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Examining the Relationship between Household Vehicle Ownership and Ridesharing Behaviors in the United States

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Abstract: To improve the sustainability and efficiency of transport systems, communities and government agencies throughout the United States (US) are looking for ways to reduce vehicle ownership and single-occupant trips by encouraging people to shift from driving to using more sustainable transport modes (such as ridesharing). Ridesharing is a cost-effective, sustainable and effective alternative transportation mode that is beneficial to the environment, the economy and society. Despite the potential effect of vehicle ownership on the adoption of ridesharing services, individuals' ridesharing behaviors and the interdependencies between vehicle ownership and ridesharing usage are not well understood. This study aims to fill the gap by examining the associations between household vehicle ownership and the frequency and probability of ridesharing usage, and to estimate the effects of household vehicle ownership on individuals' ridesharing usage in the US. We conducted zero-inflated negative binomial regression models using data from the 2017 National Household Travel Survey. The results show that, in general, one-vehicle reduction in households was significantly associated with a 7.9% increase in the frequency of ridesharing usage and a 23.0% increase in the probability of ridesharing usage. The effects of household vehicle ownership on the frequency of ridesharing usage are greater for those who live in areas with a higher population density than those living in areas with a lower population density. Young people, men, those who are unable to drive, individuals with high household income levels, and those who live in areas with rail service or a higher population density, tend to use ridesharing more frequently and are more likely to use it. These findings can be used as guides for planners or practitioners to better understand individuals' ridesharing behaviors, and to identify policies and interventions to increase the potential of ridesharing usage, and to decrease household vehicle ownership, depending on different contextual features and demographic variables. Comprehensive strategies that limit vehicle ownership and address the increasing demand for ridesharing have the potential to improve the sustainability of transportation systems.

Keywords: ridesharing; household vehicle ownership; 2017 NHTS; United States; ZINB model

1. Introduction

Many countries around the world have committed to lowering their greenhouse gas emissions, which mainly originate from the burning of fossil fuels for electricity, heat, and transportation. The United States (US) targeted to reduce its carbon population from 1.2% per year on average between 2005 and 2020, to 2.3–2.8% per year on average between 2020 and 2025, and to achieve overall reductions of 80% or more by 2050, based on 2005 levels. The US Environmental Protection Agency [1] reported that, in 2016, the transportation sector accounted for the largest share (28.5%) of greenhouse gas emissions (e.g., CO_2, CH_4, and N_2O) in the US, and these emissions primarily originated from the burning of fossil fuels for passenger cars (41.6%), freight trucks (22.9%), light-duty trucks (18.0%), aircrafts (9.1%), ships and boats (2.3%), trains (2.2%), and pipeline operations (2.1%). Passenger cars are the largest source of transportation-related greenhouse gas emissions.

The US citizens are highly dependent on automobiles, and commuting to work is the most important daily trip purpose. Each year, the US Census Bureau updates its national statistics on US citizens' commuting habits, and the latest 2016 American Community Survey (ACS) data reported that, considering all commuter trips, over 76.3% of the US citizens drive alone to work every day, while 9.0% carpool with someone else (ridesharing) and 5.1% use public transit [2]. Single-occupant trips generate several negative externalities, such as low vehicle occupancy rates, leading to low car use efficiency, severe traffic congestion, and higher per capita gas emissions. Simultaneously, the air pollution caused by vehicle emissions can have serious negative health effects. Therefore, decarbonizing the transportation sector is essential for the environment and for public health. To reduce the negative consequences of car travel and to improve the sustainability and efficiency of transport systems, changes should be implemented to reduce vehicle ownership and single-occupant trips, and governments should encourage and convince people to abandon the use of private cars for the use of public transit or ridesharing [3].

However, convincing people to shift their regular transportation mode is not easy. According to transport mode choice theory, transport mode choice is governed by a complex set of factors, such as availability, travel cost, security, convenience, personal attitude, preferences, habits, culture, and lifestyle [4,5]. Among these factors, cost and convenience are the first consideration when people choose a transportation mode [4,5]. As car travel costs are growing (e.g., the cost of buying and maintaining a car, constantly increasing fuel prices, additional insurance costs, limited availability of parking space and travel time), vehicle ownership is not always a rational choice, and alternative transportation modes are needed [6]. Public transportation systems cost less but are fixed-line systems and restrict travel freedom [7]. Under these circumstances, ridesharing seems to be an optimal compromise [8] offering on-demand mobility and combining the advantages of private cars (convenience and speed) and public transit (low cost), enabling people to maintain a degree of luxury and convenience by relying on cars instead of public transit [9].

Ridesharing is an inexpensive, flexible, and environmentally sustainable alternative transportation mode [10] that matches drivers and riders in real time and coordinates drivers to offer rides to travelers with similar itineraries and time schedules at reasonably low transaction costs. Ridesharing has been growing continuously during the last several years (i.e., Uber's global net revenue grew continuously from 2013 to 2017, from $0.1 million (M) in 2013 to $0.5 M in 2014, to $1.5 M in 2015, to $6.5 M in 2016, reaching $7.5 M in 2017), due to the wide-spread use of smart phones and online payment systems, the rapid growth of the sharing economy [11], and Internet-based peer-to-peer platforms (e.g., Uber, Didi, and Lyft). The benefits of ridesharing include increased occupancy of private vehicles, travel cost savings, improved vehicle use efficiency, reduced travel time, and overall vehicle miles, mitigation of traffic congestion, conservation of fuel, and reduction of air pollution, private car ownership, and alcohol-related crashes [9,12–17]. One additional passenger for every 10 vehicles will result in 7.54 to 7.74 billion gallons saved per year [12]. Ridesharing leads to 57% CO_2 emission reductions and 67% energy savings based on the 2016 level in Beijing using data from the DiDi Chuxing company [16].

Vehicle ownership or vehicle availability plays an important role in an individual's transport mode choice [4,18] and is one of the key determinants of people's travel behavior [19], such as frequency of trips [20] and trip chaining [21]. Vehicle ownership levels grew with the ever-increasing dependence on private transportation and the increased vehicle miles traveled. It is widely acknowledged that the growth of vehicle ownership is a major cause of traffic congestion and air pollution [22]. Ridesharing is emerging as a potentially effective way to reduce individuals' reliance on vehicle ownership by shifting personal transportation mode choice from owned assets to on-demand mobility services, which would reduce traffic jams and lower emissions.

Vehicle ownership reduction strategies would create additional ridesharing demand. One of the most important pieces of information required for travel demand modelers and transportation practitioners is to identify passengers' travel behaviors and demand patterns. This issue is of value for policy makers to improve comprehensive transportation planning and to formulate urban traffic congestion mitigation strategies. However, little is known about the interdependencies between household vehicle ownership and ridesharing behavior, and the extent of the effect of reducing household vehicle ownership on ridesharing usage.

The objective of this research is to analyze the relationship between household vehicle ownership and the frequency of ridesharing usage (the respondent's ridesharing usage in number of times in the last 30 days) and the probability of ridesharing usage (whether the respondents have used ridesharing at least once or never in the last 30 days) in the US. In addition, this study aims to determine how this relationship varies by population density, and to develop an improved understanding of the potential for increased ridesharing usage as a result of reduced household vehicle ownership. To accomplish this objective, zero-inflated negative binomial regression models (ZINB) were developed and estimated using the 2017 National Household Travel Survey (NHTS) data, in which the respondents were asked to report how many times they had purchased rides with a smartphone ridesharing application in the last 30 days. Both descriptive analysis and model estimation results highlight the negative relationship between household vehicle ownership and ridesharing usage. In general, one-vehicle reduction per household significantly increased the frequency of ridesharing usage by 7.9% and increased the likelihood of ridesharing usage by 23.0%. The effects of household vehicle ownership on the frequency of ridesharing usage are greater for those who live in areas with a high population density (more than 4000 people per square mile at the home location) than those living in areas with a low population density (less than 4000 people per square mile at the home location). Sustainable policies should be established to encourage people to replace personal vehicle travel with ridesharing, and strategies should be implemented to make ridesharing more attractive, to reduce vehicle ownership and to fulfill the ridesharing demand depending on different contextual features or different types of people.

The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 presents the data source and descriptive analysis of ridesharing usage, and Section 4 provides the methodology. The model estimation results are presented in Section 5. Section 6 presents the discussion, and conclusions are provided in Section 7.

2. Literature Review

Ridesharing is a sustainable alternative transportation mode wherein individual travelers share a vehicle and travel costs with those who have similar itineraries and time schedules on an on-demand basis [23], and provides on-demand mobility services by ridesharing platforms (e.g., Uber, Lyft and Didi). Chan and Shaheen [9] described the history of North American ridesharing since its beginnings in 1942 and divided it into five phases: car-sharing clubs during World War II (1942–1945), ridesharing reappearing as a response to energy crises (late 1960s to 1980), early forms of telephone- and Internet-based ridesharing programs (1980–1997), initial reliable online ridesharing services (1999–2004), and technology-enabled ride-matching and real-time ridesharing services (2004 to present). Modern ridesharing/on-demand mobility services have undergone continuous growth during the last several years and have attracted widespread attention from scholars.

There are number of studies of ridesharing systems, the benefits of ridesharing and regulations governing ridesharing. Furuhata et al. [14] presented a classification of existing ridesharing systems. Researchers have proposed mechanisms or algorithms for ridesharing systems to solve the ride-matching problem [24–27], to overcome safety concerns and privacy protection problems [28,29], to improve trust among peers [30] and to design dynamic ridesharing pricing [31,32]. Others have focused on the economic [33], societal [17,34], and environmental [12,16] benefits of ridesharing or have studied regulations governing ridesharing [35,36].

