific vector of thresholds:

$$y_i^* = \beta_i' \mathbf{x} + \varepsilon_i, \quad y_i = k_i \text{ if } \theta_i^{k_i-1} < y_i^* < \theta_i^{k_i} \quad (\text{A.1})$$

where $\mathbf{x}$ is an $H \times 1$ vector of exogenous variables (without a constant) and β_i is the corresponding $H \times 1$ vector of parameters carrying the effects of those variables on outcome i . Each latent propensity y_i^* is translated into the observed ordinal level y_i using a series of thresholds. The thresholds must be strictly increasing, with $\theta_i^0 = -\infty$ and $\theta_i^{K_i} = +\infty$, and the thresholds to be estimated may be stacked for each outcome into the vector $\theta_i = (\theta_i^1, \theta_i^2, \dots, \theta_i^{K_i-1})'$. The usage-frequency outcome therefore has four finite cut-points that partition its latent propensity into five ordered levels, while each binary barrier outcome has a single finite threshold. The random error terms ε_i in Equation (A.1) are assumed to be standard normally distributed and independent and identically distributed across individuals. The random error terms may be stacked into the vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_I)'$ which is assumed to follow a multivariate normal distribution with an $I \times 1$ mean vector of zeros $\mathbf{0}_I$ and an $I \times I$ correlation matrix $\boldsymbol{\Sigma}$. The diagonal elements of $\boldsymbol{\Sigma}$ are normalized to unity for identification, and its off-diagonal elements ρ_{ij} capture the error correlations among the latent propensities for each pair of endogenous outcomes i and j . Thus, this general correlation matrix accommodates the shared unobserved factors that tie transit usage and the individual barriers together. Correlations that are not statistically significant are fixed to zero and dropped from $\boldsymbol{\Sigma}$.

To write the system compactly in matrix form, stack the coefficient vectors for each outcome into the $I \times H$ matrix $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_I)'$, and stack the outcome-specific threshold vectors into a single vector $\boldsymbol{\theta} = (\theta_1', \theta_2', \dots, \theta_I')'$. Next, if the respondent under consideration selects level m_i , then the set of upper thresholds $\theta_i^{m_i}$ and the set of lower thresholds $\theta_i^{m_i-1}$ for the individual may be stacked into the $I \times 1$ vectors $\boldsymbol{\theta}_{low}$ and $\boldsymbol{\theta}_{high}$. Finally, stacking the latent propensities into the $I \times 1$ vector $\mathbf{y}^* = (y_1^*, y_2^*, \dots, y_I^*)'$ allows us to write the entire system in matrix form as:

$$\mathbf{y}^* = \boldsymbol{\beta}'\mathbf{x} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{high}, \quad \text{where} \quad \mathbf{y}^* \sim MVN_I(\boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma}) \quad (\text{A.2})$$

here, $MVN_I(\boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma})$ denotes the I -dimensional multivariate normal distribution with mean $\boldsymbol{\beta}'\mathbf{x}$ and correlation matrix $\boldsymbol{\Sigma}$. Again, for respondents who do not contribute all ten outcomes (the higher-frequency users), this collapses to a single univariate ordered-response probit formulation. The collection of parameters to be estimated may then be written as $\boldsymbol{\delta} = \left([\text{Vech}(\boldsymbol{\beta})]', \boldsymbol{\theta}', [\text{Vechup}(\boldsymbol{\Sigma})]' \right)'$, where the operator $\text{Vech}(\cdot)$ row-vectorizes the non-zero elements of its matrix or vector argument and $\text{Vechup}(\cdot)$ row-vectorizes the strictly upper-triangular elements of a square matrix. The likelihood contribution of a respondent may then be written as:

$$L(\boldsymbol{\delta}) = \Pr \left[\boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{high} \right] = \int_{D_r} f_I(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma}) d\mathbf{r} \quad (\text{A.3})$$

The integral is evaluated over the region $D_r = \{\mathbf{r} : \boldsymbol{\theta}_{low} < \mathbf{r} < \boldsymbol{\theta}_{high}\}$ which is simply the multivariate region of $\mathbf{y}^*$ delimited by the lower and upper thresholds of the observed ordinal levels. $f_I(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma})$ is the I -dimensional multivariate normal density function with mean $\boldsymbol{\beta}'\mathbf{x}$ and correlation matrix $\boldsymbol{\Sigma}$. The model is estimated by maximum likelihood, with the full-sample log-likelihood formed as the sum of the individual contributions of the logarithm of Equation (A.3) across the sample of 3,891 respondents with ten outcomes and the logarithm corresponding to a simple univariate ordered-response probit model for the sample of 1,994 high-frequency users who contribute only the transit usage frequency dimension. Because evaluating the multivariate normal cumulative distribution function for ten dimensions, as embedded in Equation (A.3), is computationally demanding, estimation relies on the matrix-based analytic approximation referenced in Section 4.