How Does Ride-hailing Service Hit Household Vehicle Ownership? Evidence from National Microdata

Yanghao Wang* Wei Shi†

Abstract

The ride-hailing service is trending up in the most recent decade. Like private driving and public transit, it becomes a major mode of commute in urban areas. The growing popularity of the ride-hailing service changes the landscape of the mobility market. Using data from the 2017 National Household Travel Survey, we examine the impacts of using ride-hailing services on the vehicle ownership for households from 43 metropolitan areas across the United States. Particularly, we estimate an ordered probit model of household vehicle ownership with endogenous treatments of using ride-hailing services in an instrumental variable approach. We find that highly frequent users are 2.21 and 3.44 percentage points more likely to possess no vehicle and one vehicle than regular users, respectively, while their probabilities of possessing two vehicles and three or more vehicles are 1.99 and 3.66 percentage points less. Also, our results show that the probabilities of possessing different numbers of vehicles do not vary significantly across respondents who use ride-hailing services no more than twice a week and that highly frequent users are more willing to reduce their vehicle holdings in contrast to others. Additionally, extrapolating our results from representative respondents to the population in the sampled areas, we find if all regular users convert to highly frequent users, their average vehicle holdings would reduce by 8.61 percent and the total decrease is approximately up to 190,000 vehicles, accounting for 1 percent of new vehicle sales in 2017.

JEL Codes: R4, D1
Keywords: Ride-hailing Service, Vehicle Ownership, National Household Travel Survey, Ordered Probit with Endogenous Treatments

* Corresponding Author. Economist, Global Data Insight and Analytics, Ford Motor Company, Dearborn, MI 48124, wyangh90@gmail.com.
† Economist, Global Data Insight and Analytics, Ford Motor Company, Dearborn, MI 48124.
Any opinions, findings, or conclusions in this study are those of the authors and do not reflect the views of Ford Motor Company. Any errors remain our own.

1. Introduction

The ride-hailing market has surged in the past decade.[1] By 2017, there was about 10 percent of the United States (US) population using ride-hailing services at least once a month on average (Conway et al., 2018). A Pew Research Center survey also finds the share of the US adults using ride-hailing services more than doubled, increasing from 15 percent in 2015 to 36 percent in 2018, while the share of the US adults not hearing of ride-hailing services dropped to 3 percent, which was one tenth of its level in 2015 (J. Jiang, 2019). According to the annual reports of Uber and Lyft, the two giant Transportation Network Companies (TNCs) had reached 14 and 3.6 billion dollars in revenue by the end of 2019, respectively (Lyft, 2020; Uber, 2020). Customers can promptly book, request, and pay for the service using smartphone apps. The demand and supply for rides are dynamically matched by the back-end system in a real-time manner. Because of the improving user experience, as well as generous marketing incentives, the number of ride-hailing customers balloons.[2]

The increasing popularity of ride-hailing services has made a splash in the mobility market. Compared to driving a privately-owned vehicle, using ride-hailing services offers an alternative mode for daily commute in urban areas, featured by time efficiency, low cost, and few concerns of vehicle maintenance and parking (Cramer & Krueger, 2016; Sperling et al., 2018). As a result, most urban residents would prefer using ride-hailing services more often to possessing vehicles, especially for individuals who have vehicles and think of making another purchase. However, the convenience of using ride-hailing services comes at the expense of less riding privacy and more concerns about riding with strangers and the qualification of drivers (Azevedo & Maciejewski,

[1] The ride-hailing service is referred to as the app-based ride-hailing service through this paper.
[2] Uber and Lyft provided substantial discounts to riders and referring incentives to both riders and drivers. In 2019, Uber spent 2.5 billion dollars in sales and marketing, while Lyft paid 814 million dollars (Lyft, 2020; Uber, 2020).

2015; Light, 2016). Hence, customers would retain their vehicles rather than adopt the ride-hailing service as the only possible transportation mode. As follows, this paper investigates how customers would change their vehicle ownership according to their degrees of using ride-hailing services.

Particularly, we examine the impact of using ride-hailing services on the number of vehicles owned by households using the microdata from the 2017 National Household Travel Survey (NHTS). We find that, compared to regular users of ride-hailing services, highly frequent users are less likely to retain the ownership of two or more vehicles. Specifically, highly frequent users (i.e., users taking more than two rides a week) are 1.99 and 3.66 percentage points less likely to possess two and three or more vehicles than regular users (i.e., users taking one to two rides a week), respectively. In comparison, the probabilities of highly frequent users not possessing vehicles and possessing one vehicle are 2.21 and 3.44 percentage points higher than the associated probabilities of regular users, respectively. These findings accordingly provide implications for transportation policies and improve our understanding of how the increasing popularity of using ride-hailing services would affect the vehicle ownership in the US.

Our paper contributes to the economic research on ride-hailing services. Large number of existing studies examine the economic association between the vehicle ownership and the availability of the ride-hailing service by reviewing relevant descriptive statistics. For example, in response to the presence of the ride-hailing service, Clewlow and Mishra (2017) develop an individual travel survey to analyze the changes in the possession of private-owned vehicles in seven major cities in the US. Their results show 91 percent of ride-hailing users are willing to retain the vehicle ownership, whereas 9 percent have disposed one or more vehicles. In contrast, Hampshire et al. (2017) investigate how the vehicle ownership would change if ride-hailing services were prohibited. They leveraged the ban on Uber in Austin in 2016 and distributed an online survey including 1,840 former Uber and/or Lyft users in the local market.[3] They find that 45 percent of the former users started driving privately-owned vehicles after the ban became effective, implying a trade-off between using ride-hailing services and possessing vehicles. Furthermore, using the 2017 NHTS data, Conway et al. (2018) estimate a multivariate logistic model and find a negative relationship between the vehicle ownership and the usage of ride-hailing services. According to the same data, Sabouri, Brewer, and Ewing (2020) revisit this topic using a multilevel Poisson model as well as a random forest model. Their findings are in line with previous literature, showing a negative relationship between the vehicle ownership and the presence of Uber. Adding to the existing studies that have assessed the economic association, this paper evaluates the causal impacts of using ride-hailing services on the vehicle ownership in an ordered probit model with an instrumental approach.

There is sparse causal literature in this field. Ward et al. (2019) is the most relevant study focusing on the US market. They investigate the entry effect of TNCs on the vehicle ownership using the state-level registration data. Developing a difference-in-difference (DID) model weighted by propensity scores, they find the entry of TNCs leads to a decline of 3 percent in the vehicle registration rate per-capita at the state level. Also, Gong, Greenwood, and Song (2017) employ a DID model to quantify the impact of the Uber entry on the vehicle sales in China. They examine the change in the number of newly registered vehicles by comparing the vehicle registration data from 14 cities with Uber services to 262 cities without. Their results show, on average, the Uber entry raises the sales of new vehicles by 11 to 12 percent. In contrast to the

[3] Uber and Lyft suspended their services in Austin on May 9, 2016 as a response to the city authorities' decision on requiring Uber and/or Lyft to conduct the fingerprint background check. In May 2017, Uber and Lyft resumed their services in Austin after the Texas lawmakers passed the House Bill 100 which does not ask for the fingerprint background check but require the annual criminal background check and an operating permit issued by the Texas Department of Licensing and Regulations.

existing literature based on aggregated vehicle registration data, this paper uses the microdata from the 2017 NHTS, a nationwide representative household survey in the US.

Our work also relates to the research on the mobility market. It is documented that the app-based ride-hailing service reshapes the outlook of the mobility market by providing a supplement to the traditional transit system. Previous literature has provided some evidence of how the usage of ride-hailing services would affect the traditional transportation modes (e.g., taxi, bus, and subway). For example, Hall, Palsson, and Price (2018) measure the Uber entry effect on the public transit ridership using a DID model with the transit ridership data in 2004 and 2015 from the National Transit Database. They find the Uber service is a complement to the average transit agency and it increases public transit ridership by 5 percent in two years. Small transit agencies and transit agencies in large cities benefit from such an increase inspired by the Uber entry.[4] Moreover, Berger, Chen, and Frey (2018) examine the impacts of the Uber entry across metropolitan areas in the US. They develop a triple-difference model, as well as a benchmark DID model, using the American Community Survey data from 2009 to 2015. Their results show incumbent drivers experienced a 10 percent decline in earnings after the entry of Uber, though there is no evidence of an increase in the labor supply for drivers.

The rest of the paper proceeds as follows. Section 2 briefly reviews the development of the ride-hailing service and its relation to the vehicle ownership. Section 3 describes the data. The empirical strategy and results are presented in Section 4 and 5. Lastly, we discuss the implications of our findings for the vehicle ownership in the US in Section 6 and conclude in Section 7.

[4] A small transit agency is referred to as a transit agency with the volume of ridership less than the median. Analogously, a large city is defined as a city with a population greater than the median population in the study.

2. Ride-hailing Service and Vehicle Ownership

Along with the establishment and growth of technology-driven TNCs, the app-based ride-hailing service has become popular in metropolitan areas over the past decade.[5] It evolves from an arrangement of carpooling, which encourages participants to travel together by sharing their journeys in one vehicle. Powered by the back-end dynamic matching system and the Internet, the ride-hailing service is distinct from the carpooling in nature. Instead of sharing planned trips with participants, customer requests for rides are submitted to an online platform via smartphone apps and dispatched by a real-time system with the support of dynamic pricing models.