Based on consumer choice theory, travelers are assumed to rationally choose a transport mode to travel from their origins to their destinations by evaluating the characteristics of various available competing alternatives, and weighing their options in an attempt to maximize personal utility [4,37,38]. Individuals' transport mode choices and travel behaviors are affected by a complex set of factors, such as availability, travel costs, personal attitudes, personal demographics, habits, perceptions of safety and convenience, cultures, and built environments [39–44]. Ridesharing provides a more flexible, more convenient, and often faster option than public transit [14], and a lower cost than private cars (ridesharing riders could share some costs with drivers, and riders do not need to pay for ownership) [3].

However, the literature on ridesharing behaviors and the factors affecting the adoption of ridesharing services is rather sparse. This paucity of research may exist because of the proprietary nature of data; low data availability makes it difficult to study ridesharing behaviors [45]. Nielsen et al. [3] used a small data sample from research interviews and focus groups to study the impact of perceptions of availability and safety, the environment, and climate change on the adoption of ridesharing in Denmark, and Zolnik [46] found that higher gasoline prices will increase the likelihood of individuals' ridesharing service usage. Dias et al. [47] conducted a bivariate ordered probit model using the data from the 2014–2015 Puget Sound Regional Travel Study to examine the influence of various exogenous socio-economic and demographic variables on the frequency of ridesharing usage, and found that ridesharing users tend to be individuals who are young, those with higher education levels and incomes, or workers living in areas with high population densities.

Vehicle ownership affects individuals' travel behaviors and transport mode choices [4,19,20,48]. Household vehicle ownership is significantly positively associated with the likelihood of choosing driving modes [20]. Vehicle ownership is the dominant factor affecting travel mode choice, and households with more cars have a substantially higher probability of driving and a lower probability of walking, cycling, or using public transit [48]. Clewlow [49] found that the adoption of car sharing is linked with low levels of vehicle ownership. Coll et al. [50] reported that in households without any vehicles, car sharing is a substitute for vehicle ownership. Dias et al. [47] found that individuals in households with fewer vehicles are more likely to use ridesharing services.

Ridesharing may reduce individuals' reliance on vehicle ownership by shifting their mode choice from owned assets to on-demand mobility services. Despite the potential effect of vehicle ownership on the adoption of ridesharing services, individuals' ridesharing behaviors, and the interdependencies between vehicle ownership and ridesharing usage are not well understood. This study aims to fill this gap by conducting a descriptive analysis and developing ZINB models to examine the associations between household vehicle ownership and ridesharing behavior.

3. Data

3.1. Data Source

The 2017 NHTS was a large-scale national travel survey conducted by the US Federal Highway Administration between March 2016 and May 2017 [51], which collected detailed information on respondents' travel behaviors, demographics, household socio-economic characteristics, and geographic characteristics at their home locations. Initially, address-based sampling with mail-back technology was used to select the potential household respondents (phase 1: the household recruitment survey), and the weighed response rate of this survey was 30.4%. Next, a phone- or web-based method was used as the response mode to collect information regarding all the people in those households recruited during the first phase (phase 2: the person-level retrieval survey), and the weighed response rate of this survey was 51.4%. The survey day for each household with all family members was randomly assigned, and the overall weighted response rate for the whole survey was 15.6%. A total of 264,234 people in 129,696 households were included in the 2017 NHTS dataset.

In the present study, data from 15 states (West Virginia, Mississippi, Wyoming, South Dakota, Arkansas, Kansas, North Dakota, Montana, Idaho, Delaware, Maine, Alabama, Utah, Vermont, and Oregon) were excluded from our analysis because ridesharing services are not as popular in these states (the percent of ridesharing usage within these states is under 4%) as in the other 35 states and in the federal district. A total of 228,002 individuals in these areas answered the question about ridesharing usage (how many times have you purchased rides from ridesharing applications in the last 30 days?). A total of 8976 people were excluded from the analysis because of missing data for some key variables (e.g., count of household vehicles, age, gender, education level, and household income level), leaving 219,026 individuals in our analysis. We used the statistics software STATA 13.1 to process the data and conduct the analysis in this study.

3.2. Descriptive Analysis of Ridesharing Usage

All respondents in the survey were asked to report how many times they had purchased ridesharing services in the last 30 days. Figure 1 shows that most of the respondents reported that they had not used ridesharing at all or had used it only once in the last 30 days. In total, 202,209 (92.32%) people did not use a ridesharing service in the last 30 days, and 16,817 (7.68%) respondents did use a ridesharing service between 1 and 99 times in the last 30 days. Among those who used a ridesharing service between 1 and 99 times, 4763 (28.32%) people used it once, while 4230 (25.15%) used it twice, and the majority used it no more than five times (13,653, 81.19%); 2961 (17.61%) individuals used it six to 20 times and 203 (1.21%) people used ridesharing 21 to 99 times.

As the dependent variable is the count value, ZINB models were employed to conduct the analysis. The sample size is 219,026, with 202,209 zero values, and 16,817 non-zero values for the frequency of ridesharing usage. If the two-sided p-value is less than 0.05, it is considered to be statistically significant. A binomial test with unequal sizes (ratio = 0.0768/0.9232, the proportion of zero counts/the proportion of non-zero counts) was employed to estimate the statistical power. For this study, with a sample size of 219,026 and a significance level of 0.05, the statistical power is 1. Therefore, the sample size of 219,026 is sufficiently large to provide robust statistical power.

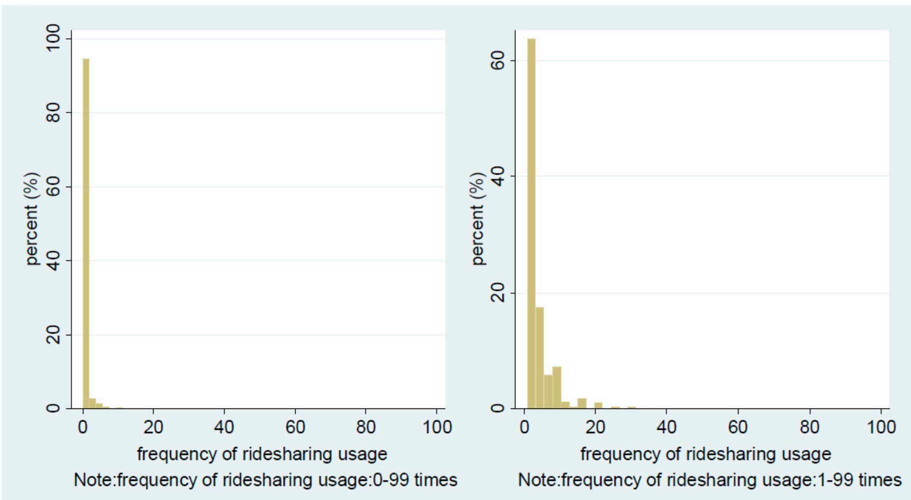


Figure 1. Frequency distribution of monthly ridesharing usage.

Figure 2 shows how the average monthly ridesharing usage varies by household vehicle ownership. For all of the following figures, the (a) panels include those who used ridesharing more than once in the last 30 days and the (b) panels include all of the people in the sample. Generally, household vehicle ownership is negatively related to an individual's average ridesharing usage per month. For all the people in the sample, the average monthly ridesharing ridership was 0.31, while the number was 4.02 for those who used ridesharing at least once in the last 30 days.

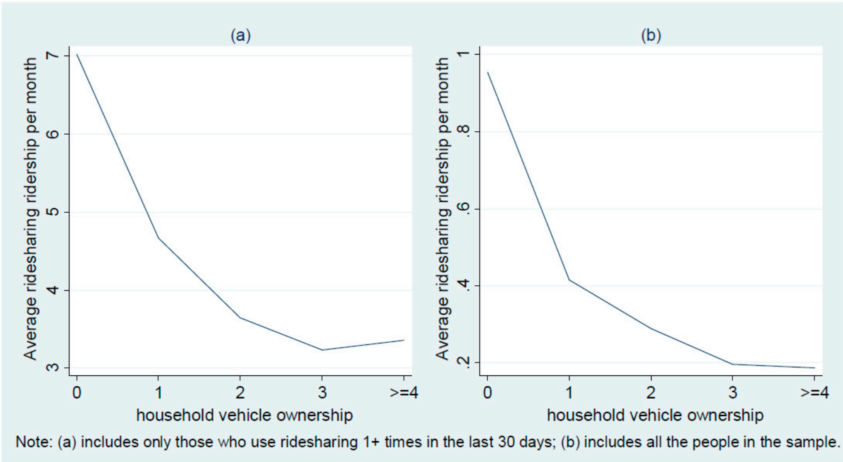


Figure 2. Average monthly ridesharing usage varying by household vehicle ownership.

Figures 3 and 4 show how the relationship between ridesharing and household vehicle ownership varies by personal demographic characteristics. For all the figures in the following parts, the X-axis represents household vehicle ownership; 0 denotes zero vehicles owned, 1 denotes one vehicle owned, 2 denotes two vehicles owned, 3 denotes three vehicles owned and 4 denotes more than three vehicles owned. Very similar patterns for the relationships between ridesharing and household vehicle ownership were observed for different gender, age, race, and worker status groups, while the associations are more sensitive to individuals' driver status and education levels. The mean count for monthly ridesharing usage for men was clearly larger than that for women, suggesting that men use ridesharing more frequently than women. The frequency of monthly ridesharing trips increased with age, with those under 29 years of age showing the highest frequency of ridesharing usage. Workers used ridesharing more frequently than non-workers. Generally, people with higher education levels showed a higher likelihood of ridesharing usage, but among those who used ridesharing, individuals with higher education levels used ridesharing less frequently than those with lower education levels. Individuals who were unable to drive used ridesharing more frequently than those who are able to drive.

