Mobility Gaps between Low-Income and Non–Low-Income Households: A Case Study in New York State

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ABSTRACT

Understanding the travel challenges faced by low-income residents continues to be one of the most important transportation equity topics. This study explored the mobility gaps between low-income households (HHs) and non–low-income HHs, as well as how the gaps vary within different sociodemographic population groups in New York State. The latest National Household Travel Survey data were used as the primary data source for the analysis. The study employed the K-prototype clustering algorithm to categorize the HHs based on their sociodemographic attributes. Five population groups were identified based on nine HH features. The mobility differences, measured by trip frequency, trip distance, travel time, and person miles traveled, were examined among the five population groups. Results suggested that the individuals in low-income HHs consistently took fewer and shorter trips compared with non–low-income HHs. Travel distance gaps were most obvious among white HHs with more vehicles than drivers. Although the population from low-income HHs made shorter trips on average, they experienced longer travel times than those from non–low-income HHs. These findings provide more understanding of the travel behavior disparities between low-income and non–low-income HHs. The findings could help policymakers and transportation planners address critical needs of residents in low-income HHs and provide inputs for designing a more equitable transportation system.

INTRODUCTION

The *2019 Consumer Expenditure Survey* shows that transportation cost is the second highest among all expense categories—lower than housing expenditures but higher than food costs (US Bureau of Labor Statistics 2019). According to the survey, around 17% of the expenditures of a consumer unit in 2019 were spent on transportation. This relatively high share of expenditures for transportation poses financial burdens, especially to those in low-income households (HHs). Based on the *2017 National Household Travel Survey* (NHTS), lower-income households were more likely to express being cost-conscious regarding travel (US Federal Highway Administration [FHWA] 2019a). Constrained by their limited budgets and resources, low-income HHs face more travel challenges than their non–low-income counterparts. In general, traveling for the low-income HHs occurs less frequently, takes more time, traverses less distance, and relies more on alternative modes than higher-income HHs (Clifton 2003; Banerjee 2018).

A recent study explored the full array of travel behaviors of the HHs below and above the poverty level in the United States (Banerjee 2018). Travel behavior disparities were identified for daily trip rate, trip distance, and mode choices. Banerjee showed that on average, the daily person trip rate for low-income HHs was 2.9 compared with 3.5 for those in non–low-income HHs. Low-income HHs were also more likely to travel shorter distances compared with their non–low-income counterparts. In addition to daily trips and trip distance, the mode choice decision of low-income individuals was found to be affected by their limited budgets. In making mode decisions, low-income travelers carefully evaluated the costs of travel (time and out-of-pocket expenses) against the benefits of each mode available to them (Agrawal et al. 2011). Overall, compared with higher income populations, low-income populations were more likely to use public transit and nonmotorized transportation modes instead of driving to meet their daily travel needs. Despite this fact, encouraging people to use public transport instead of cars was found to be just as challenging for low-income HHs as for other-income HHs (Taylor 2009). A recent report based on the 2017 NHTS found that people in lower-income households did not agree that they walked or took public transit to save money (FHWA 2019b).

Several factors were shown to affect low-income household travel behavior and mobility patterns. Among them, vehicle ownership or having access to privately owned vehicles was one of the most influential factors. For low-income HHs, having a car is essential for easing access to and participation in a variety of important services and activities (Blumenberg and Pierce 2012; Rozynek et al. 2022; Taylor 2009). Although having a car boosts personal miles traveled (PMT) for all persons, it has a significant impact on boosting travel for those with lower incomes. Moving from zero to one car generates bigger marginal advantages for HHs than buying more when they already have one or more (Blumenberg and Pierce 2012).

Previous studies explored the travel behaviors of low-income HHs from diverse perspectives, including differences between different income groups, low-income individuals' travel concerns, their travel decision-making process, and the influencing factors. However, one limitation of previous studies is that they either treated the low-income HHs as a single group or focused on one or two dimensions of the low-income HHs, such as those who own vehicles vs. those without vehicles. Very few studies were conducted to examine low-income HH travel behavior within various demographic groups. To facilitate the understanding of mobility gaps within different population classes, this study conducted a case study in New York State (NYS), USA. The study first adopted a K-prototype algorithm–based method to categorize NYS low-income HHs into representative groups. Then, the mobility gaps between low-income and non–low-income HHs in NYS were evaluated among these groups based on several mobility measurements.