The market share and popularity of using ride-hailing services vary across the US due to the differences in local transportation policies and transit systems. According to the 2017 NHTS data, Figure 1 shows the percentages of respondents using ride-hailing services at least once in the past month over 43 metropolitan statistical areas across the US.[6] We find that the ride-hailing service is more popular in California and the Northeast than the Midwest. For example, 33.93 percent of respondents in San Francisco use ride-hailing services at least once a month, compared to 6.80 percent in Kansas City.

Meanwhile, the market of individual vehicles has constantly remained in the US over recent decades. On average, the number of privately-owned vehicles per household was about 1.83 in 2001 and 1.89 in 2009 (Hu & Reuscher, 2004; Santos et al., 2011). However, it fell back to 1.83 in 2017. Moreover, households become more willing to retain their existing vehicles. Specifically, the average tenure of household vehicle ownership increased from 9.3 years in 2009 to 10.5 years

[5] Uber and Lyft, the two giant technology driven TNCs, were founded in 2009 and 2012, respectively.
[6] These included metropolitan statistical areas are the geographic regions with 1 million population or more based on the 2010-2014 five-year American Community Survey.

in 2017 (Schipper, 2018). These findings suggest individuals are less interested in purchasing new vehicles than a decade ago.

The rise of ride-hailing services changes the landscape of the mobility market. It affects individual attitudes toward the vehicle ownership in the short run and hence the sales in the long run. The increasing popularity of using ride-hailing services can be associated with the decline of driving privately-owned vehicles. Documented by existing studies in marketing, this tradeoff stems from the cannibalization effect between substitutes, implying customers would prefer an alternative to an existing product (Gong et al., 2017; B. Jiang & Tian, 2018). Particularly, because of the higher cost of the vehicle ownership covering gas, auto insurance, and vehicle maintenance and parking, using ride-hailing services is more appealing than possessing vehicles for people living in the metropolitan areas (Belk, 2014; Clewlow & Mishra, 2017; Cramer & Krueger, 2016; Sperling et al., 2018). As follows, the ride-hailing service would hit the sales and detain the increase in the vehicle ownership. Also, it is worth noting that the impact of the ride-hailing service on the vehicle ownership might vary with the degree of its usage. For example, Rayle et al. (2016) find frequent users are more likely to discontinue their vehicle ownerships than infrequent users.

3. Data

Our data are primarily from the 2017 National Household Travel Survey, a main source of information on the travel behavior of American households. The 2017 NHTS is led and sponsored by the US Department of Transportation Federal Highway Administration. It is the most-recent survey in the NHTS series, following the 2009 NHTS. The 2017 NHTS includes a national sample of 26,099 households across 50 States and the District of Columbia over the period between March 2016 and May 2017 (McGuckin & Fucci, 2018).

In this study, we focus on individuals from densely populated, urban areas where the ride-hailing service is popular and widely used as an alternative option serving individual needs of commute. Particularly, the 2017 NHTS data comprise 10,088 households living in the core-based statistical areas (CBSAs) with one million population or more. After removing the responses with missing values, we end up using a sample of primary respondents from 9,543 households in 43 CBSAs across 34 States and the District of Columbia.

The number of privately-owned vehicles is the dependent variable. It has a positive-skewed distribution with an average of 1.76 units, ranging from 0 to 10 units. Specifically, in our analysis, 750 respondents do not possess any vehicle, while 3,438 and 3,575 respondents own one and two vehicles, respectively. The rest 1,780 respondents hold the possession of three or more vehicles, including 1,207 respondents having three vehicles. As a result, we group respondents into four categories, i.e., possessing no vehicle, one vehicle, two vehicles, and three or more vehicles. Each category corresponds 8 percent, 36 percent, 37 percent, and 19 percent of respondents in our sample, respectively.

The variable of interest represents a respondent's degree of using ride-hailing services. Suppose people's needs of commute and their behavior in using ride-hailing services are relatively constant. The variable of interest then can be referred to as the respondent's number of using ride-hailing services via apps in the past 30 days. This variable has a long-tailed distribution with an average of 0.8 time, ranging from 0 to 50 times. Overall, there are 1,686 respondents using ride-hailing services via apps in the past 30 days, accounting for 18 percent of respondents in our sample. Figure 2 presents the cumulative distributions of the usage of ride-hailing services by the number of privately-owned vehicles, suggesting a negative association between these two measures. In other words, using ride-hailing services is more popular among respondents without a vehicle or with one or two vehicles than their counterparts with three or more vehicles. Particularly, Figure 2 shows over 30 percent of respondents without a vehicle used ride-hailing services more than once in the past 30 days. This proportion is about 12, 15, and 19 percentage points higher than that of respondents with one, two, and three or more vehicles, respectively. Also, the figure shows cumulative distribution curves increase at different rates as the number of using ride-hailing services arises. It implies that there is a non-linear relationship between individuals' behavior in using ride-hailing services and the number of their privately-owned vehicles and that such a relationship can vary as the respondent's usage of ride-hailing services increases. Therefore, we divide the number of using ride-hailing services in the past 30 days into four degrees of usage, that is, none (not using the service), one to three times, four to eight times, and more than eight times.[7] For simplicity, let respondents be denoted as nonusers (i.e., no ride), occasional users (i.e., less than one ride a week), regular users (i.e., one to two rides a week), and highly frequent users (i.e., more than two rides a week), respectively.

Moreover, demographic variables are included to account for the heterogeneity across respondents. Overall, 47 percent of sampled respondents are male, 62 percent are employed, 71 percent are homeowners, 79 percent are white Americans, 32 percent have graduate or professional degrees, and 88 percent are netizens. On average, a respondent in our sample is 54 years old, living a household with little less than two drivers. Additionally, there are 51 percent of respondents with annual household income more than 75,000 dollars, including 10 percent over 200,000 dollars.

[7] As for the robustness check, we also re-divide the number of using ride-hailing services into another four degrees of usage, that is, none, one to four, five to nine, and more than nine times. The corresponding model estimates are close to the results presented in this study. Additionally, we examine the data on the usage of ride-hailing services for respondents from suburban and rural areas, i.e., non-metropolitan statistical areas. There are 7,657 suburban and rural respondents enrolled in the 2017 NHTS, of which 7,506 do not use any ride-hailing services in the past 30 days, 64 use once, 39 use twice, 19 use three times, and 29 use four times or above. From these counts, this study properly set the cutoff number at three for an occasional user and a regular user.

Finally, variables of neighborhood environment are included in our analysis. In particular, the Census block group of a respondent's home location defines a neighborhood. On average, the population density in a neighborhood is 8.36 thousand persons per square mile, of which 2.62 thousand are employed. The average housing density is 4.74 thousand units per square mile, of which 30.78 percent are occupied by renters. These neighborhood characteristics briefly reflect the local economy condition and population density, both of which affect the choice of transportation mode. Also, the availability of rail transit can shape a respondent's ownership of vehicles as well as his or her behavior in using ride-hailing services. In our sample, 52 percent of respondents reside in a Metropolitan Statistical Area with access to rail transit.

4. Empirical Framework

Our study is interested in evaluating the impact of using ride-hailing services on the vehicle ownership, characterized by the number of privately-owned vehicles. The usage of ride-hailing services, however, is endogenous in the vehicle ownership model because of its association with the unobservable, such as the ease of accessing the public transport (i.e., taxi, bus, and subway), personal budgets on commute, and individual preference for the flexibility of travel schedules and the convenience in transit. This endogeneity would result in biased estimates of the impact. To address this problem, we use an ordered probit model with endogenous treatments (e.g., Munkin & Trivedi, 2008; Pudney & Shields, 2000).