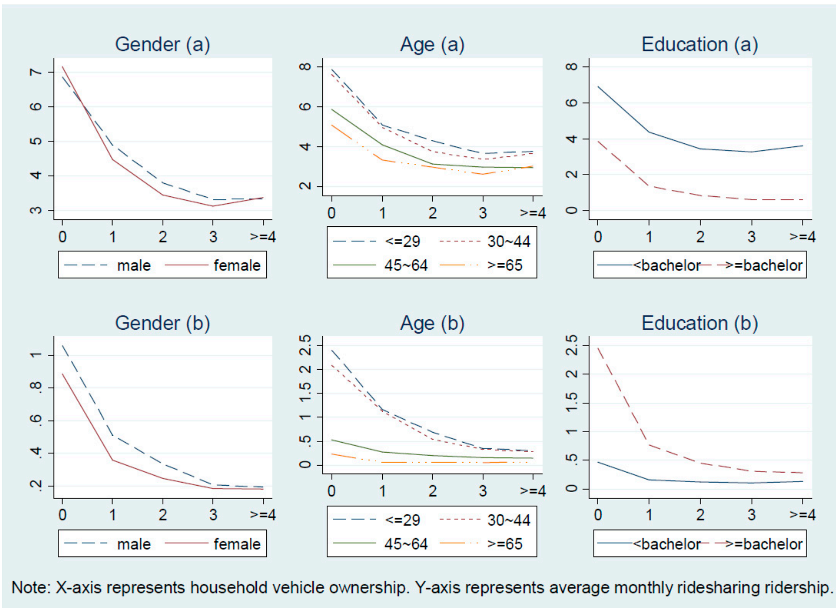


Figure 3. Associations between ridesharing and household vehicle ownership varying by gender, age and education.

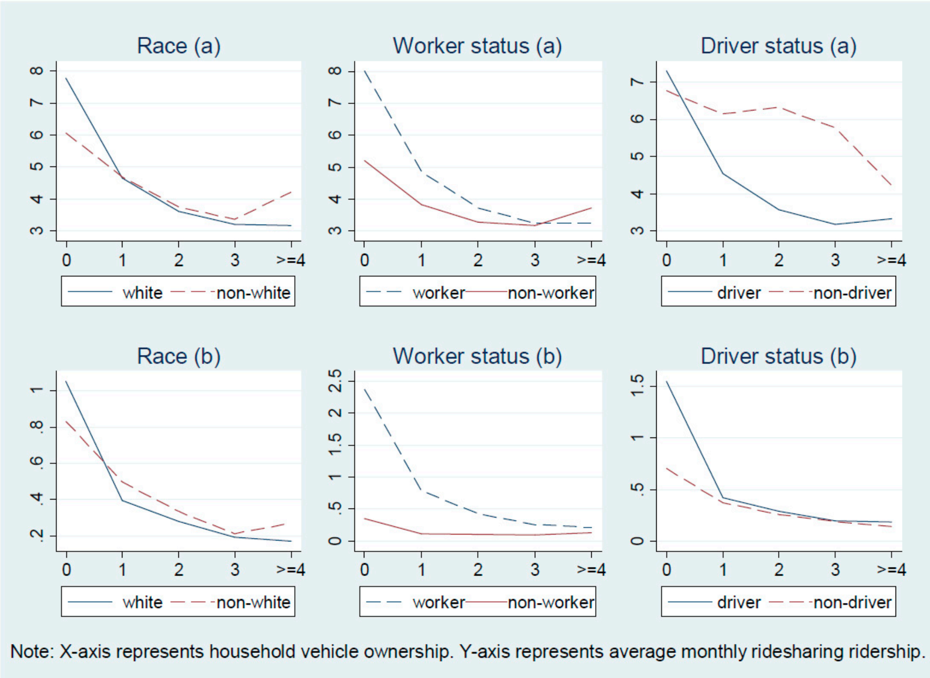


Figure 4. Associations between ridesharing and household vehicle ownership varying by race, worker and driver status.

Figure 5 shows how the relationships between ridesharing usage and household vehicle ownership vary by annual household income level and home ownership/rental status. Individuals in households with higher annual income levels showed a clearly higher frequency of ridesharing ridership than those in households with lower income levels. People who live in rental houses tended to use ridesharing services more frequently than those who own their houses.

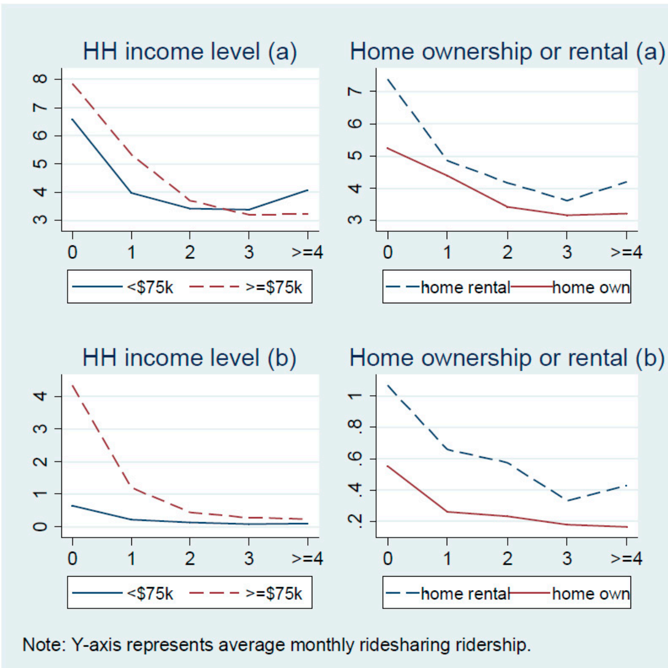


Figure 5. Associations between ridesharing and household vehicle ownership varying by household characteristics.

Figure 6 shows how the relationships between ridesharing usage and household vehicle ownership vary by population density at the home location (persons per square mile), rail service status (has rail service or has no rail service at the home location), and urban status (home located in an urban or rural area). Among different groups, the associations between ridesharing usage and household vehicle ownership were similar, indicating that ridesharing ridership is negatively correlated with household vehicle ownership within all the groups. People who live in areas with a higher population density show a higher frequency of ridesharing usage than those who live in areas with a lower population density. In terms of rail service status, individuals living in areas with rail service used ridesharing more frequently than those who lived in areas without rail service. People who live in urban areas had a higher frequency of ridesharing usage than those living in rural areas.

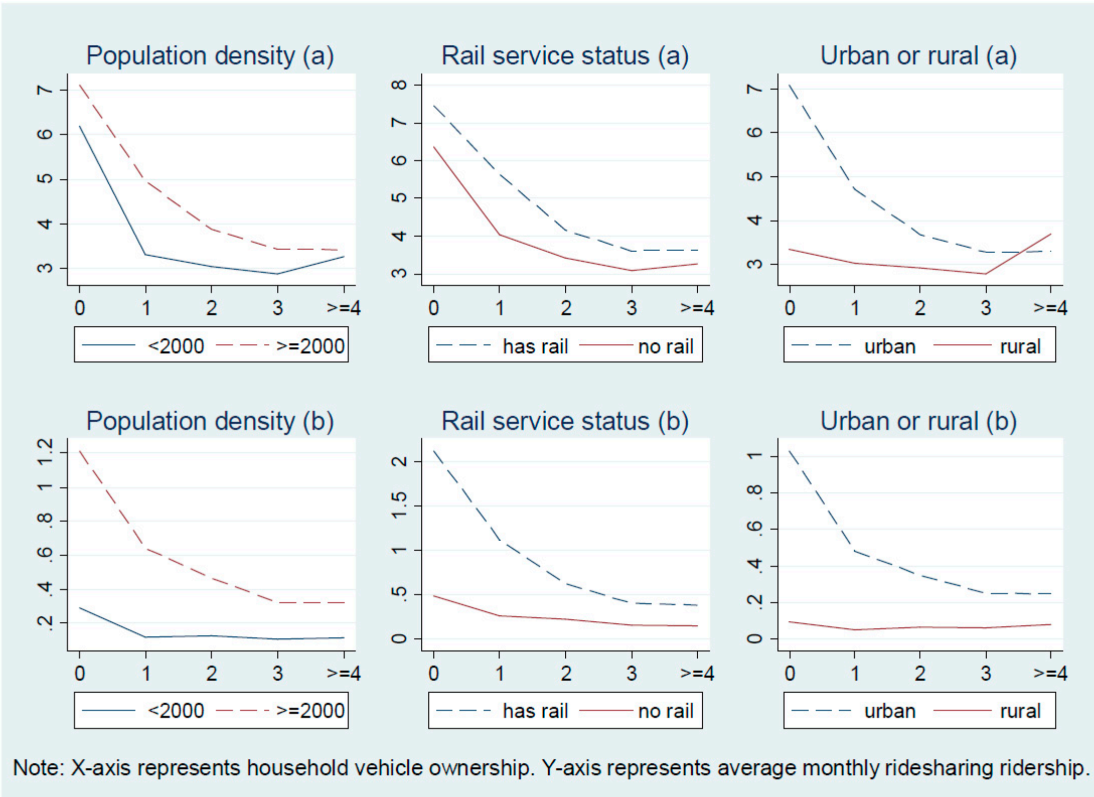


Figure 6. Associations between ridesharing and household vehicle ownership varying by regional characteristics.