DATA SOURCE

NHTS

NHTS is a national travel survey of US households sponsored by FHWA (FHWA, 2017). The survey collects daily travel information that is linked to individual personal and household characteristics and vehicle attributes, such as trip frequency, travel distance and time, mode of transportation, and trip purpose. The latest NHTS was done in 2017, which surveyed more than 129,000 HHs. Among these HHs, 26,000 were from a national sample, and the rest were from add-on samples purchased by 13 state or metropolitan planning organization partners. The New

York State Department of Transportation (NYSDOT) was an add-on partner in the 2017 NHTS. Consequently, NYSDOT received travel data for over 17,000 HHs in NYS. This study was conducted with all the data samples in NYS, including those from the NYS add-on programs.

Defining Low-Income Households

A widely adopted approach in the literature to define low-income HHs is to use a simple cutoff value for HH income (Lou et al. 2020; Moniruzzaman et al. 2015). Any HHs below the cutoff value (household income threshold) are defined as low-income HHs. This method, although straightforward to implement, does not consider HH properties such as size or composition and location (urban or rural). This study explored and examined five different low-income definitions (other than the simple cutoff value method) used in literature or published by different agencies, as presented in Table 1. Generally, these thresholds are updated on a yearly basis. To be consistent with the 2017 NHTS, the low-income definitions for 2017 were compared with each other. Comparing these five different low-income household thresholds, the first two thresholds—the US Census Bureau poverty threshold and US Health and Human Services (HHS) poverty guidelines—are established at the national level without considering the cost of living and the housing market in different areas (e.g., urban and rural areas). As presented in the table, their income thresholds for four-person low-income HHs in New York City (NYC) are the lowest among all definitions. The other three thresholds—the US Census Bureau Supplementary Poverty Measure (SPM), Lower Living Standard Income Level (LLSIL) Guidelines, and US Housing and Urban Development (HUD) income limit—consider regional differences and establish the low-income threshold at a finer resolution level, such as metropolitan areas. Among these three definitions, the low-income threshold developed by HUD provides the highest geographical resolution (at the county level or metropolitan area level, depending on the location) and thus was selected and used as the low-income HH threshold in this study.

Table 1. Summary of low-income definitions

Source	Threshold name	Geographical resolution	HH properties	2017 HH low-income threshold for four-person HHs in NYC
US Census Bureau (2017a)	US Census Bureau poverty threshold	Nation	Household size and composition	$25,094
US Department of Health and Human Services (2017)	HHS poverty guidelines	Nation	Household size	$24,600
US Census Bureau (2017b)	US Census Bureau SPM	Metropolitan area	Household size and housing tenure status	$31,672 (two adults and two children) $38,737 (four adults and no children)
US Department of Labor (2017)	LLSIL guidelines	Selected metropolitan areas	Household size	$31,852
US Department of Housing and Urban Development (2017)	HUD income limits	County/metropolitan statistical area	Household size	Very low-income: $47,700 Low income: $76,300

The HUD developed low-income/very low-income thresholds to determine the eligibility for assisted housing programs that include public housing. The income limits were set based on HUD estimates of median family income during each fiscal year. A very low-income family is defined as those with incomes that do not exceed 50% of the median family income for the areas, and 80% was chosen as the threshold for low-income families. Comparing the two definitions found that the low-income threshold (80% of median family income) classifies nearly 50% of NYS HHs as low-income HHs, which provides less value to low-income studies. Therefore, in this study, the HUD very low-income family definition was used to define the low-income HHs. Approximately 30% of NYS HHs were classified as low-income HHs based on this threshold. All subsequent mention of low-income HHs in this study was defined using the HUD very low-income family threshold.