4.1. Model

Let the number of privately-owned vehicles be denoted by a categorical variable y, where $y = 0$ if a respondent does not have any vehicles and $y = 1$, 2, and 3, if possesses one, two, and three or more vehicles. Also, let the ride-hailing services usage be denoted by a categorical variable R, where $R = 0$ if a respondent does not use any ride-hailing services via apps in the past 30 days and $R = 1$, 2, and 3 if use ride-hailing services less than once a week, one to two times a week, and more than two times a week, respectively. As follows, a set of associated binary variables R_0, R_1, R_2, and R_3 are accordingly defined, where $R_k = 1$ if $R = k$ and 0 otherwise for $k = 0$, 1, 2, and 3. Hence, the outcome equation of the vehicle ownership is an ordered probit model given by,

$$y = j \text{ if } \tau_{j-1} < x'\beta + \tilde{R}'\gamma + u \leq \tau_j, j = 0,1,2,3 \qquad (1)$$

where x is a vector of demographic variables, $\tilde{R} = [R_1, \dots, R_3]'$ is a vector using R_0 as the reference, u is an error term, and τ_j's are threshold parameters such that $\tau_{-1} = -\infty$ and $\tau_2 = \infty$. The conformable vector γ of coefficients represent the impacts of different degrees of using ride-hailing services on the probability of possessing j vehicle(s) compared to the reference. The treatment equation of using ride-hailing services is then specified as

$$R = k \text{ if } \xi_{k-1} < x'\beta + z\alpha + v \leq \xi_k, k = 0,1,2,3 \qquad (2)$$

where z represents the frequency of internet access, v is an error term, and ξ_k's are threshold parameters such that $\xi_{-1} = -\infty$ and $\xi_3 = \infty$. The error terms (u, v) follows the standard bivariate normal distribution with correlation ρ, suggesting the endogeneity. Lastly, the associated likelihood function of our model is the product of joint probabilities of outcomes. For a respondent possessing j vehicles and taking k rides per week, the likelihood contribution is given by

$$\begin{aligned}\Pr(y = j, R = k) = \Phi_2&\left[\tau_j - x'\beta - \tilde{R}'\gamma, \xi_k - x'\beta - z\alpha; \rho\right] \\ -\Phi_2&\left[\tau_{j-1} - x'\beta - \tilde{R}'\gamma, \xi_k - x'\beta - z\alpha; \rho\right] \\ -\Phi_2&\left[\tau_j - x'\beta - \tilde{R}'\gamma, \xi_{k-1} - x'\beta - z\alpha; \rho\right] \\ +\Phi_2&\left[\tau_{j-1} - x'\beta - \tilde{R}'\gamma, \xi_{k-1} - x'\beta - z\alpha; \rho\right]\end{aligned} \qquad (3)$$

where $\Phi_2(\cdot)$ is the cumulative distribution function of the standard bivariate normal distribution.

Marginal effects of continuous (discrete) variables in the vehicle ownership model are obtained by differentiating (differencing) the conditional probabilities. Particularly, the marginal effect of a continuous variable x is given by,

$$\frac{\partial \Pr(y = j \mid R = k)}{\partial x} = \partial \left(\frac{\Pr(y = j, R = k)}{\Pr(R = k)} \right) / \partial x \text{ for } j = 0,1,2,3 \text{ and } k = 0,1,2,3, \quad (4)$$

where the marginal probability for $R = k$ is

$$\Pr(R = k) = \Phi(\xi_k - x'\beta - z\alpha) - \Phi(\xi_{k-1} - x'\beta - z\alpha) \quad (5)$$

and $\Phi(\cdot)$ is the cumulative distribution function the standard normal distribution. Accordingly, we can evaluate the relative treatment effects (TE's) of using ride-hailing services on a respondent's probability of possessing vehicles. For example, a respondent's probability of possessing j vehicles will increase by TE_{kl}^{j} percentage points, if his or her degree of using ride-hailing services escalates from l to k; that is,

$$TE_{kl}^{j} = \Pr(y = j \mid R = k) - \Pr(y = j \mid R = l) \text{ for } k, l = 0,1,2,3 \text{ and } k > l. \quad (6)$$

All marginal and treatment effects are averaged over the sample. Their standard errors are calculated by the bootstrap procedure with 500 draws.

4.2. Identification Strategy

Our estimation approach proceeds by maximizing the likelihood function. As above-mentioned, the usage of ride-hailing services is endogenous as is correlated with the unobservable in the outcome equation of the vehicle ownership. To accommodate this issue, we leverage the nonlinear functional form (i.e., bivariate normality of error terms) of our model and, as well, employ an instrument variable following the exclusion restriction. In particular, we use an instrument variable that is included in the treatment equation, closely related to the ride-hailing service usage, but excluded from the outcome equation of the vehicle ownership.

Millennials, born between 1981 and 1998, are digital natives and grow up in the Information Age. The Internet has become a part of their lives and penetrated their daily activities from entertainment, education, to grocery shopping and travel. Subsequently, they have a more favorable preference for using ride-hailing services via apps than older generations in the daily commute (Montgomery et al., 2020). Figure 3 shows the age distribution by the degree of using ride-hailing services and by the number of privately-owned vehicles, respectively. The solid line displays the full sample distribution of respondents' ages, whereas the dashed lines present the subsample distributions. On the left, we find the subsample age distributions for the users of ride-hailing services are different from the overall age distribution while the nonusers are not. In particular, the majority of the users comprises the respondents aged less than 40, whereas the main part of the nonusers consists of the respondents aged over 40. On the right, except for the age distribution for respondents possessing three or more vehicles, we find the age distributions for respondents possessing two or less vehicles display a shape the same as the overall age distribution. These findings intuitively suggest that the difference between generations can be used to identify the treatment effects. Specifically, we can estimate the model by adding an indicator of Millennials in the treatment equation. This indicator, however, may raise some concerns since it is a variant of age-relevant variable and does not contain much extra information that was excluded from the existing covariate of respondent age.

Alternatively, we employ an exogenous variable related to the Internet access. We assume that the frequency at which a respondent accesses the Internet signals his or her preference for the Internet-based service and hence affects the usage of ride-hailing services via apps. As a result, we include the status of being a netizen as an instrument in the treatment equation and then test the exclusion restriction in our subsequent analysis.

5. Results

The maximum likelihood estimates of model parameters are presented in Table A1 on the appendix. The results show the error terms (u, v) are not independent and the null hypothesis $\rho = 0$ is rejected at the significance level of 1 percent. This rejection implies the endogeneity of the ride-hailing services usage, and hence justifies the joint estimation of these two equations. We also find using ride-hailing services plays a statistically significant role in the outcome equation. The degree of using ride-hailing services is negatively associated with the number of privately-owned vehicles at the 1 percent level of significance. Additionally, in the treatment equation, the status of being a netizen has a positive impact on the ride-hailing service usage at the 1 percent level of significance. In contrast, if added to the outcome equation, the status of being a netizen is statistically insignificant with the Wald test statistics at 1.10 and the p-value at 0.29. These diagnostic results justify the credibility of the exclusion restriction in our analysis.[8]

5.1. Average Treatment Effects of Weekly Rides

We evaluate the impacts of using ride-hailing services on the number of privately-owned vehicles. Table 2 shows the average treatment effects of weekly rides on the probabilities of possessing vehicles. Panel A presents the results as the endogeneity issue has been addressed. We find that using ride-hailing services two times a week or less will not significantly affect the number of

[8] The exclusion restriction also holds if both the status of being a netizen and an indicator of Millennials are included in our analysis. These two variables are jointly significant in the treatment equation but insignificant in the outcome equation. The resulting estimates are close to the estimates presented in this study.

vehicles owned by a respondent. In other words, there is no significant difference in possessing vehicles between nonusers, occasional users, and regular users. By comparison, highly frequent users are more likely to possess fewer vehicles. For example, the probability of possessing one (three or more) vehicle(s) for highly frequent users is 4.70 (5.21) percentage points higher (lower) than the corresponding probability for nonusers at the significance level of 1 percent. On average, compared to occasional users and regular users, highly frequent users are 2.23 and 1.99 percentage points less likely to own two vehicles but 2.51 and 2.21 percentage points more likely not to possess vehicles. Overall, these results suggest using ride-hailing services is a significant factor affecting the vehicle ownership if it reaches a certain degree, i.e., more than two rides a week in this study.

In addition, it is instructive to learn the estimation bias raised by the endogeneity of the ride-hailing usage. Accordingly, Panel B presents the treatment effects as if weekly rides were exogenous. In particular, we find the magnitude order of the treatment effects in Panel B is the same as that in Panel A. The more frequently a respondent uses ride-hailing services, the more willing he or she is to possess fewer vehicles. For example, compared to a nonuser, a highly frequent user is, on average, 4.28 percentage points more likely to possess no vehicle but 6.77 percentage points less likely to possess three or more vehicles at the significance level of 1 percent. As opposed to Panel A, Panel B shows that occasional users and regular users are significantly different from nonusers in possessing vehicles. In Panel B, regardless of the degree, using ride-hailing services always implies a respondent is willing to possess no or one vehicle. In fact, these treatment effects are overstated and the impacts of using ride-hailing services are hence larger than the impacts that would have been estimated had the endogeneity issue been addressed. The comparison between Panel A and B, therefore, reflects the severity of the estimation bias and suggests the accommodation of the endogeneity.

5.2. Marginal Effects Conditional on Weekly Rides

Conditional on weekly rides, we evaluate the marginal effects of other covariates on the probabilities of possessing no vehicle, one vehicle, two vehicles, and three or more vehicles, respectively. Table 3 to 6 present the estimates of marginal effects for the variables of neighborhood environment and respondent's demographics.

Our results show that the variables of neighborhood environment have quantitatively small but statistically significant impacts on the number of vehicles owned by a respondent. Not surprisingly, in a metropolitan area with one million population or more, an average respondent is more likely to possess no (or one) vehicle and less likely to possess three or more (or two) vehicles, if he or she lives in a neighborhood with higher percentage of renter-occupied housing, higher housing density, and access to rail transit. Specifically, as for a neighborhood, a high proportion of rental housing, a high housing density, and access to rail transit implicitly suggest large numbers of migrants, limited space for parking, and an alternative option for public transport, and hence dampen a respondent's willingness to own a vehicle. In Table 3 and 6, conditional on no weekly ride, if the percentage of renter-occupied housing goes up by 1 percentage point, on average, the probability of possessing no vehicle will increase by 3.00 base points (i.e., one hundredth of a percentage point), whereas the probability of possessing three or more vehicles will decrease by 5.69 base points. Similarly, Table 3 and 6 also show that, conditional on weekly ride less than one, if there is a rail transit system across the residential area, on average, the probability of possessing no vehicle will increase by 1.52 percentage points, while the probability of possessing three or more vehicles will decrease by 4.93 percentage points.