Figure 7 shows how the relationship between ridesharing and household vehicle ownership varies by individuals' monthly public transit usage and season. The average number of monthly ridesharing trips showed that the greater the public transit usage was, the more frequent the ridesharing usage, with individuals who used public transportation modes more than 31 times per month showing the highest frequency of ridesharing usage. Regarding the associations between ridesharing usage and household vehicle ownership, the relationships among different seasons showed very similar patterns, while the relationships were more sensitive to public transit usage. Individuals who travel in the spring show the highest frequency of ridesharing usage, while those who travel in the summer used ridesharing the least frequently, but the differences among the four seasons are very small. Generally, the frequency of ridesharing usage was slightly higher in spring and fall, and lower in winter and summer.

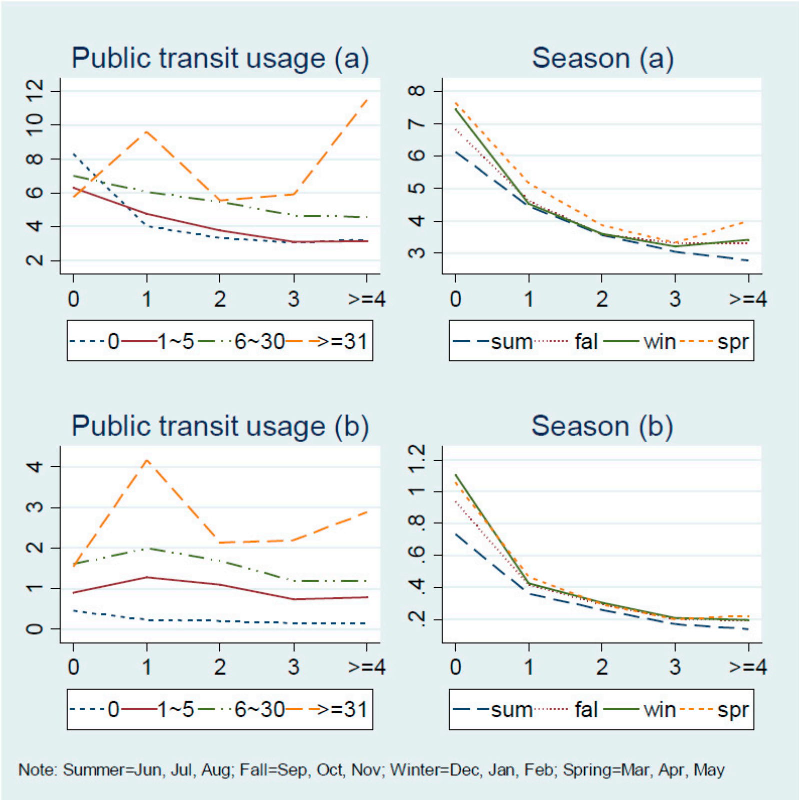


Figure 7. Associations between ridesharing and household vehicle ownership varying by public transit usage and season.

3.3. Variable Definitions and Descriptive Statistics

3.3.1. Dependent Variable

The dependent variable, Rideshare, was defined as the frequency (number of times) ridesharing was used in the last 30 days. The average monthly ridesharing ridership for the whole sample was 0.31. Detailed information about individuals' ridesharing usage is provided in Section 3.2. Table 1 lists the variable definitions and their descriptive statistics.

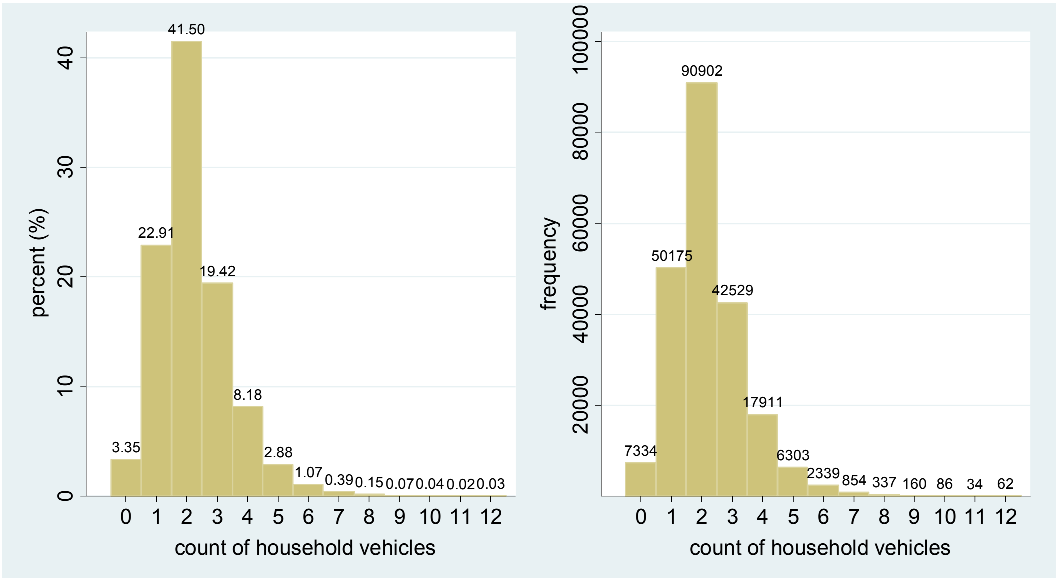
3.3.2. Independent Variables

Individuals were asked to report how many vehicles their households owned. The reported household vehicle ownership ranged from 0 to 12. On average, a US household owns 2.23 vehicles. The distribution of household vehicle ownership is shown in Figure 8. A total of 7334 (3.35%) people reported that their household has no vehicles, 50,175 (22.91%) individual households have one vehicle, and 90,902 (41.50%) people reported having two vehicles in their household, while 70,615 (32.24%) people live in households with more than three vehicles.

The independent variable household vehicle ownership is measured by two variables: (1) count of household vehicles (HHvehcount), which is an ordinal/count variable, ranging from 0 to 12; this variable was used to examine the effect of an increase/decrease by one household vehicle on individuals' ridesharing usage; (2) household vehicle ownership level, which is represented by four dummy variables, including households with zero vehicles (Vehicle 0), one vehicle (Vehicle 1), two vehicles (Vehicle 2) or three or more vehicles (Vehicle 3). As the marginal effects may diminish upon increasing the count of household vehicles, we classified individuals in households with three or more vehicles into one group. These four dummy variables were used to examine the effects of households' different vehicle ownership levels on individuals' ridesharing usage.

Table 1. Variable definitions and descriptive statistics.

Variable	Definition	Type	Obs.	Mean	Std. Dev.	Min	Max
	Dependent Variable						
Rideshare	Frequency of ridesharing usage in the last 30 days	Ordinal	219,026	0.309	1.757	0	99
	Independent Variables						
HHvehcount	Count of household vehicles	Ordinal	219,026	2.232	1.231	0	12
Vehicle 0	Count of household vehicles is zero	Dummy	219,026	0.033	0.180	0	1
Vehicle 1	Count of household vehicles is one	Dummy	219,026	0.229	0.420	0	1
Vehicle 2	Count of household vehicles is two	Dummy	219,026	0.415	0.493	0	1
Vehicle 3	Count of household vehicles is three or more	Dummy	219,026	0.322	0.467	0	1
	Control Variables						
	Individual characteristics						
Female	Individual is female (Yes = 1, No = 0)	Dummy	219,026	0.531	0.499	0	1
Age	Individual's age (years)	Ordinal	219,026	53.025	18.245	16	92
Education	Individual's education level: 1 = less than high school, 2 = high school/General Educational Development (GED), 3 = some college/associate, 4 = bachelor, 5 = graduate/professional	Ordinal	219,026	3.332	1.185	1	5
White	Individual's race is white (Yes = 1, No = 0)	Dummy	219,026	0.822	0.383	0	1
Worker	Individual is a worker (Yes = 1, No = 0)	Dummy	219,026	0.549	0.498	0	1
Driver	Individual is a driver (Yes = 1, No = 0)	Dummy	219,026	0.919	0.272	0	1
	Household characteristics						
HHincome	Household income level: 1 = less than \$10 k, 2 = \$10 k to \$15 k, 3 = \$15 k to \$25 k, 4 = \$25 k to \$35 k, 5 = \$35 k to \$50 k, 6 = \$50 k to \$75 k, 7 = \$75 k to \$100 k, 8 = \$100 k to \$125 k, 9 = \$125 k to \$150 k, 10 = \$150 k to \$200 k, 11 = \$200 k or more	Ordinal	219,026	6.315	2.593	1	11
Homerent	Home is rental (Yes = 1, No = 0)	Dummy	219,026	0.212	0.409	0	1
	Regional characteristics						
Pdensity	Population density (persons per square mile) in the census block group of household's home location in log	Continuous	219,026	7.172	1.752	3.9	10.3
Rail	Home location has heavy rail service (Yes = 1, No = 0)	Dummy	219,026	0.161	0.368	0	1
Urban	Household is in an urban area (Yes = 1, No = 0)	Dummy	219,026	0.770	0.421	0	1
	Public transit usage and season						
Ptused	Count of public transit usage in the last 30 days	Ordinal	219,026	0.895	4.345	0	240
Spring	The survey was conducted in March, April, or May	Dummy	219,026	0.205	0.403	0	1
Summer	The survey was conducted in June, July, or August	Dummy	219,026	0.259	0.438	0	1
Fall	The survey was conducted in September, October, or November	Dummy	219,026	0.266	0.442	0	1
Winter	The survey was conducted in December, January, or February	Dummy	219,026	0.270	0.444	0	1



(**a**) (**b**)

Figure 8. Distribution of household vehicle ownership: (**a**) percentage, (**b**) frequency.