METHODOLOGY

The objective of this study was to explore how the mobility differences between low-income HHs and their counterparts vary among distinct sociodemographic groups. To achieve this goal, sociodemographic groups first needed to be defined. Sociodemographic groups in the literature are generally self-defined based on one or two attributes (e.g., elderly household vs. nonelderly HHs, elderly HHs in urban areas vs. nonelderly HHs in urban areas). If more attributes were considered, the full combination of these attributes would result in a long list of HH categories, which was not preferred. To this end, this study adopted a clustering approach to automatically identify distinct sociodemographic groups based on attributes that were found to affect low-income HH travel behavior. These attributes were identified based on an explorative analysis of the 2017 NHTS statistics in NYS. Table 2 summarizes the nine sociodemographic attributes, as well as the associated variable types and descriptive statistics among the entire population in NYS. Among the nine variables, HH size and HH vehicle ownership were numerical variables.

The remaining seven variables were divided into different categories as presented in the descriptive statistics column. For example, the HH location was classified into three categories: NYC, other NYS urban areas other than NYC, and rural areas. The share of the HHs among each group is presented in the table as well.

Table 2. Summary statistics of low-income HHs' sociodemographic variables

Variable	**Type**	**Descriptive statistics**
HH size	Numerical	Median: 2
HH vehicle ownership	Numerical	Median: 2
HH location	Categorical	8.41% NYC, 70.28% other urban, 21.31% rural
Elderly status	Categorical	40.66% elderly HH, 49.34% nonelderly HH
HH race	Categorical	89.86% white, 10.14% nonwhite
Employment status	Categorical	64.16% working HH, 35.84% nonworking HH
Education status	Categorical	82.42% higher educated HH, 17.58% lower educated HH
Gender distribution	Categorical	31.63% #males < #females, 44.94% #males = #females, 23.43% #males > #females
Vehicle/driver distribution	Categorical	11.49% #vehicles < #drivers, 68.04% #vehicles = #drivers, 20.47% #vehicles > #drivers

Notes: Urban *is defined as metropolitan areas in NYS.*
An elderly HH *is defined as at least one household member who is 65 or older.*
Working HH *is defined as at least one household member who is employed.*
Higher education *is defined as a college or higher degree.* Lower education *is defined as only a high school degree/GED or no high school degree/GED.*

A K-prototype algorithm (Huang 1998) was employed in this study to categorize the sample data based on the sociodemographic attributes. The K-prototype algorithm is an improvement of the K-Means and K-Mode clustering algorithms; K-prototype handles clustering with mixed data types, such as a mixture of categorical and numerical variables. The algorithm was implemented using the Python kmodes library (De Vos 2022).

RESULTS AND DISCUSSION

Sociodemographic Clusters

Figure 1 displays the number of clusters and the average dispersion. The average dispersion is based on a cost function that considers the sum of distances of all points to their respective cluster centroids. To determine the optimal number of clusters, the elbow method was used. Based on the figure, five was selected as the optimal cluster number because the marginal benefit in average dispersion (decrease in average dispersion) was not significant once the number of clusters exceeded five.