On the contrary, all else being equal, population density and worker density are negatively associated with the probability of possessing no (or one) vehicle but positively with the probabilities of possessing three or more vehicles. Given the size of a neighborhood, higher population and worker density imply larger demand for transportation and personal needs for commute, and hence may boost the vehicle ownership. Table 4 and 6 show that, conditional on weekly rides between one and two, if population density rises by 1 percent, on average, the probability of possessing one vehicle will decrease by 1.36 base points, while the probability of possessing three or more vehicle will increase by 1.86 base points.

Also, the variables of demographics account for the heterogeneity across respondents and explain a respondent's ownership of vehicles in detail. Unsurprisingly, our results show that the impacts of respondent's demographics are relatively larger than the impacts of the neighborhood environment. We find respondent's age, gender, race, number of drivers in the household, home ownership, household income, and status of being a netizen are essential in determining the vehicle ownership. Particularly, a male respondent who is a homeowner from a household with more drives and higher household income is more likely to possess three or more (or two) vehicles and less likely to possess one (or no) vehicle. For example, Table 3 and 4 (5 and 6) show that conditional on no weekly ride, the probabilities of possessing no and one (two and three or more) vehicle(s) for a male respondent are, on average, 1.09 and 1.85 (0.84 and 2.11) percentage points less (more) than the corresponding probabilities for a female respondent, respectively. All else being equal, compared to a non-homeowner respondent, a homeowner respondent is 2.72 and 4.49 (2.51 and 4.71) percentage points less (more) likely to possess no and one (two and three or more) vehicle(s), respectively. Similarly, the presence of additional driver in a household is associated with a decrease of 11.90 and 19.43 percentage points in a respondent's probabilities of possessing no and one (two and three or more) vehicle(s), respectively. Lastly, using household income less than 15,000 dollars as a reference group, we find that, on average, conditional on weekly rides between one and two, a respondent with household income between 75,000 and 99,999 dollars is 3.88 and 10.05 percentage points less likely to possess no and one vehicle but 2.54 and 11.39 percentage points more likely to possess two and three or more vehicles, respectively.

In comparison, it is aged, Asian, and non-netizen respondents that are more willing to reduce the number of privately-owned vehicles. For example, in Table 4 and 6, as a respondent's age increases by 10 years, conditional on weekly rides greater than two, his or her probability of possessing one vehicle will increase by 4.50 percentage points, while the probability of possessing three or more vehicles will decrease by 6.16 percentage points. Similarly, the probability of possessing one (three or more) vehicle(s) for Asian respondents is 2.34 (3.38) percentage points higher (lower) than the probability for other races. In addition, the status of being a netizen affects the vehicle ownership via the path of the ride-hailing services usage. Table 4 and 6 show that, relative to non-netizens, conditional on weekly ride less than one, netizen respondents are, on average, 1.03 percentage point more likely to possess one vehicle and 1.36 less likely to possess three or more vehicles.

6. Discussions

The change in the vehicle ownership interests auto makers and dealerships and subsequently affects their business practices. Hence, we examine the implications of our results with regard to the auto market. Particularly, using the 2017 NHTS sampling weights, we extrapolate the estimates from representative respondents to the population in our sampled CBSAs. In this session, we mainly discuss the simulation results in response to the change in the behavior of regular users. It is suggested by the estimated average treatment effects that regular users would modify their attitude toward the possession of vehicles as increasing their degrees of using ride-hailing services. On average, switching from a regular user to a highly frequent user, a respondent will reduce his or her vehicle holdings by 0.1152 unit, corresponding to 8.61 percent.[9]

According to the 2017 NHTS sampling scheme, the respondents in our data represent a total of 31.10 million individuals, of who 1.64 million are regular users, accounting for 5.27 percent. To understand the impact of the change in the behavior of regular users on the auto market, we calculate the upper bound of this change by assuming all regular users would become highly frequent users. In this scenario, we find the maximum decrease in the number of vehicle holdings is about 190 thousand units, accounting for 1 percent of the new vehicle sales in the US in 2017.[10] Given the market condition and the population size of regular users, the current impact of this change is negligible. However, in the long run, as more occasional users become regular users and regular users come to be highly frequent users, the ride-hailing service would play a significant role in the auto market.

Also, we examine the heterogeneity of the impact of using ride-hailing services on the vehicle ownership by CBSA. Figure 4 presents the simulated changes in probabilities of possessing vehicles at different levels as an average regular user converts to an average highly frequent user in different CBSAs. Not surprisingly, we find there is a considerable variation in the changes

[9] The change in the vehicle holdings for a respondent stems from the changes in his probabilities of possessing vehicles. For example, compared to a regular user, a highly frequent user is 2.21 and 3.44 percentage points more likely to possess no vehicle and one vehicle, while 1,99 and 3.66 percentage points less likely to possess two vehicles and three or more vehicles. We then calculate this change in the vehicle holdings by the following formula, $0.0221 \times 0 + 0.0344 \times 1 - 0.0199 \times 2 - 0.0366 \times 3$, which equals to 0.1152 unit.

[10] The total sales volume of new vehicles is about 17.55 million in 2017 according to the US Bureau of Economic Analysis, available at https://fred.stlouisfed.org/series/TOTALSA.

across CBSAs. For example, as increasing the degrees of using ride-hailing services and becoming a highly frequent user, an average regular user from the Charlotte-Concord-Gastonia statistical area experience a decrease of 5.23 percentage points in the probability of possessing three or more vehicles, so are the regular users from the Sacramento-Roseville-Arden-Arcade statistical area and the Orlando-Kissimmee-Sanford statistical area. By contrast, their peers from the San Francisco-Oakland-Hayward statistical area and the Washington-Arlington-Alexandria statistical area experience the lowest decrease of 2.57 percentage points. As for the possession of one vehicle, the regular users from the Indianapolis-Carmel-Anderson statistical area increase the probability by 5.28 percentage points, ranked in the first place, followed by the regular users from the Austin-Round Rock statistical area and the Sacramento-Roseville-Arden-Arcade statistical area.

Additionally, we evaluate the percentage change in the number of vehicle holdings by CBSA as an average regular user converts to an average highly frequent user. The simulated change in the vehicle holdings for an average regular user vary across CBSAs, ranging from 0.1047 to 0.1237 unit. The regular users from the Jacksonville statistical area lead the change, together with their counterparts from the Indianapolis-Carmel-Anderson statistical area and the Sacramento-Roseville-Arden-Arcade statistical area. According to the simulated change at the individual level, we can assess the percentage change in the number of vehicle holdings averaged over all regular users by CBSA. Figure 5 shows the simulated results and demonstrates the geographic variation in the impacts of using ride-hailing services on the vehicle ownership of regular users. The Providence-Warwick statistical area takes the first place, amounting to a decrease of 24.02 percent, followed by the New York-Newark-Jersey City statistical area, and the Seattle-Tacoma-Bellevue statistical area. In contrast, the Minneapolis-St. Paul-Bloomington statistical area and the Salt Lake City statistical area experience the decreases as low as 5.59 percent and 4.81 percent, respectively.

7. Conclusions

The ride-hailing service is trending up in the most recent decade. Like private driving and public transit, it becomes a major mode of commute in urban areas. The growing popularity of the ride-hailing service changes the landscape of the mobility market and raises the interest of how it affects the vehicle ownership. Therefore, this paper evaluates the impacts of using ride-hailing services on the possession of privately-owned vehicles using the microdata from the 2017 NHTS and discusses the implications of our results in the US auto market.

We develop an ordered probit model of household vehicle ownership with endogenous treatments of using ride-hailing services. We estimate the model by leveraging its nonlinear functional form and address the endogeneity issue with an instrumental variable approach. Grouping the respondents by their degrees of using ride-hailing services, we find highly frequent users are less likely to retain the ownership of two or more vehicles than regular users. Our results show that compared to regular users, highly frequent users are 2.21 and 3.44 percentage points more likely to possess no vehicle and one vehicle, respectively, while 1.99 and 3.66 percentage points less to possess two and three or more vehicles, respectively.

We evaluate the marginal effects of the covariate variables. We find respondents from a neighborhood with higher percentage of renter-occupied housing, higher housing density, and an access to rail transit are more willing to possess no vehicle and one vehicle. On the contrary, all else being equal, respondents from a neighborhood with higher population density and higher worker density are more likely to retain three or more vehicles.

Compared to the effects of neighborhood environment variables, we find the effects of respondent’s demographics are larger in magnitude. Specifically, respondent’s age, gender, race, number of drivers in the household, home ownership, household income, and status of being a netizen are essential in determining the vehicle ownership. For example, a male respondent who is a homeowner from a household with more drives and higher household income is more likely to possess three or more vehicles. In contrast, an aged, Asian, and non-netizen respondent is more willing to possess one vehicle.