3.3.3. Control Variables

We controlled for four other types of variables that may affect ridesharing usage, including individual characteristics, household characteristics, regional characteristics, public transit usage, and season. First, individual characteristics are measured by Female (whether the respondent is female or not), Age (respondent's age in years), Education (respondent's education level), White (whether the respondent's race is white or not), Worker (whether the respondent is a worker or not), and Driver (whether the respondent is able to drive or not). Second, household characteristics were measured by HHincome (household annual income level), and Homerent (whether the home is rented or not). Third, regional characteristics were measured by Pdensity (population density at the home location), Rail (whether the home location has rail service or not), and Urban (whether the home is located in an urban area or not). Lastly, Ptused represented the number of times the respondent used public transit in the last 30 days. Seasons were also controlled for, including four dummy variables: Spring (the survey is conducted in spring), Summer (the survey is conducted in summer), Fall (the survey is conducted in fall) and Winter (the survey is conducted in winter).

4. Methodology

4.1. Model Selection

In terms of methodological approaches, for a discrete non-negative integer outcome, the Poisson regression model and negative binomial regression model (NB) are appropriate statistical modeling techniques that can account for "count" characteristics of frequency data [52]. The limitation of the Poisson model is that it requires the mean of the data to be equal to the variance; therefore, the model cannot account for the possibility of over-dispersion (the variance is significantly greater than the mean), which may lead to biased, inefficient parameter estimates. The NB model can be used to address the over-dispersion problem by relaxing the constraint that the variance must be equal to the mean [53].

The zero-inflated Poisson regression model (ZIP) and zero-inflated negative binomial regression model (ZINB) are extensions of the traditional Poisson and NB models, which can be used to handle observed data characterized by a large number of zero values [53,54]. When the predicted variable has excess zero counts, the zero-inflated models are developed to address the probability of zero-inflated counting processes. The ZINB model can address the over-dispersion problem, while the ZIP model has the limitation that the mean and variance of the data must be equal [55].

Many studies have used ZINB models to handle data with the characteristics of over-dispersion and zero-inflation. A review of the literature on transportation safety revealed that zero-inflated models are more appropriate modeling techniques when the zero values for the observed variable are over 65% [56]. Crash-frequency data are count data with excess zeroes and are often studied by researchers in transportation safety fields [52]. Shen and Neyens [57] developed ZINB models to examine the associations between teen drivers' hospital length of stay and the possible factors, and the dependent variable had 96.7 and 94.2% zero values for girls and boys, respectively. As in this study, the observed data are over-dispersed (the variance 3.09 is clearly greater than the mean 0.31 of individuals' ridesharing usage in the last 30 days) and zero-inflated (there are 92.32% zero counts in the observations of ridesharing usage in the last 30 days); thus, the ZINB model is the best model for the analysis.

4.2. Zero-Inflated Negative Binomial Regression Model

4.2.1. ZINB Distribution

ZINB models consist of two different counting processes [55,58]. One process is the true zero-count process (zero state, odds of always being 0), which is governed by a logit model with the probability p_i. The other process is the count-data process (non-zero state, odds of not always being 0), which is governed by an NB model with the probability $(1 - p_i)$; zero counts are also generated in this process. Therefore, if we combine the probability of zeroes generated from these two processes, we can obtain the overall probability of zero values. Let Y_i be the frequency of ridesharing usage in the last 30 days, $P(Y_i = 0)$ be the probability of zero counts, and $P(Y_i = y)$ be the probability of non-zero counts. Thus, the form of zero-inflated negative binomial distribution [59] can be written as follows:

$$P(Y_i = 0) = p_i + (1 - p_i)\left(\frac{1/k}{\mu_i + 1/k}\right)^{1/k} \tag{1}$$

$$P(Y_i = y) = (1 - p_i)\frac{\Gamma(y + 1/k)}{\Gamma(1/k)\Gamma(y + 1)}\left(\frac{1/k}{\mu_i + 1/k}\right)^{1/k}\left(\frac{\mu_i}{\mu_i + 1/k}\right)^{y} y = 1, 2, 3, \ldots \tag{2}$$

where k is the dispersion parameter of the corresponding NB distribution, and μ_i is the mean. The mean and variance of the predicted variable can be written as follows:

$$E(Y_i) = (1 - p_i)\mu_i \tag{3}$$

$$Var(Y_i) = (1 - p_i)(1 + \mu_i k + p_i \mu_i)\mu_i \tag{4}$$

4.2.2. ZINB Fixed Model

Let $y_{ij}(i = 1, 2, \ldots m; j = 1, 2, \ldots n_i)$ be a count of the jth observation in the ith cluster. In this study, the observations are nested in clusters and the total number of observations is $\sum_{i=1}^{m} n_i = n$. In the regression setting, $\log(\frac{p_{ij}}{1-p_{ij}})$ represents the logistic component and $\log(\mu_{ij})$ represents the NB component. Both components depend on a set of explanatory variables, and the linear functions are as follows:

$$\log(\frac{p_{ij}}{1 - p_{ij}}) = \delta_{ij} = A_{ij}{}^T \alpha + \lambda_i \tag{5}$$

$$\log(\mu_{ij}) = \eta_{ij} = B_{ij}{}^T \beta + \pi_i \tag{6}$$

where A_{ij} and B_{ij} are the vectors of covariates for the logistic component and the NB component, respectively, and A_{ij} and B_{ij} are not necessarily the same. α and β are the corresponding vectors of coefficients of these two components. Let $\lambda_i = (\lambda_1, ..., \lambda_m)^T$ and $\pi_i = (\pi_1, ..., \pi_m)^T$ denote the vectors of the cluster-level random effects. For simplicity, λ_i and π_i are assumed to be independent of the distributions as $N(0, \sigma_\lambda^2 R_m)$ and $N(0, \sigma_\pi^2 R_m)$, respectively, where R_m represents an $m \times m$ identity matrix. The coefficients of the ZINB models are estimated by using maximum likelihood methods.

4.2.3. Application of the ZINB Model

ZINB models were employed to examine the relationship between household vehicle ownership and ridesharing usage. In our analysis models, A_{ij} and B_{ij} are the same variables. We used the logistic component (zero state) to examine the relationship between the probability of ridesharing usage and household vehicle ownership, and the NB component (non-zero state) to examine the relationship between the frequency of ridesharing usage and household vehicle ownership.

5. Results

This section presents the detailed ZINB model results. We examined the relationships between household vehicle ownership and the frequency of ridesharing usage (the number of times the respondents used ridesharing in the last 30 days; the result is shown in the non-zero state), and the probability of ridesharing usage (whether the respondent used ridesharing at least once or never used it in the last 30 days; the result is shown in the zero state). We also assessed the effects of household vehicle ownership on individuals' adoption of ridesharing services. In general, the correlation between household vehicle ownership and ridesharing usage is significantly negative with significance at the 0.1% level (p-value < 0.001), indicating that household vehicle ownership has negative effects on ridesharing usage. As associations between ridesharing usage and household vehicle ownership are influenced by population density, we also constructed ZINB models to examine how the relationships vary by population density, and the results showed that people who lived in areas with higher population density were more sensitive to household vehicle ownership than those living in areas with lower population density.

5.1. Results for the Relationship between Household Vehicle Ownership and Ridesharing Usage

Table 2 shows the results for the ZINB models after controlling for all the other variables. The coefficients of most variables (including the independent and control variables) were highly significant at the 0.1% level (p-value < 0.001). These results showed the significant effects of household vehicle ownership on the frequency and probability of ridesharing usage.

Table 2A shows the effects of the count of household vehicles on individuals' ridesharing usage. The marginal effects ($e^\beta - 1$) in the non-zero state indicate the proportion of change in the frequency of ridesharing usage in the last 30 days for a one-unit change in an independent variable, holding all other variables constant. To be more specific, a one-vehicle reduction in a household significantly increased an individual's frequency of ridesharing usage by 7.9%, with significance at the 0.1% level (p-value < 0.001). The marginal effects ($e^\alpha - 1$) in the zero state provide the proportion of change in the probability of ridesharing usage in the last 30 days for a one-unit change in an independent variable, holding all other variables constant. The negative marginal effects in the zero state indicated that individuals were less likely to have zero counts of ridesharing usage, and thus were more likely to have used ridesharing at least once in the last 30 days, suggesting a higher probability of ridesharing usage. A one-vehicle reduction in a household significantly increased an individual's likelihood of ridesharing usage by 23.0%, with significance at the 0.1% level (p-value < 0.001). In general, the count of household vehicles was significantly negatively associated with the frequency of ridesharing usage and the probability of ridesharing usage.

Table 2B shows the effects of the household vehicle ownership level on individuals' ridesharing usage. Compared to those in households with one vehicle, the likelihood of ridesharing usage increased by 42.1% when households had no vehicles, decreased by 55.5% when households had two vehicles, and decreased by 94.5% when households had three or more vehicles. The frequency of ridesharing usage rose by 33.3% in households without any vehicles compared to those living in households with one vehicle. Individuals in households with two vehicles used ridesharing 23.4% less frequently than those who lived in households with only one vehicle. People in households with three or more vehicles exhibited a 30.1% lower frequency of ridesharing usage than those in households with one vehicle.