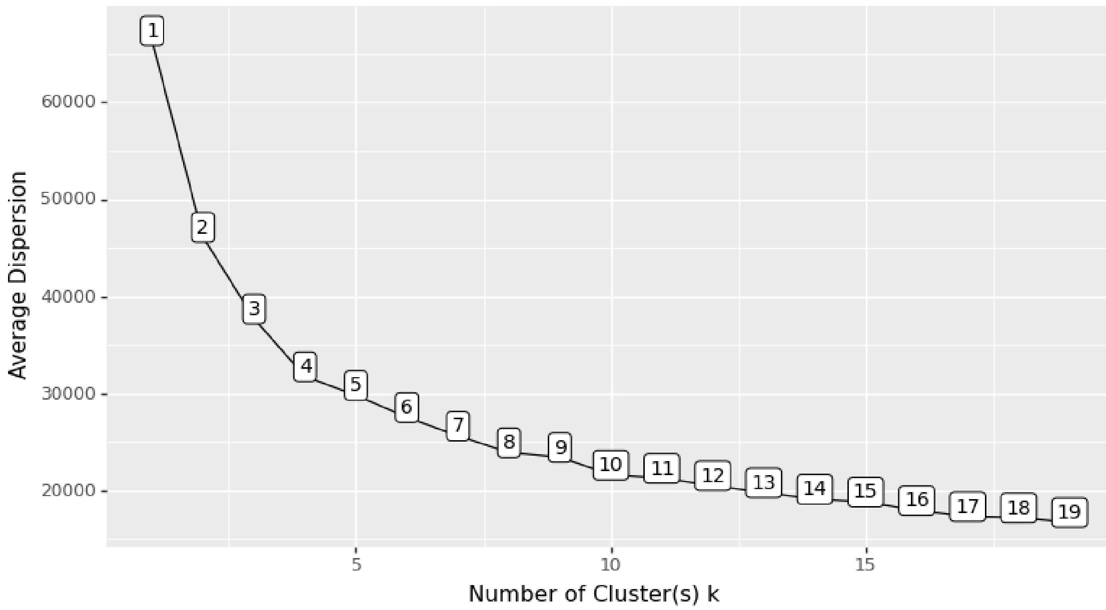

Figure 1. Number of clusters by average dispersion.

Table 3 summarizes the sociodemographic variable statistics within each cluster. For the two numeric variables, the statistic presented is the median value. For example, the median HH size for Cluster 1 is two people. The proportion of each category is presented for the categorical variables. Take Cluster 1 HH location as an example: 69.6% of HHs in this cluster lived in other urban areas, and 28.6% lived in rural NYS areas.

Table 3. Summary statistics for variables by cluster

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	All
HH size (median)	2	2	4	1	1	2
HH vehicle ownership (median)	3	2	2	1	1	2
HH location (% other urban)	69.6	73.1	74.2	64.9	67.4	70.3
HH location (% NYC)	1.8	5.1	8	10.5	**16.3**	8.4
HH location (% rural)	28.6	21.8	17.8	24.6	16.2	21.3
Elderly status (% elderly HH)	36.3	60.8	10.8	**75.6**	14.5	40.7
Elderly status (% nonelderly HH)	63.7	39.2	**89.3**	24.4	85.5	59.3
HH race (% white)	**95.1**	94.2	86.7	86.9	85.2	89.9
HH race (% nonwhite)	4.9	5.8	13.3	13.1	14.8	10.1
Employment status (% working HH)	76.7	58.6	95	8.1	79.9	64.2
Employment status (% nonworking HH)	23.3	41.4	5	91.9	20.1	35.8
Education status (% higher educated HH)	88.6	87.2	**91.8**	46.3	91.3	82.4
Education status (% lower educated HH)	11.4	12.8	8.2	53.7	8.7	17.6
Gender distribution (% #males < #females)	12.6	6.3	41	72.2	40.5	31.6
Gender distribution (% #males = #females)	68.4	**86.4**	27.5	7.4	15.1	44.9
Gender distribution (% #males > #females)	19	7.3	31.5	20.4	**44.4**	23.5
Vehicle/driver distribution (% #vehicles < #drivers)	0	10.9	18	8.6	16.5	11.5
Vehicle/driver distribution (% #vehicles = #drivers)	2.4	81.7	73.6	**85.8**	74.4	68
Vehicle/driver distribution (% #vehicles > #drivers)	**97.6**	7.4	8.4	5.6	9.1	20.5

Table 3. Summary statistics for variables by cluster (continued)

Notes: Urban *is defined as metropolitan areas in NYS.*
An elderly HH *is defined as at least one household member who is 65 or older.*
Working HH *is defined as at least one household member who is employed.*
Higher education *is defined as a college or higher degree.* Lower education *is defined as only a high school degree/GED or no high school degree/GED.*

Examining the statistics presented in Table 3, some representative sociodemographic statistics in each cluster were identified and highlighted. Each cluster was given a name based on the representative statistics presented in Table 4. The first cluster was dominated by HHs that had more vehicles than drivers. Over 14% of the total NYS HHs were part of this cluster. The majority (77%) of HHs in Cluster 1 were non–low-income HHs. Cluster 2 included HHs with an equal number of male and female residents. The median household size was two. Cluster 3 was dominated by higher educated, nonelderly HHs. In total, 95% of these HHs were working HHs. As expected, Cluster 3 had a much lower proportion of low-income HHs. The majority of Cluster 4 were elderly HHs with more females than males and had an equal number of vehicles and drivers. These HHs had lower education status compared to other clusters. The share of the low-income HHs in Cluster 4 was the highest—over 70% of them had an income below the low-income threshold. Lastly, Cluster 5 included NYC HHs with more male residents than female—most of these were one-person HHs.