To understand the implications of our results in the US auto market, we extrapolate the estimates from representative respondents to the population in the study CBSAs using the 2017 NHTS sampling weights. We mainly discuss the simulation results from the change in the degree of using ride-hailing services for regular users. We find when converting to a highly frequent user, an average regular user will reduce his or her vehicle holdings by 0.1152 unit, corresponding to 8.61 percent. Accordingly, the maximum decrease over all study CBSAs can be added up to 190,000 vehicles, accounting for 1 percent of the new vehicle sales in the US in 2017. Given the current market condition and the population size of regular users, the impact of this simulated change is negligible. However, it could be significant in the long run, as customers become more often to use ride-hailing services.

Finally, the economic and social impacts of the growing ride-hailing market also interest policymakers and business stakeholders. On one hand, there are potential concerns resulting from the weak demand for vehicles, which might damage the auto industry and the regional economy growth. On the other hand, the decrease in the number of privately-owned vehicles can mitigate the relevant negative externality, such as traffic congestion and carbon emission (e.g., Erhardt et al., 2019; Leard & Xing, 2020). Future research on the change in the vehicle ownership and efficiency in response to the presence of the ride-hailing service can improve our understanding of the TNC-induced congestion and the substitution of vehicle mileages contributed by privately-owned vehicles.

References

Azevedo, F., & Maciejewski, M. (2015). *Social, economic and legal consequences of Uber and similar transportation network companies (TNCs)* (Briefing PE 563.398). European Parliament Think Tank.

Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, *67*(8), 1595–1600.

Berger, T., Chen, C., & Frey, C. B. (2018). Drivers of disruption? Estimating the Uber effect. *European Economic Review*, *110*, 197–210.

Clewlow, R. R., & Mishra, G. S. (2017). *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States* (Research Report UCD-ITS-RR-17-07). Institute of Transportation Studies at the University of California, Davis.

Conway, M. W., Salon, D., & King, D. A. (2018). Trends in taxi use and the advent of ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Science*, *2*(3), 79.

Cramer, J., & Krueger, A. B. (2016). Disruptive change in the taxi business: The case of Uber. *American Economic Review*, *106*(5), 177–182.

Erhardt, G. D., Roy, S., Cooper, D., Sana, B., Chen, M., & Castiglione, J. (2019). Do transportation network companies decrease or increase congestion? *Science Advances*, *5*(5), eaau2670.

Gong, J., Greenwood, B. N., & Song, Y. (2017). *Uber Might Buy Me a Mercedes Benz: An Empirical Investigation of the Sharing Economy and Durable Goods Purchase* (SSRN Scholarly Paper ID 2971072). Social Science Research Network.

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, *108*, 36–50.

Hampshire, R., Simek, C., Fabusuyi, T., Di, X., & Chen, X. (2017). *Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX* (SSRN Scholarly Paper ID 2977969). Social Science Research Network.

Hu, P. S., & Reuscher, T. R. (2004). *Summary of travel trends: 2001 national household travel survey*. U.S. Department of Transportation Federal Highway Administration.

Jiang, B., & Tian, L. (2018). Collaborative Consumption: Strategic and Economic Implications of Product Sharing. *Management Science*, *64*(3), 983–1476.

Jiang, J. (2019). *More Americans are using ride-hailing apps*. Pew Research Center. https://www.pewresearch.org/fact-tank/2019/01/04/more-americans-are-using-ride-hailing-apps/

Leard, B., & Xing, J. (2020). *What Does Ridesharing Replace?* (Working Paper 20-03). Resources for the Future.

Light, S. E. (2016). Precautionary federalism and the sharing economy. *Emory Law Journal*, *66*, 333.

Lyft. (2020). *Annual Report 2019* (p. 56). Lyft, Inc.

McGuckin, N., & Fucci, A. (2018). *Summary of Travel Trends: 2017 National Household Travel Survey* (FHWA-PL-18-019). U.S. Department of Transportation Federal Highway Administration.

Montgomery, A. W., Wolske, K. S., & Lyon, T. P. (2020). The Millennial “Meh”: Correlated Groups as Collective Agents in the Automobile Field. *Journal of Management Studies*.

Munkin, M. K., & Trivedi, P. K. (2008). Bayesian analysis of the ordered probit model with endogenous selection. *Journal of Econometrics*, *143*(2), 334–348.

Pudney, S., & Shields, M. (2000). Gender, race, pay and promotion in the British nursing profession: Estimation of a generalized ordered probit model. *Journal of Applied Econometrics*, *15*(4), 367–399.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy*, *45*, 168–178.

Sabouri, S., Brewer, S., & Ewing, R. (2020). Exploring the relationship between ride-sourcing services and vehicle ownership, using both inferential and machine learning approaches. *Landscape and Urban Planning*, *198*, 103797.

Santos, A., McGuckin, N., Nakamoto, H. Y., Gray, D., & Liss, S. (2011). *Summary of travel trends: 2009 national household travel survey* (FHWA-PL-ll-022). U.S. Department of Transportation Federal Highway Administration.

Schipper, M. (2018). *U.S. households are holding on to their vehicles longer* (Today in Energy). U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=36914

Sperling, D., Pike, S., & Chase, R. (2018). Will the Transportation Revolutions Improve Our Lives—Or Make Them Worse? In *Three Revolutions* (pp. 1–20). Springer.

Uber. (2020). *2019 Annual Report* (p. 55). Uber Technologies, Inc.

Ward, J. W., Michalek, J. J., Azevedo, I. L., Samaras, C., & Ferreira, P. (2019). Effects of on-demand ridesourcing on vehicle ownership, fuel consumption, vehicle miles traveled, and emissions per capita in US States. *Transportation Research Part C: Emerging Technologies*, *108*, 289–301.

Table 1. Sample Statistics

Variable	Definition	Mean	SD
Number of Own Vehicles	Number of privately-owned vehicles	1.76	1.08
Ridesharing Usage	Usage of ridesharing services via apps in the past 30 days	0.80	2.73
Continuous Explanatory Variable			
Characteristics of the Census block group of respondent's home location			
Rent Percent	Percentage point of renter-occupied housing	30.78	25.86
Population Density	1000 Persons per square mile	8.36	8.21
Housing Density	1000 Housing units per square mile	4.74	6.80
Worker Density	1000 Employed persons per square mile	2.62	1.65
Age	Age	54.25	16.44
Driver	Number of drivers in the household	1.64	0.79
Binary Explanatory Variable (Yes = 1 and No = 0)			
Rail	Reside in a Metropolitan Statistical Area with rail transit	0.52	
Male	Male	0.47	
Work	Employed	0.62	
Home Owner	Home owner	0.71	
White	White	0.79	
Black	African American	0.09	
Asian	Asian	0.06	
Other Race	Other races (Reference)	0.05	
Less High School	Less than a high school graduate (Reference)	0.02	
High School	High school graduate	0.11	
Some College	Some college or associates degree	0.24	
College	Bachelor's degree	0.31	
Graduate	Graduate or professional degree	0.32	
≤ $14,999	Household income less than or equal to 14,999 dollars (Reference)	0.08	
$15,000 to $24,999	Household income between 15,000 and 24,999 dollars	0.07	
$25,000 to $34,999	Household income between 25,000 and 34,999 dollars	0.08	
$35,000 to $49,999	Household income between 35,000 and 49,999 dollars	0.11	
$50,000 to $74,999	Household income between 50,000 and 74,999 dollars	0.17	
$75,000 to $99,999	Household income between 75,000 and 99,999 dollars	0.14	
$100,000 to $124,999	Household income between 100,000 and 124,999 dollars	0.12	
$125,000 to $149,999	Household income between 125,000 and 149,999 dollars	0.08	
$150,000 to $199,999	Household income between 150,000 and 199,999 dollars	0.08	
≥ $200,000	Household income greater than or equal to 200,000 dollars	0.10	
Netizen	Access the internet via computers every day or a few times a week	0.88	
Sample Size		9,543	

Table 2. Average Treatment Effects of Weekly Rides on Probability of Possessing Vehicles