Table 2A also shows that individuals' frequency and probability of ridesharing usage was influenced by control variables. Women used ridesharing 9.5% less frequently, and were 11.6% less likely to use ridesharing than men. A one-unit increase in age would decrease the frequency of ridesharing usage by 1.0%, and the odds of ridesharing usage by 4.1%, meaning that younger people used ridesharing more frequently and were more likely to use it than older people; this may be because it is more difficult for older people to accept and use a new technology and service [47]. The probability of ridesharing usage grew by 37.1% as the education level increased by one level. A higher education level increased individuals' odds of ridesharing usage by 37.1%, but slightly decreased the frequency of ridesharing usage by 3.2%. People with a higher education level are more likely to use a ridesharing service, which may be because they have a greater awareness of this new technology and service than those with a lower education level [45]. The race status and worker status have no significant effect on individuals' frequency of ridesharing usage. It was somewhat surprising to find that the frequency and the likelihood of ridesharing use would increase by 6.0% and 21.5%, respectively, when the household annual income level increased by one level, indicating that wealthier people tend to be more willing to use a ridesharing service. Not surprisingly, people who live in areas with a higher population density used ridesharing 14.8% more frequently and were 23.2% more likely to use ridesharing than those living in areas with a lower population density. The frequency of ridesharing usage increased by 11.5%, and the odds of ridesharing usage rose by 26.4% in areas with rail service. One additional instance of public transit usage slightly increased the frequency of ridesharing usage, and the likelihood of ridesharing usage by 1.2% and 5.7%, respectively, suggesting that those who live in households with few vehicles may use both ridesharing and public transit as a substitute for vehicle ownership. In general, individuals who traveled in the spring used ridesharing 14.0% more frequently than those who traveled in the fall, while traveling in the summer decreased the frequency of ridesharing usage by 8.6% compared to traveling in the fall, which may be because travelers are less willing to use a ridesharing service in uncomfortably hot weather.

5.2. Results for the Relationship between Count of Household Vehicles and Ridesharing Usage Varying by Population Density

Table 3 shows how the associations between the count of household vehicles, and the frequency and probability of ridesharing usage vary by population density. We divided the population density into two groups: (1) if there were more than 4000 persons per square mile at the home location, then individuals lived in an area with a high population density, and (2) if there were fewer than 4000 persons per square mile at the home location, then individuals lived in an area with a low population density. The results showed that negative relationships between ridesharing usage and the count of household vehicles were more pronounced in high-density urban areas.

A one-household vehicle reduction was associated with a 12.7% increase in the frequency of ridesharing usage for people who lived in areas with a high population density, which was greater than the effect of a one-household vehicle reduction on the increase in frequency of ridesharing usage (5.5%) for those living in areas with a low population density. However, the effects of the count of household vehicle reduction on the increased probability of ridesharing usage showed no significant difference between these two groups; the values were 29.9% and 30.1% for people who lived in high- and low-population density areas, respectively.

5.3. Results for the Relationship between Household Vehicle Ownership Level and Ridesharing Usage Varying by Population Density

Table 4 shows how the associations between the household vehicle ownership level and the frequency and probability of ridesharing usage vary by population density. In areas with a high population density, individuals in households without any vehicles showed a 28.7% higher frequency of ridesharing usage than those who lived in households with one vehicle. However, in areas with a low population density, the frequency of ridesharing usage did not show a significant difference between households that had no vehicles, and those with one vehicle. Compared to individuals in households with one vehicle, individuals in households with two vehicles had a 25.4% lower frequency of ridesharing usage in areas with a high population density, and the effect was slightly greater than the negative effect (23.4%) for those who lived in areas with a low population density. When individuals lived in areas with a high population density, those in households with three or more vehicles used ridesharing 35.8% less frequently than those who lived in households with only one vehicle, and the negative effect was significantly greater for those who lived in areas with a low population density (29.2%).

In areas with a high population density, individuals in households without any vehicles had a 43.4% higher probability of ridesharing usage than those in households with one vehicle. The results also showed that the more vehicles there were in a household, the less likely individuals were to use ridesharing, and this was evidenced by the marginal effects of Vehicle 2 and Vehicle 3 on the probability of ridesharing usage (the effect of 107.2% for those in households with three or more vehicles is greater than the effect of 62.0% for those in households with two vehicles).

Table 2. Results for the relationship between household vehicle ownership and ridesharing usage (dependent variable: Rideshare).

	(A) Independent Variable: Count of Household Vehicles					**(B) Independent Variable: Household Vehicle Ownership Level**				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
	Non−zero state (not always 0)					Non−zero state (not always 0)				
HHvehcount	−0.082 ***	0.009	−8.75	**0.000**	−7.9%					
Vehicle 0						0.288 ***	0.050	5.74	**0.000**	33.3%
Vehicle 2						−0.266 ***	0.027	−9.71	**0.000**	−23.4%
Vehicle 3						−0.359 ***	0.033	−10.95	**0.000**	−30.1%
Female	−0.100 ***	0.022	−4.63	**0.000**	−9.5%	−0.106 ***	0.021	−4.95	**0.000**	−10.1%
Age	−0.010 ***	0.001	−12.70	**0.000**	−1.0%	−0.011 ***	0.001	−13.65	**0.000**	−1.1%
Education	−0.032 **	0.013	−2.58	**0.010**	−3.2%	−0.035 **	0.013	−2.77	**0.006**	−3.4%
White	0.014	0.027	0.50	0.618	1.4%	0.025	0.027	0.92	0.357	2.5%
Worker	0.009	0.029	0.30	0.762	0.9%	0.008	0.029	0.27	0.784	0.8%
Driver	−0.445 ***	0.044	−10.02	**0.000**	−35.9%	−0.342 ***	0.046	−7.39	**0.000**	−29.0%
HHincome	0.059 ***	0.005	12.67	**0.000**	6.0%	0.067 ***	0.005	14.37	**0.000**	6.9%
Homerent	0.234 ***	0.027	8.81	**0.000**	26.3%	0.181 ***	0.027	6.78	**0.000**	19.8%
Pdensity	0.138 ***	0.010	13.64	**0.000**	14.8%	0.126 ***	0.010	12.44	**0.000**	13.5%
Rail	0.109 ***	0.025	4.39	**0.000**	11.5%	0.087 ***	0.025	3.54	**0.000**	9.1%
Urban	−0.358 ***	0.055	−6.48	**0.000**	−30.1%	−0.317 ***	0.055	−5.75	**0.000**	−27.2%
Ptused	0.012 ***	0.002	7.17	**0.000**	1.2%	0.010 ***	0.002	6.23	**0.000**	1.0%
Spring	0.131 ***	0.031	4.24	**0.000**	14.0%	0.124 ***	0.031	4.06	**0.000**	13.2%
Summer	−0.090 **	0.030	−3.05	**0.002**	−8.6%	−0.084 **	0.030	−2.85	**0.004**	−8.1%
Winter	0.004	0.028	0.14	0.885	0.4%	0.005	0.028	0.17	0.868	0.5%
Intercept	0.572 ***	0.105	5.45	0.000		0.561 ***	0.105	5.35	0.000	
	Zero state (odds of always 0)					Zero state (odds of always 0)				
HHvehcount	0.207 ***	0.012	17.74	**0.000**	23.0%					
Vehicle 0						−0.546 ***	0.071	−7.71	**0.000**	−42.1%
Vehicle 2						0.442 ***	0.031	14.10	**0.000**	55.5%
Vehicle 3						0.670 ***	0.036	18.58	**0.000**	95.4%
Female	0.109 ***	0.023	4.77	**0.000**	11.6%	0.115 ***	0.023	4.99	**0.000**	12.2%
Age	0.040 ***	0.001	50.49	**0.000**	4.1%	0.041 ***	0.001	50.86	**0.000**	4.1%
Education	−0.464 ***	0.012	−38.15	**0.000**	−37.1%	−0.465 ***	0.012	−38.21	**0.000**	−37.2%
White	−0.160 ***	0.029	−5.43	**0.000**	−14.8%	−0.164 ***	0.030	−5.55	**0.000**	−15.1%
Worker	−0.368 ***	0.028	−13.13	**0.000**	−30.8%	−0.372 ***	0.028	−13.23	**0.000**	−31.0%
Driver	−0.342 ***	0.050	−6.77	**0.000**	−28.9%	−0.456 ***	0.054	−8.49	**0.000**	−36.6%
HHincome	−0.242 ***	0.005	−44.29	**0.000**	−21.5%	−0.253 ***	0.006	−45.30	**0.000**	−22.4%
Homerent	−0.610 ***	0.029	−20.71	**0.000**	−45.6%	−0.573 ***	0.030	−19.23	**0.000**	−43.6%
Pdensity	−0.264 ***	0.011	−24.45	**0.000**	−23.2%	−0.262 ***	0.011	−24.26	**0.000**	−23.1%
Rail	−0.307 ***	0.028	−11.01	**0.000**	−26.4%	−0.299 ***	0.028	−10.71	**0.000**	−25.9%

Table 2. *Cont.*

	(A) Independent Variable: Count of Household Vehicles					(B) Independent Variable: Household Vehicle Ownership Level				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
Urban	−0.238 ***	0.051	−4.71	**0.000**	−21.2%	−0.249 ***	0.051	−4.92	**0.000**	−22.0%
Ptused	−0.059 ***	0.003	−17.96	**0.000**	−5.7%	−0.052 ***	0.003	−16.16	**0.000**	−5.1%
Spring	0.072 *	0.033	2.19	**0.028**	7.5%	0.068 *	0.033	2.06	**0.039**	7.0%
Summer	0.114 ***	0.032	3.58	**0.000**	12.1%	0.114 ***	0.032	3.59	**0.000**	12.1%
Winter	−0.080 **	0.031	−2.60	**0.009**	−7.6%	−0.078 *	0.031	−2.55	**0.011**	−7.5%
Intercept	6.071 ***	0.106	57.07	0.000		6.293 ***	0.107	58.85	0.000	
Number of observations (obs.)			219,026				219,026			
Nonzero obs.			16,817				16,817			
Zero obs.			202,209				202,209			
Log likelihood			−82,654.76				−82,462.38			
LR chi2			1749.03 ***				1881.69 ***			

p−value: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 3. Results for the relationship between count of household vehicles and ridesharing usage varying by population density.