Table 4. Names and properties of clusters

Cluster	Cluster name	Share (sample size)	Low-income vs. non–low-income share
1	White HH with more vehicles than drivers	14.2% (2,339)	Non–low-income dominated (77.1% non–low-income)
2	HH with equal number of male and female residents	29.8% (4,893)	Non–low-income dominated (88.6% non–low-income)
3	Higher educated, nonelderly HH	18.6% (3,063)	Non–low-income dominated (85.1% non–low-income)
4	Elderly HH with equal number of vehicles and drivers	16.4% (2,691)	Low-income dominated (71.7% low-income)
5	NYC HH with more male residents than female	21.1% (3,466)	Non–low-income dominated (81.0% non–low-income)

The mobility difference between low-income HHs and their non–low-income neighbors, including average daily person trips, PMT, average trip length, and trip duration, were examined among each demographic group (i.e., cluster). Notably, the differences were calculated as the statistics in non–low-income HHs minus those in low-income HHs. Figures 2 through 5 summarize all the mobility differences.

Figure 2 shows the average daily person trip differences in each group. Overall, the residents from low-income HHs made fewer personal trips compared with their non–low-income counterparts. The differences were most obvious within Cluster 1 (white HH with more vehicles than drivers) and Cluster 4 (elderly HH with equal numbers of vehicles and drivers). However, although the daily trip gaps were significant for the entire population, they were not statistically significant at any individual group level.

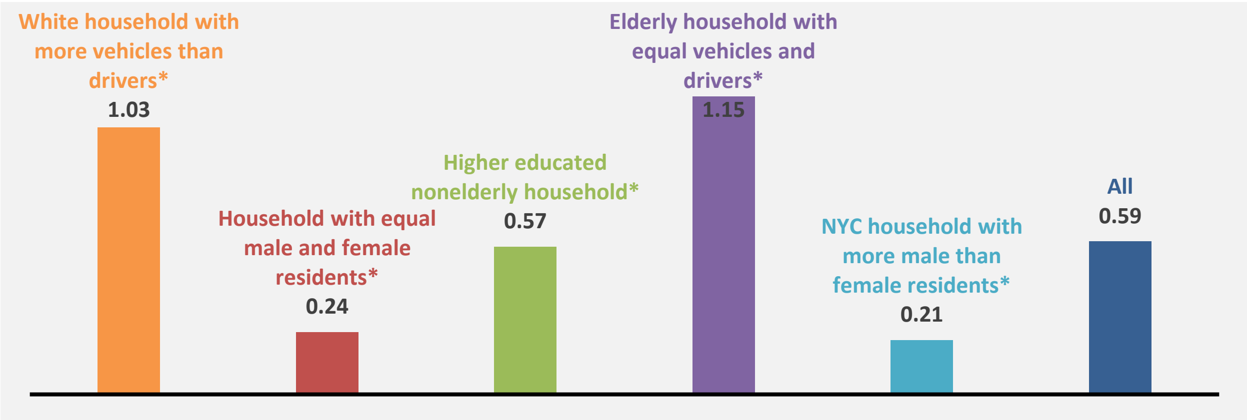

Figure 2. Average daily person trip differences (non–low-income HHs − low-income HHs).
**not statistically significant at 5% confidence level.*

Figure 3 shows the PMT differences in miles between the two income groups across each demographic group. On average, the daily PMT made by residents from low-income HHs was 12.4 miles less than that of residents from non–low-income HHs. Among all demographic groups, the white household with more vehicles than drivers showed the largest differences. In particular, low-income household members generally traveled 21.5 miles less per day than their non–low-income counterparts. No obvious difference was found in the NYC household with more male residents than female.