	Weekly Ride = 0		Weekly Ride < 1		Weekly Ride = 1~2	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Panel A. Endogenous Weekly Ride						
Probability of not Possessing Vehicles						
Weekly Ride < 1	0.47	(0.37)				
Weekly Ride = 1~2	0.77	(0.54)	0.30	(0.57)		
Weekly Ride > 2	2.98***	(1.05)	2.51**	(1.04)	2.21**	(1.07)
Probability of Possessing One Vehicle						
Weekly Ride < 1	0.71	(0.71)				
Weekly Ride = 1~2	1.26	(1.00)	0.55	(1.03)		
Weekly Ride > 2	4.70***	(1.42)	3.99***	(1.43)	3.44**	(1.52)
Probability of Possessing Two Vehicles						
Weekly Ride < 1	–0.24	(0.30)				
Weekly Ride = 1~2	–0.48	(0.45)	–0.24	(0.45)		
Weekly Ride > 2	–2.47**	(1.02)	–2.23**	(1.00)	–1.99**	(1.01)
Probability of Possessing Three or More Vehicles						
Weekly Ride < 1	–0.94	(0.79)				
Weekly Ride = 1~2	–1.55	(1.10)	–0.61	(1.15)		
Weekly Ride > 2	–5.21***	(1.45)	–4.27***	(1.49)	–3.66**	(1.60)
Panel B. Exogenous Weekly Ride						
Probability of not Possessing Vehicles						
Weekly Ride < 1	1.05***	(0.38)				
Weekly Ride = 1~2	1.76***	(0.56)	0.70	(0.62)		
Weekly Ride > 2	4.28***	(1.12)	3.23***	(1.13)	2.53**	(1.19)
Probability of Possessing One Vehicle						
Weekly Ride < 1	1.89***	(0.65)				
Weekly Ride = 1~2	3.00***	(0.87)	1.12	(0.97)		
Weekly Ride > 2	6.27***	(1.28)	4.38***	(1.33)	3.26**	(1.41)
Probability of Possessing Two Vehicles						
Weekly Ride < 1	–0.81***	(0.31)				
Weekly Ride = 1~2	–1.41***	(0.50)	–0.60	(0.53)		
Weekly Ride > 2	–3.78***	(1.11)	–2.97***	(1.11)	–2.37**	(1.15)
Probability of Possessing Three or More Vehicles						
Weekly Ride < 1	–2.13***	(0.72)				
Weekly Ride = 1~2	–3.35***	(0.94)	–1.22	(1.06)		
Weekly Ride > 2	–6.77***	(1.29)	–4.65***	(1.37)	–3.42**	(1.47)

Notes: Panel A presents the results as the endogeneity of weekly rides has been addressed, while Panel B presents the results as if weekly rides were exogenous. All estimates are multiplied by 100 and standard errors (in parentheses) are derived from the bootstrap procedure with 500 draws. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

Table 3. Marginal Effects of Explanatory Variables on Probability of Possessing No Vehicle Conditional on Weekly Ride

	Cond. on Weekly Ride = 0		Cond. on Weekly Ride < 1		Cond. on Weekly Ride = 1~2		Cond. on Weekly Ride > 2	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Rent Percent / 100	3.00***	(0.53)	2.25***	(0.40)	1.99***	(0.36)	1.70***	(0.33)
Log(Population Density)	–0.71***	(0.27)	–0.55***	(0.20)	–0.49***	(0.18)	–0.41***	(0.16)
Log(Housing Density)	2.51***	(0.25)	2.00***	(0.19)	1.76***	(0.19)	1.49***	(0.19)
Log(Worker Density)	–0.54**	(0.21)	–0.34**	(0.16)	–0.30**	(0.14)	–0.27**	(0.12)
Age / 10	2.26***	(0.43)	1.61***	(0.32)	1.41***	(0.30)	1.22***	(0.28)
Drivers	–11.90***	(0.36)	–8.74***	(0.47)	–7.71***	(0.57)	–6.61***	(0.67)
Rail	1.94***	(0.21)	1.52***	(0.16)	1.33***	(0.15)	1.13***	(0.15)
Male	–1.09***	(0.21)	–0.72***	(0.16)	–0.64***	(0.15)	–0.55***	(0.13)
Work	–0.47*	(0.27)	–0.20	(0.20)	–0.18	(0.18)	–0.17	(0.16)
Home Owner	–2.72***	(0.31)	–2.08***	(0.24)	–1.82***	(0.23)	–1.53***	(0.23)
White	0.56	(0.49)	0.47	(0.35)	0.42	(0.31)	0.35	(0.27)
Black	0.95	(0.59)	0.67	(0.42)	0.59	(0.37)	0.51	(0.32)
Asian	1.54**	(0.65)	0.94**	(0.46)	0.83**	(0.41)	0.73**	(0.35)
High School	–0.35	(1.05)	–0.49	(0.77)	–0.43	(0.68)	–0.35	(0.58)
Some College	–1.18	(1.02)	–1.00	(0.75)	–0.88	(0.66)	–0.74	(0.56)
College	0.01	(1.03)	0.03	(0.75)	0.02	(0.66)	0.02	(0.57)
Graduate	1.03	(1.05)	0.76	(0.77)	0.67	(0.68)	0.58	(0.59)
$15,000 to $24,999	–3.05***	(0.83)	–2.15***	(0.61)	–1.90***	(0.55)	–1.63***	(0.48)
$25,000 to $34,999	–4.71***	(0.80)	–3.51***	(0.58)	–3.09***	(0.53)	–2.64***	(0.49)
$35,000 to $49,999	–5.39***	(0.79)	–3.76***	(0.59)	–3.31***	(0.55)	–2.84***	(0.51)
$50,000 to $74,999	–6.22***	(0.77)	–4.22***	(0.59)	–3.71***	(0.56)	–3.19***	(0.53)
$75,000 to $99,999	–6.63***	(0.81)	–4.41***	(0.63)	–3.88***	(0.60)	–3.34***	(0.57)
$100,000 to $124,999	–7.15***	(0.80)	–4.72***	(0.65)	–4.15***	(0.63)	–3.57***	(0.60)
$125,000 to $149,999	–7.41***	(0.84)	–4.83***	(0.68)	–4.25***	(0.65)	–3.67***	(0.62)
$150,000 to $199,999	–7.37***	(0.85)	–4.74***	(0.68)	–4.17***	(0.65)	–3.62***	(0.62)
≥ $200,000	–8.65***	(0.81)	–5.55***	(0.70)	–4.87***	(0.68)	–4.24***	(0.66)
Netizen	0.20***	(0.06)	0.41***	(0.11)	0.36***	(0.10)	0.29***	(0.07)

Notes: Estimates are multiplied by 100 and standard errors (in parentheses) are derived from the bootstrap procedure with 500 draws. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

Table 4. Marginal Effects of Explanatory Variables on Probability of Possessing One Vehicle Conditional on Weekly Ride

	Cond. on Weekly Ride = 0		Cond. on Weekly Ride < 1		Cond. on Weekly Ride = 1~2		Cond. on Weekly Ride > 2	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Rent Percent / 100	4.88***	(0.87)	5.54***	(0.95)	5.57***	(0.95)	5.51***	(0.94)
Log(Population Density)	–1.16***	(0.44)	–1.36***	(0.49)	–1.36***	(0.49)	–1.35***	(0.49)
Log(Housing Density)	4.06***	(0.40)	4.91***	(0.44)	4.93***	(0.43)	4.86***	(0.42)
Log(Worker Density)	–0.89***	(0.34)	–0.85**	(0.38)	–0.85**	(0.39)	–0.86**	(0.38)
Age / 10	3.79***	(0.72)	4.52***	(0.80)	4.54***	(0.81)	4.50***	(0.80)
Drivers	–19.43***	(0.52)	–21.51***	(0.50)	–21.60***	(0.53)	–21.41***	(0.65)
Rail	3.18***	(0.35)	3.82***	(0.39)	3.84***	(0.39)	3.79***	(0.38)
Male	–1.85***	(0.37)	–1.81***	(0.40)	–1.82***	(0.40)	–1.81***	(0.40)
Work	–0.80*	(0.44)	–0.49	(0.50)	–0.50	(0.50)	–0.52	(0.49)
Home Owner	–4.49***	(0.52)	–5.41***	(0.58)	–5.45***	(0.59)	–5.39***	(0.58)
White	0.94	(0.87)	1.21	(0.93)	1.21	(0.93)	1.18	(0.91)
Black	1.58	(1.01)	1.69	(1.10)	1.69	(1.10)	1.68	(1.07)
Asian	2.50**	(1.05)	2.32**	(1.16)	2.33**	(1.16)	2.34**	(1.14)
High School	–0.51	(1.67)	–1.21	(1.87)	–1.21	(1.87)	–1.15	(1.85)
Some College	–2.01	(1.64)	–2.58	(1.82)	–2.58	(1.82)	–2.52	(1.80)
College	0.02	(1.63)	0.07	(1.80)	0.07	(1.81)	0.06	(1.79)
Graduate	1.55	(1.65)	1.72	(1.81)	1.74	(1.82)	1.74	(1.81)
$15,000 to $24,999	–3.29***	(0.84)	–4.01***	(1.09)	–4.17***	(1.13)	–4.29***	(1.16)
$25,000 to $34,999	–5.63***	(0.86)	–7.27***	(1.10)	–7.48***	(1.13)	–7.58***	(1.14)
$35,000 to $49,999	–6.93***	(0.85)	–7.94***	(1.06)	–8.15***	(1.10)	–8.27***	(1.12)
$50,000 to $74,999	–8.61***	(0.84)	–9.27***	(1.02)	–9.48***	(1.06)	–9.61***	(1.09)
$75,000 to $99,999	–9.56***	(0.96)	–9.85***	(1.14)	–10.05***	(1.17)	–10.20***	(1.21)
$100,000 to $124,999	–10.80***	(0.98)	–10.80***	(1.17)	–11.00***	(1.21)	–11.15***	(1.25)
$125,000 to $149,999	–11.49***	(1.14)	–11.18***	(1.31)	–11.37***	(1.34)	–11.54***	(1.38)
$150,000 to $199,999	–11.43***	(1.15)	–10.89***	(1.31)	–11.09***	(1.34)	–11.29***	(1.38)
≥ $200,000	–15.12***	(1.20)	–13.70***	(1.37)	–13.86***	(1.41)	–14.07***	(1.45)
Netizen	0.26***	(0.07)	1.03***	(0.32)	1.03***	(0.31)	0.97***	(0.29)