	High Population Density (Dependent Variable: Rideshare)					Low Population Density (Dependent Variable: Rideshare)				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
	Non−zero state (not always 0)					Non−zero state (not always 0)				
HHvehcount	−0.136 ***	0.012	−10.92	**0.000**	−12.7%	−0.057 ***	0.015	−3.79	**0.000**	−5.5%
Female	−0.077 **	0.027	−2.82	**0.005**	−7.5%	−0.077 *	0.037	−2.07	**0.038**	−7.4%
Age	−0.011 ***	0.001	−10.48	**0.000**	−1.1%	−0.013 ***	0.001	−10.86	**0.000**	−1.3%
Education	−0.01	0.016	−0.64	0.521	−1.0%	0.047 *	0.020	2.29	**0.022**	4.8%
White	0.122 ***	0.034	3.63	**0.000**	13.0%	−0.207 ***	0.049	−4.19	**0.000**	−18.7%
Worker	0.011	0.039	0.27	0.788	1.1%	0.130 **	0.045	2.88	**0.004**	13.9%
Driver	−0.438 ***	0.051	−8.64	**0.000**	−35.5%	0.052	0.073	0.72	0.474	5.4%
HHincome	0.077 ***	0.006	13.12	**0.000**	8.0%	0.075 ***	0.008	9.37	**0.000**	7.8%
Homerent	0.241 ***	0.032	7.51	**0.000**	27.2%	0.301 ***	0.049	6.12	**0.000**	35.1%
Rail	0.193 ***	0.029	6.65	**0.000**	21.3%	0.120 **	0.046	2.63	**0.009**	12.8%
Ptused	0.009 ***	0.002	5.23	**0.000**	0.9%	0.004	0.003	1.54	0.122	0.4%
Spring	0.113 **	0.040	2.84	**0.005**	11.9%	0.169 **	0.052	3.23	**0.001**	18.4%
Summer	−0.071	0.038	−1.87	0.061	−6.8%	−0.076	0.051	−1.50	0.134	−7.3%
Winter	−0.011	0.036	−0.31	0.758	−1.1%	0.093	0.048	1.93	**0.053**	9.8%
Intercept	1.337 ***	0.100	13.32	0.000		−0.273 *	0.125	−2.19	0.029	

Table 3. *Cont.*

	High Population Density (Dependent Variable: Rideshare)					Low Population Density (Dependent Variable: Rideshare)				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
	Zero state (odds of always 0)					Zero state (odds of always 0)				
HHvehcount	0.262 ***	0.018	14.91	**0.000**	29.9%	0.263 ***	0.019	13.74	**0.000**	30.1%
Female	0.102 **	0.033	3.14	**0.002**	10.8%	0.153 ***	0.042	3.65	**0.000**	16.6%
Age	0.047 ***	0.001	40.48	**0.000**	4.8%	0.038 ***	0.001	27.07	**0.000**	3.9%
Education	−0.466 ***	0.017	−26.99	**0.000**	−37.3%	−0.487 ***	0.022	−21.98	**0.000**	−38.6%
White	−0.294 ***	0.039	−7.50	**0.000**	−25.5%	0.093	0.058	1.60	0.109	9.8%
Worker	−0.413 ***	0.040	−10.26	**0.000**	−33.8%	−0.360 ***	0.050	−7.25	**0.000**	−30.2%
Driver	−0.360 ***	0.063	−5.69	**0.000**	−30.2%	0.011	0.110	0.10	0.920	1.1%
HHincome	−0.216 ***	0.008	−28.51	**0.000**	−19.4%	−0.311 ***	0.010	−30.70	**0.000**	−26.7%
Homerent	−0.650 ***	0.039	−16.59	**0.000**	−47.8%	−0.669 ***	0.058	−11.44	**0.000**	−48.8%
Rail	−0.465 ***	0.036	−13.05	**0.000**	−37.2%	−0.363 ***	0.061	−5.97	**0.000**	−30.4%
Ptused	−0.042 ***	0.003	−12.86	**0.000**	−4.1%	−1.536 ***	0.109	−14.13	**0.000**	−78.5%
Spring	0.086	0.047	1.82	0.068	9.0%	0.154 **	0.060	2.59	**0.010**	16.7%
Summer	0.154 ***	0.045	3.43	**0.001**	16.6%	0.192 **	0.059	3.27	**0.001**	21.1%
Winter	−0.101 *	0.044	−2.32	**0.020**	−9.6%	0.013	0.056	0.23	0.822	1.3%
Intercept	3.125 ***	0.106	29.45	0.000		3.330 ***	0.153	21.79	0.000	
Number of obs.	64,468					162,356				
Nonzero obs.	9023					8007				
Zero obs.	55,445					154,349				
Log likelihood	−41,684.62					−42,105.86				
LR chi2	940.26 ***					388.41 ***				

$p-$value: * $p < 0.05$; ** $p < 0.01$; ***$p < 0.001$.

Table 4. Results for the relationship between household vehicle ownership level and ridesharing usage varying by population density.

	High Population Density (Dependent Variable: Rideshare)					Low Population Density (Dependent Variable: Rideshare)				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
	Non−zero state (not always 0)					Non−zero state (not always 0)				
Vehicle0	0.252 ***	0.054	4.69	**0.000**	28.7%	0.167	0.100	1.68	0.093	18.2%
Vehicle2	−0.293 ***	0.033	−8.84	**0.000**	−25.4%	−0.266 ***	0.052	−5.09	**0.000**	−23.4%
Vehicle3	−0.443 ***	0.043	−10.43	**0.000**	−35.8%	−0.346 ***	0.058	−6.00	**0.000**	−29.2%
Female	−0.088 **	0.027	−3.19	**0.001**	−8.4%	−0.079 *	0.037	−2.13	**0.034**	−7.6%
Age	−0.012 ***	0.001	−11.06	**0.000**	−1.2%	−0.015 ***	0.001	−11.58	**0.000**	−1.5%
Education	−0.011	0.016	−0.69	0.490	−1.1%	0.045 *	0.020	2.22	**0.027**	4.6%

Table 4. *Cont.*

	High Population Density (Dependent Variable: Rideshare)					Low Population Density (Dependent Variable: Rideshare)				
Variables	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**	**Coef.**	**Std. Err.**	***z* Value**	***p* Value**	**Marginal Effects**
White	0.128 ***	0.033	3.83	**0.000**	13.7%	−0.195 ***	0.049	−3.94	**0.000**	−17.7%
Worker	0.006	0.039	0.14	0.887	0.6%	0.134 **	0.045	2.95	**0.003**	14.3%
Driver	−0.368 ***	0.053	−6.92	**0.000**	−30.8%	0.148	0.077	1.93	0.054	15.9%
HHincome	0.082 ***	0.006	13.94	**0.000**	8.6%	0.087 ***	0.008	10.64	**0.000**	9.1%
Homerent	0.202 ***	0.032	6.26	**0.000**	22.4%	0.238 ***	0.050	4.74	**0.000**	26.8%
Rail	0.163 ***	0.029	5.60	**0.000**	17.7%	0.108 *	0.046	2.36	**0.018**	11.5%
Ptused	0.008 ***	0.002	4.59	**0.000**	0.8%	0.004	0.003	1.46	0.145	0.4%
Spring	0.105 **	0.040	2.66	**0.008**	11.1%	0.169 **	0.052	3.23	**0.001**	18.4%
Summer	−0.069	0.038	−1.83	0.068	−6.7%	−0.074	0.051	−1.46	0.146	−7.1%
Winter	−0.015	0.036	−0.41	0.685	−1.4%	0.098 *	0.048	2.03	**0.043**	10.3%
Intercept	1.239 ***	0.101	12.27	0.000		−0.317 *	0.130	−2.44	0.015	
	Zero state (odds of always 0)					Zero state (odds of always 0)				
Vehicle0	−0.569 ***	0.083	−6.88	**0.000**	−43.4%	−1.160 ***	0.199	−5.84	**0.000**	−68.6%
Vehicle2	0.482 ***	0.042	11.59	**0.000**	62.0%	0.528 ***	0.063	8.39	**0.000**	69.5%
Vehicle3	0.729 ***	0.050	14.44	**0.000**	107.2%	0.933 ***	0.069	13.59	**0.000**	154.3%
Female	0.102 **	0.033	3.12	**0.002**	10.8%	0.167 ***	0.043	3.91	**0.000**	18.1%
Age	0.048 ***	0.001	40.73	**0.000**	4.9%	0.039 ***	0.001	26.90	**0.000**	4.0%
Education	−0.465 ***	0.017	−26.88	**0.000**	−37.2%	−0.493 ***	0.022	−22.03	**0.000**	−38.9%
White	−0.299 ***	0.039	−7.59	**0.000**	−25.9%	0.082	0.059	1.39	0.165	8.6%
Worker	−0.418 ***	0.040	−10.36	**0.000**	−34.2%	−0.363 ***	0.050	−7.24	**0.000**	−30.5%
Driver	−0.479 ***	0.068	−7.10	**0.000**	−38.1%	−0.135	0.116	−1.16	0.244	−12.7%
HHincome	−0.228 ***	0.008	−29.42	**0.000**	−20.4%	−0.325 ***	0.011	−30.84	**0.000**	−27.8%
Homerent	−0.618 ***	0.040	−15.65	**0.000**	−46.1%	−0.628 ***	0.060	−10.48	**0.000**	−46.6%
Rail	−0.449 ***	0.036	−12.52	**0.000**	−36.1%	−0.369 ***	0.062	−5.98	**0.000**	−30.9%
Ptused	−0.037 ***	0.003	−11.06	**0.000**	−3.6%	−1.586 ***	0.117	−13.60	**0.000**	−79.5%
Spring	0.083	0.047	1.76	0.078	8.7%	0.150 *	0.060	2.48	**0.013**	16.1%
Summer	0.150 ***	0.045	3.34	**0.001**	16.2%	0.186 **	0.059	3.14	**0.002**	20.5%
Winter	−0.100 *	0.044	−2.27	**0.023**	−9.5%	0.014	0.056	0.25	0.800	1.4%
Intercept	3.431 ***	0.108	31.85	0.000		3.617 ***	0.159	22.69	0.000	
Number of obs.		64,468					162,356			
Nonzero obs.		9023					8007			
Zero obs.		55,445					154,349			
Log likelihood		−41,582.4					−42,028.79			
LR chi2		1012.03 ***					433.12 ***			