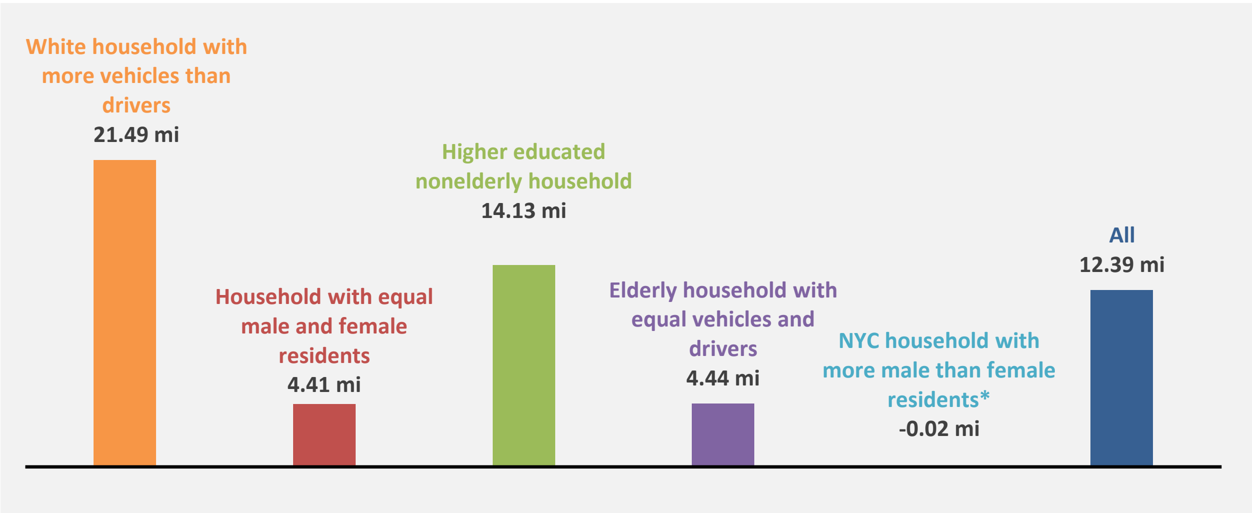

Figure 3. Average daily PMT differences in miles (non–low-income HHs − low-income HHs).
**not statistically significant at 5% confidence level.*

Figure 4 shows the trip length differences per trip between the two income groups. Trips by air were excluded in this trip length calculation. Similar to PMT, the trip length gaps within white HHs with more vehicles than drivers and higher educated, nonelderly HHs were most evident. The trip length gaps in the other three sociodemographic groups were not statistically significant. Overall, the average trip length made by a person from a low-income HH was 2.7 miles shorter than from non–low-income HHs in NYS.

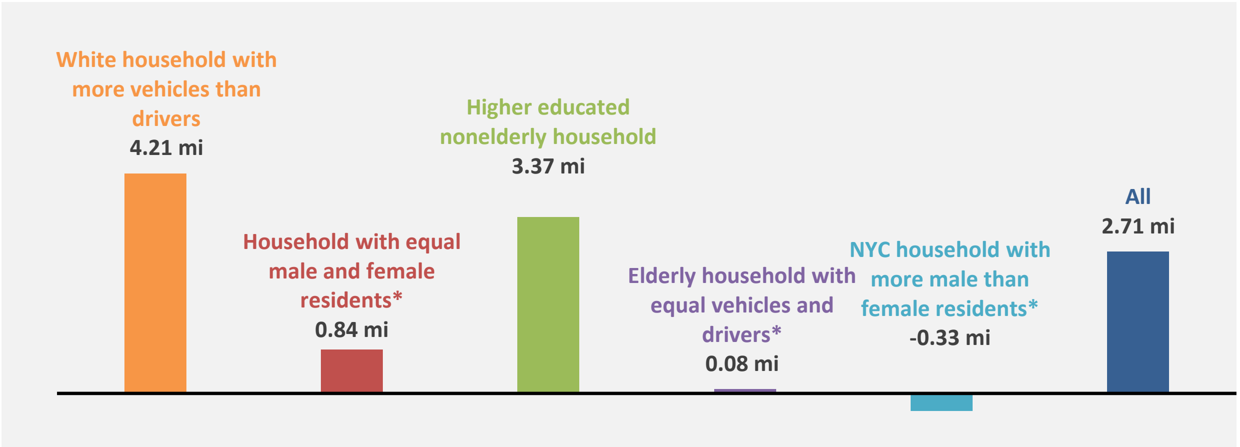

Figure 4. Trip length differences in miles (non–low-income HHs − low-income HHs).
**not statistically significant at 5% confidence level.*

Figure 5 presents the average trip duration differences within each group. Air trips were excluded from this trip duration calculation. In contrast to the average daily person trip length, the average trip duration for residents from low-income HHs was longer than that of residents from non–low-income HHs. Possible reasons could be that the low-income HHs either suffered more from traffic congestion or took less time-efficient modes such as public transit or walking instead of driving. However, the difference in each group varied. The disparity was most obvious among elderly HHs with equal numbers of vehicles and drivers. On the other hand, for those from white HHs with more vehicles than drivers, the average trip duration was higher for residents from non–low-income HHs compared with that of low-income HHs.