Notes: Estimates are multiplied by 100 and standard errors (in parentheses) are derived from the bootstrap procedure with 500 draws. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

Table 5. Marginal Effects of Explanatory Variables on Probability of Possessing Two Vehicles Conditional on Weekly Ride

	Cond. on Weekly Ride = 0		Cond. on Weekly Ride < 1		Cond. on Weekly Ride = 1~2		Cond. on Weekly Ride > 2	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Rent Percent / 100	–2.19***	(0.40)	–0.56*	(0.33)	0.05	(0.41)	0.73	(0.53)
Log(Population Density)	0.52**	(0.20)	0.14	(0.10)	–0.01	(0.11)	–0.18	(0.15)
Log(Housing Density)	–1.83***	(0.21)	–0.50*	(0.28)	0.04	(0.36)	0.65	(0.45)
Log(Worker Density)	0.40**	(0.15)	0.09	(0.06)	–0.01	(0.07)	–0.11	(0.10)
Age / 10	–1.78***	(0.34)	–0.52*	(0.29)	–0.06	(0.35)	0.44	(0.43)
Drivers	8.71***	(0.44)	2.17*	(1.18)	–0.21	(1.54)	–2.85	(1.90)
Rail	–1.46***	(0.18)	–0.41*	(0.21)	0.01	(0.28)	0.48	(0.35)
Male	0.84***	(0.17)	0.19	(0.12)	–0.01	(0.14)	–0.24	(0.17)
Work	0.35*	(0.21)	0.05	(0.07)	0.003	(0.05)	–0.06	(0.09)
Home Owner	2.51***	(0.34)	1.13***	(0.34)	0.50	(0.41)	–0.22	(0.51)
White	–0.39	(0.34)	–0.08	(0.09)	0.05	(0.14)	0.19	(0.23)
Black	–0.68	(0.42)	–0.14	(0.13)	0.05	(0.17)	0.25	(0.28)
Asian	–1.15**	(0.49)	–0.22	(0.19)	0.03	(0.21)	0.31	(0.30)
High School	0.23	(0.73)	0.08	(0.23)	–0.05	(0.20)	–0.19	(0.36)
Some College	0.75	(0.72)	0.09	(0.26)	–0.19	(0.26)	–0.48	(0.40)
College	–0.01	(0.72)	–0.01	(0.21)	0.001	(0.16)	0.01	(0.31)
Graduate	–0.77	(0.74)	–0.25	(0.25)	–0.06	(0.21)	0.16	(0.34)
$15,000 to $24,999	3.53***	(0.95)	2.17***	(0.68)	1.69***	(0.63)	1.11*	(0.61)
$25,000 to $34,999	5.45***	(0.93)	3.26***	(0.76)	2.38***	(0.82)	1.34	(0.93)
$35,000 to $49,999	6.24***	(0.92)	3.41***	(0.81)	2.45***	(0.87)	1.33	(1.00)
$50,000 to $74,999	7.16***	(0.93)	3.65***	(0.88)	2.53***	(0.98)	1.24	(1.13)
$75,000 to $99,999	7.60***	(0.98)	3.73***	(0.93)	2.54**	(1.02)	1.18	(1.18)
$100,000 to $124,999	8.11***	(0.97)	3.82***	(0.98)	2.52**	(1.09)	1.03	(1.26)
$125,000 to $149,999	8.34***	(1.02)	3.84***	(0.99)	2.50**	(1.10)	0.96	(1.27)
$150,000 to $199,999	8.30***	(1.02)	3.82***	(0.98)	2.52**	(1.09)	1.02	(1.26)
≥ $200,000	9.21***	(1.00)	3.82***	(1.08)	2.19*	(1.24)	0.32	(1.47)
Netizen	–0.13***	(0.04)	–0.08	(0.05)	0.03	(0.09)	0.16	(0.13)

Notes: Estimates are multiplied by 100 and standard errors (in parentheses) are derived from the bootstrap procedure with 500 draws. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

Table 6. Marginal Effects of Explanatory Variables on Probability of Possessing Three or More Vehicles Conditional on Weekly Ride

	Cond. on Weekly Ride = 0		Cond. on Weekly Ride < 1		Cond. on Weekly Ride = 1~2		Cond. on Weekly Ride > 2	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Rent Percent / 100	–5.69***	(1.00)	–7.23***	(1.26)	–7.61***	(1.33)	–7.94***	(1.38)
Log(Population Density)	1.35***	(0.51)	1.77***	(0.65)	1.86***	(0.68)	1.94***	(0.71)
Log(Housing Density)	–4.75***	(0.46)	–6.41***	(0.61)	–6.74***	(0.65)	–7.00***	(0.67)
Log(Worker Density)	1.03**	(0.40)	1.11**	(0.51)	1.17**	(0.53)	1.23**	(0.55)
Age / 10	–4.27***	(0.82)	–5.61***	(1.01)	–5.89***	(1.06)	–6.16***	(1.10)
Drivers	22.62***	(0.55)	28.08***	(0.94)	29.52***	(1.05)	30.86***	(1.07)
Rail	–3.66***	(0.40)	–4.93***	(0.53)	–5.19***	(0.57)	–5.40***	(0.59)
Male	2.11***	(0.41)	2.34***	(0.51)	2.47***	(0.54)	2.61***	(0.56)
Work	0.91*	(0.51)	0.64	(0.65)	0.68	(0.68)	0.75	(0.71)
Home Owner	4.71***	(0.49)	6.36***	(0.67)	6.77***	(0.73)	7.14***	(0.78)
White	–1.11	(1.03)	–1.60	(1.26)	–1.68	(1.32)	–1.73	(1.36)
Black	–1.84	(1.18)	–2.22	(1.47)	–2.33	(1.54)	–2.43	(1.60)
Asian	–2.89**	(1.22)	–3.03**	(1.53)	–3.19**	(1.61)	–3.38**	(1.67)
High School	0.63	(1.99)	1.61	(2.49)	1.68	(2.61)	1.69	(2.71)
Some College	2.45	(1.95)	3.49	(2.41)	3.64	(2.53)	3.74	(2.64)
College	–0.02	(1.95)	–0.09	(2.40)	–0.09	(2.51)	–0.09	(2.62)
Graduate	–1.81	(1.97)	–2.23	(2.41)	–2.35	(2.53)	–2.47	(2.64)
$15,000 to $24,999	2.82***	(0.72)	3.99***	(1.10)	4.37***	(1.22)	4.80***	(1.34)
$25,000 to $34,999	4.90***	(0.75)	7.53***	(1.20)	8.19***	(1.34)	8.88***	(1.47)
$35,000 to $49,999	6.08***	(0.73)	8.28***	(1.13)	9.00***	(1.27)	9.78***	(1.40)
$50,000 to $74,999	7.66***	(0.69)	9.84***	(1.06)	10.66***	(1.19)	11.56***	(1.32)
$75,000 to $99,999	8.59***	(0.80)	10.53***	(1.15)	11.39***	(1.28)	12.36***	(1.42)
$100,000 to $124,999	9.84***	(0.81)	11.70***	(1.15)	12.63***	(1.27)	13.69***	(1.40)
$125,000 to $149,999	10.56***	(0.98)	12.17***	(1.30)	13.12***	(1.42)	14.24***	(1.56)
$150,000 to $199,999	10.50***	(1.00)	11.81***	(1.32)	12.74***	(1.44)	13.88***	(1.58)
≥ $200,000	14.56***	(1.05)	15.43***	(1.34)	16.54***	(1.46)	17.99***	(1.59)
Netizen	–0.33***	(0.09)	–1.36***	(0.44)	–1.43***	(0.47)	–1.42***	(0.46)

Notes: Estimates are multiplied by 100 and standard errors (in parentheses) are derived from the bootstrap procedure with 500 draws. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.