p−value: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

6. Discussion

In this study, ZINB models were employed to examine the associations between household vehicle ownership and ridesharing usage, and to estimate the effects of household vehicle ownership on ridesharing behaviors, using the 2017 NHTS dataset. Our findings suggest that household vehicle ownership is significantly negatively associated with individuals' frequency and probability of ridesharing usage, indicating that household vehicle reduction is related to ridesharing demand increase. In general, a one-vehicle reduction in households significantly increased the frequency of ridesharing usage by 7.9%, and increased the likelihood of ridesharing usage by 23.0%. This may be because people in households with more vehicles have more alternatives to driving their own car than those in households with fewer vehicles, suggesting that people may use ridesharing as a substitute for vehicle ownership.

The negative relationship between household vehicle ownership and the probability of ridesharing usage was also found by Dias et al. [47], but their study did not examine the effect of household vehicle ownership on the frequency of ridesharing usage, which is important when attempting to understand individuals' travel behaviors using travel frequency data. Vehicle ownership reduction is associated with incremental ridesharing demand; thus, improving ridesharing service quality may be beneficial for reducing vehicle ownership and for the environment. Policies aimed at reducing vehicle ownership should consider how to promote the service quality of ridesharing to attract more individuals to shift from driving to on-demand ridesharing. The Department of Transport's Commission on Congestion has called for an increase in the efficiency of use of existing private vehicles, and certain public authorities have made ridesharing part of their political agenda. For the most part, however, ridesharing coordination is an informal and disorganized activity, and in only certain cases can travelers make use of ridesharing as a regular transportation alternative. However, if ridesharing service improvements could encourage ridesharing as an acceptable routine transportation mode, it would have the potential to improve the sustainability of transportation systems.

The effects of household vehicle ownership on the frequency of ridesharing usage are greater for those who live in areas with a higher population density than those living in areas with a lower population density, as evidenced by the effect of the count of household vehicles on the frequency of ridesharing usage in the high population density group (12.7%), which is greater than that in the low population density group. In addition, the effects of household vehicle ownership level on the frequency of ridesharing usage are more pronounced for those who live in areas with a higher population density than for those living in areas with a lower population density (compared to one vehicle, the significant effect of no vehicles is 28.7% in the high population density group, but is not significant in the low population density group; the effect of two vehicles in the high population density group, at 25.4%, is greater than the effect in the low population density group, at 23.4%; and the effect of three or more vehicles in the high population density group, at 35.8%, is greater than the effect in the low population density group, at 29.2%). The explanation may be that people are more likely to have easy access to a ridesharing service in more densely populated urban areas relative to those living in less densely populated rural or suburban areas. In the denser urban areas, the on-demand mobility service market is more active, as there are more drivers to supply ridesharing services and more riders to use them, making it easier for ridesharing platforms/systems to match riders and drivers in real time. Effective interventions and policies should be developed depending on different contextual features.

The descriptive and model results also suggest that personal demographics and household socio-economic and regional characteristics significantly influence individuals' ridesharing usage. The results showed that younger people, men, those who are unable to drive, individuals with higher household income levels, and those who live in areas with rail service or a higher population density tend to use ridesharing more frequently and are more likely to use it. Similar findings have been found in other studies [47]. Ridesharing service providers and policy makers should have a clear understanding of individuals' heterogeneous ridesharing preferences, as different parts of the population, based on personal demographics, household characteristics, and geographical locations, show heterogeneous ridesharing behaviors. Companies and authorities planning to improve ridesharing usage need to know the factors driving their adoption, so that they can optimally position these services in a cost-effective way that will maximize their use [6].

7. Conclusions

Ridesharing is an inexpensive, sustainable, and effective alternative transportation mode that can be used to reduce vehicle ownership and single-occupant trips to improve the sustainability and efficiency of transport systems. Ridesharing is beneficial for the environment, the economy, and society. However, the literature on ridesharing behaviors and the factors affecting the adoption of a ridesharing service is rather sparse. Vehicle ownership affects individuals' travel behaviors and transport mode choices. Despite the potential effect of vehicle ownership on the adoption of ridesharing services, individuals' ridesharing behaviors and the interdependencies between vehicle ownership and ridesharing usage have not been well understood. In this study, ZINB models are developed to understand and quantify the effects of household vehicle ownership on personal ridesharing behavior in the US.

Using the data from the 2017 NHTS, this study developed ZINB models to examine how household vehicle ownership influences individuals' ridesharing behaviors. Household vehicle ownership does have a significant impact on individuals' ridesharing behaviors, and the cross-sectional analysis demonstrates that household vehicle ownership is significantly negatively associated with travelers' monthly ridesharing ridership and the probability of ridesharing usage. The negative associations between household vehicle ownership and ridesharing usage are more pronounced for people who live in areas with higher population densities than for those who live in areas with lower population densities. This research provides information to support policy discussions regarding the prospect of encouraging increased ridesharing usage in conjunction with low household vehicle ownership, depending on different contextual features or different types of people. The model results from this study may also be adopted by planners to estimate ridesharing demand in the on-demand mobility market.

Promoting ridesharing engagement will result in sustainable transportation. Policy initiatives that enhance the quality of ridesharing services and offer sufficiently attractive ridesharing services to help reduce household vehicle ownership are important. Many solutions have been proposed by scholars and practitioners to encourage ridesharing service expansion and promote ridesharing usage. Encouraging household vehicle ownership reduction and a modal shift from driving to on-demand ridesharing services are necessary, and this can be implemented by changing the travel cost of driving one's own vehicle (such as increasing the fuel tax, to make driving more expensive than ridesharing). Policies that encourage people to engage in the adoption of ridesharing, including high occupancy vehicle (HOV) lanes or toll-free lanes, are already in place in many cities in the US [9]. Additional sustainable policies should be identified to encourage people to replace personal vehicle travel with ridesharing and to implement strategies that make ridesharing more attractive to reduce vehicle ownership and fulfill ridesharing demand.

This study contributes to the literature in the following ways. First, we examine how and to what extent household vehicle ownership is associated with individuals' ridesharing use, offering empirical evidence for governments and transportation operators to adjust the policies or interventions that aim to improve the sustainability of transportation systems. Second, we also investigate how the associations vary across areas with different population density, offering significant implications for policy makers or ridesharing platforms to decide where it is beneficial to adjust the interventions. Third, to our knowledge, this is the first study to examine the associations between household vehicle ownership and ridesharing use utilizing individual level travel frequency data from a national travel survey, and ZINB models were employed to analyze the frequency data.

This study has limitations. First, ridesharing behaviors may be influenced by other factors, such as culture, personal lifestyle, attitudes and habits. As the 2017 NHTS includes no such data, we could not control for all the factors that may influence ridesharing usage. Second, this study used the number of times ridesharing was used in the last 30 days; therefore, the trip purpose, trip distance, and travel time for each ridesharing trip are not reflected. Third, ridesharing behaviors should include both the supply of and demand for ridesharing service. We can examine only the effect of vehicle ownership on the ridesharing demand side (riders/passengers), but cannot examine the effect of vehicle ownership on the ridesharing supply side (drivers), as we have no data for the question "How many times have you used the ridesharing application to supply a ridesharing service in the last 30 days?" The supply and demand of ridesharing services should be balanced because if the supply of ridesharing services surges ahead of demand (i.e., more drivers than riders), the ridesharing market will stagnate, while if the demand for ridesharing services expands ahead of supply (i.e., more riders than drivers), then passengers will be more likely to lose interest after being frustrated by many unsuccessful matches with drivers or waiting for longer periods of time [3]. The supply side of ridesharing services and behaviors should be an area of priority for future research.

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