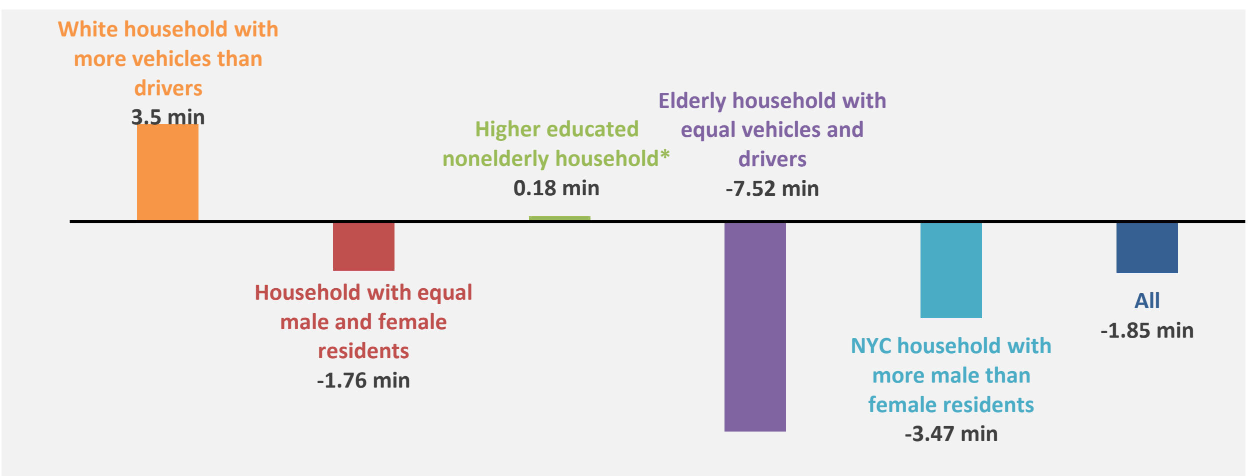

Figure 5. Trip duration differences in minutes (non–low-income HHs − low-income HHs).
**not statistically significant at 5% confidence level.*

CONCLUSION

Using the 2017 NHTS, this study investigated the mobility gaps between low-income and non–low-income HHs in NYS. Different from previous studies that used a single low-income threshold for the entire study area, this study used a low-income threshold of 50% of the median income, which was published by HUD. HUD established the threshold in county or metropolitan areas that captures the cost of living in different regions and is considered a more reasonable measurement than those established at the national level. Furthermore, to better understand the mobility gaps among different sociodemographic groups, a K-prototype clustering approach was adopted to categorize the population based on various attributes, such as household size, vehicle ownership, gender, employment status, and education. Then, the mobility differences among the entire population in NYS as well as within each population group were examined. Results from the analysis confirmed the findings from other studies, namely that individuals from low-income HHs generally made fewer trips and shorter trip distances compared with their non–low-income counterparts. The trip length differences and PMT between low-income HHs and non–low-income HHs were most obvious among white HHs with more vehicles than drivers. Although the residents from low-income HHs on average made shorter trips, they experienced longer travel times than those from non–low-income HHs.

In this study, the demographic variables were selected based on an explorative analysis. In future studies, additional variables, such as household vehicle ownership (zero vs. nonzero) and household composition (one adult, two adults, etc.), will be evaluated to better capture household characteristics. The authors also aim to investigate other travel behavior gaps (e.g., transportation mode and trip purpose) between low-income and non–low-income HHs. Additionally, the authors plan to apply the methodology used in this study to other geographical regions to evaluate whether the mobility gaps within distinct sociodemographic groups vary from region to region.

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