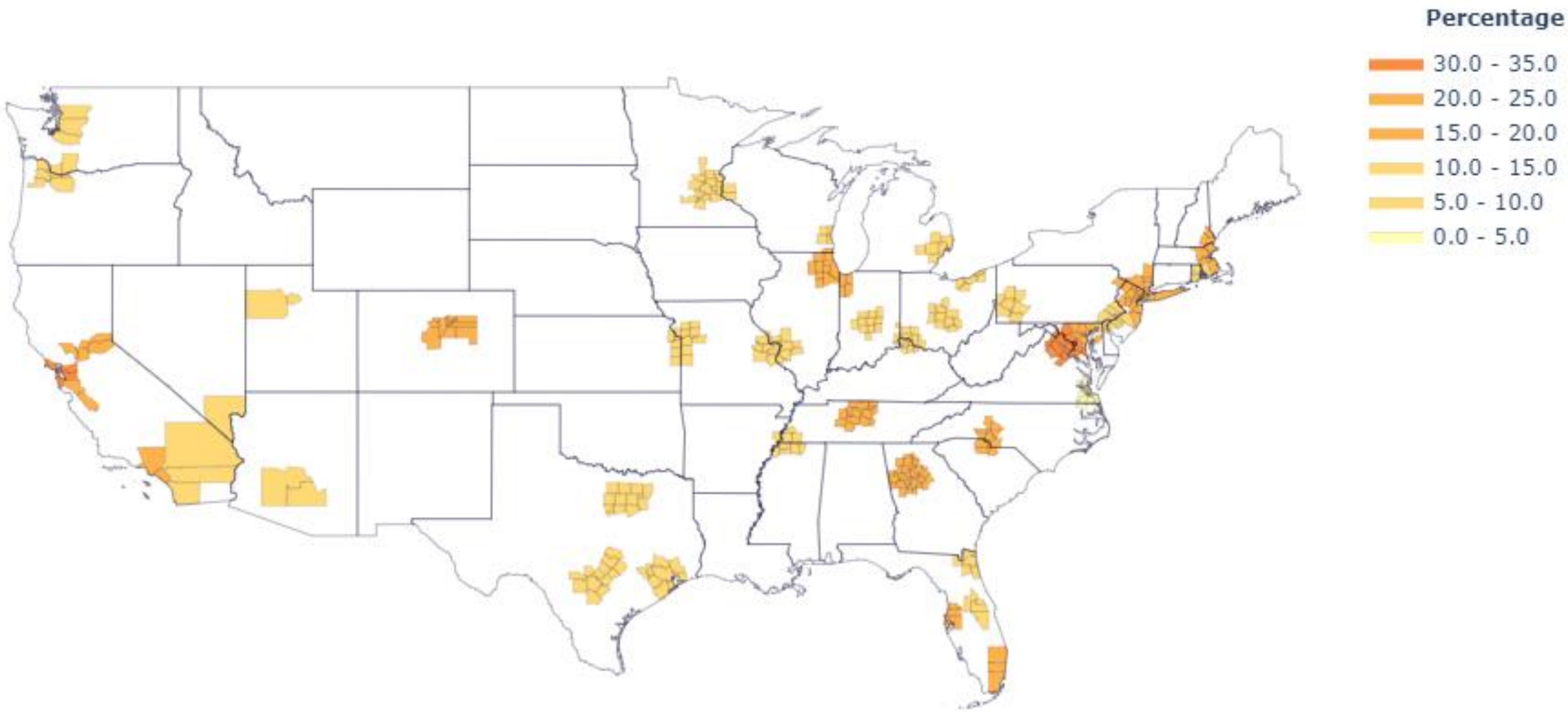

Figure 1. Percentage of Respondents Using Ride-hailing Services

Notes: All respondents using ride-haling services at least once a month are taken into account.

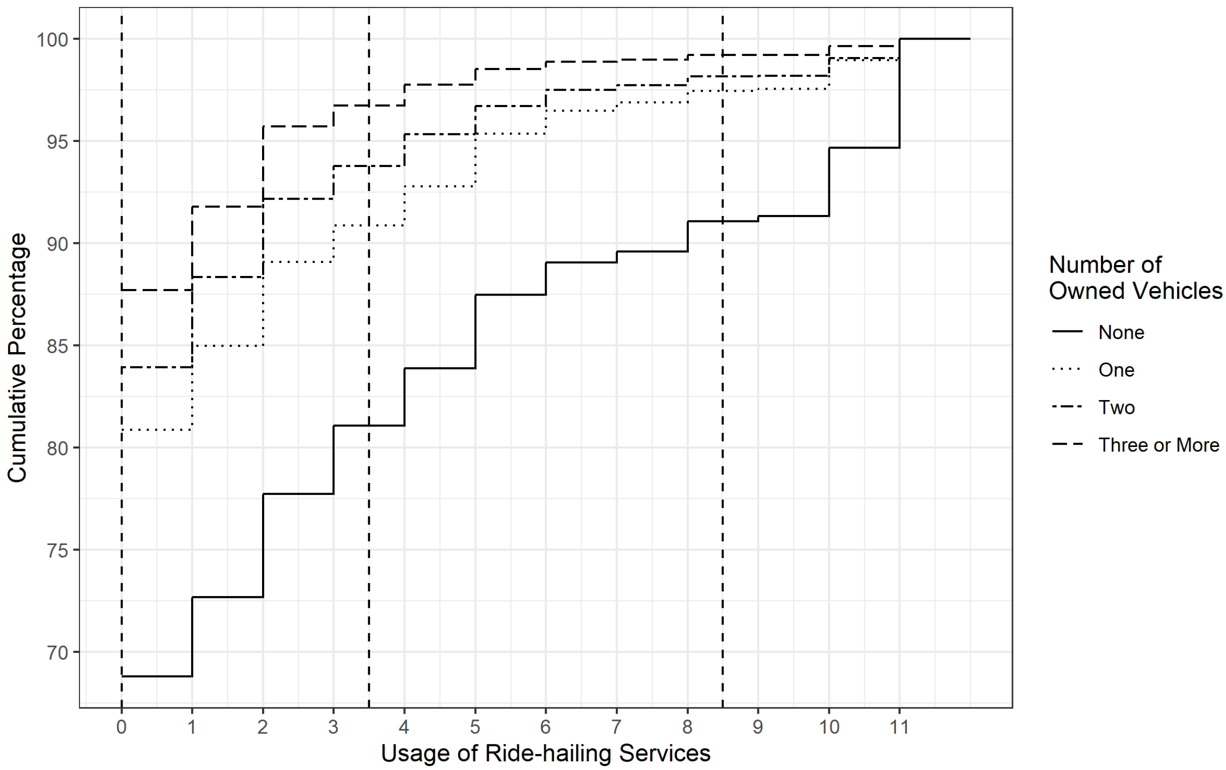

Figure 2. Cumulative Distributions of Usage of Ride-hailing Services

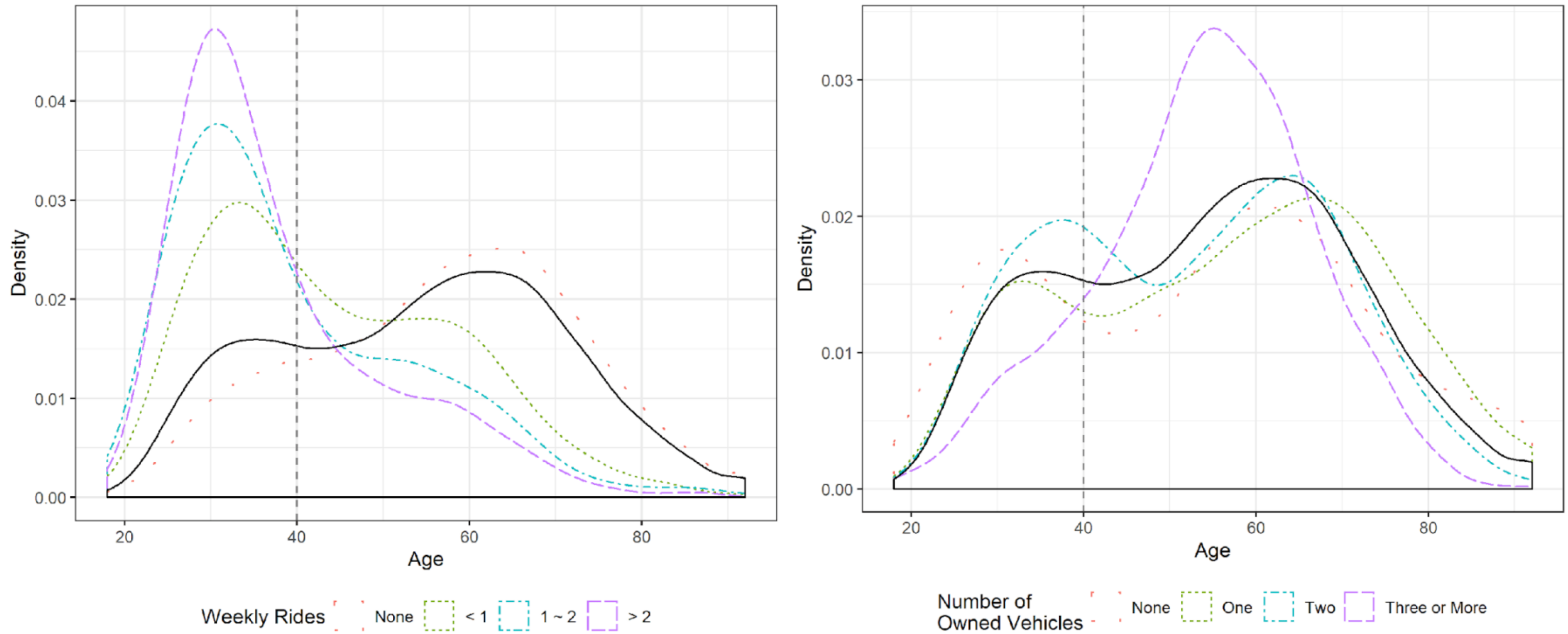

Figure 3. Respondent's Age Distribution by Number of Owned Vehicles and Weekly Rides

Notes: The solid line shows the overall age distribution for the entire sample.

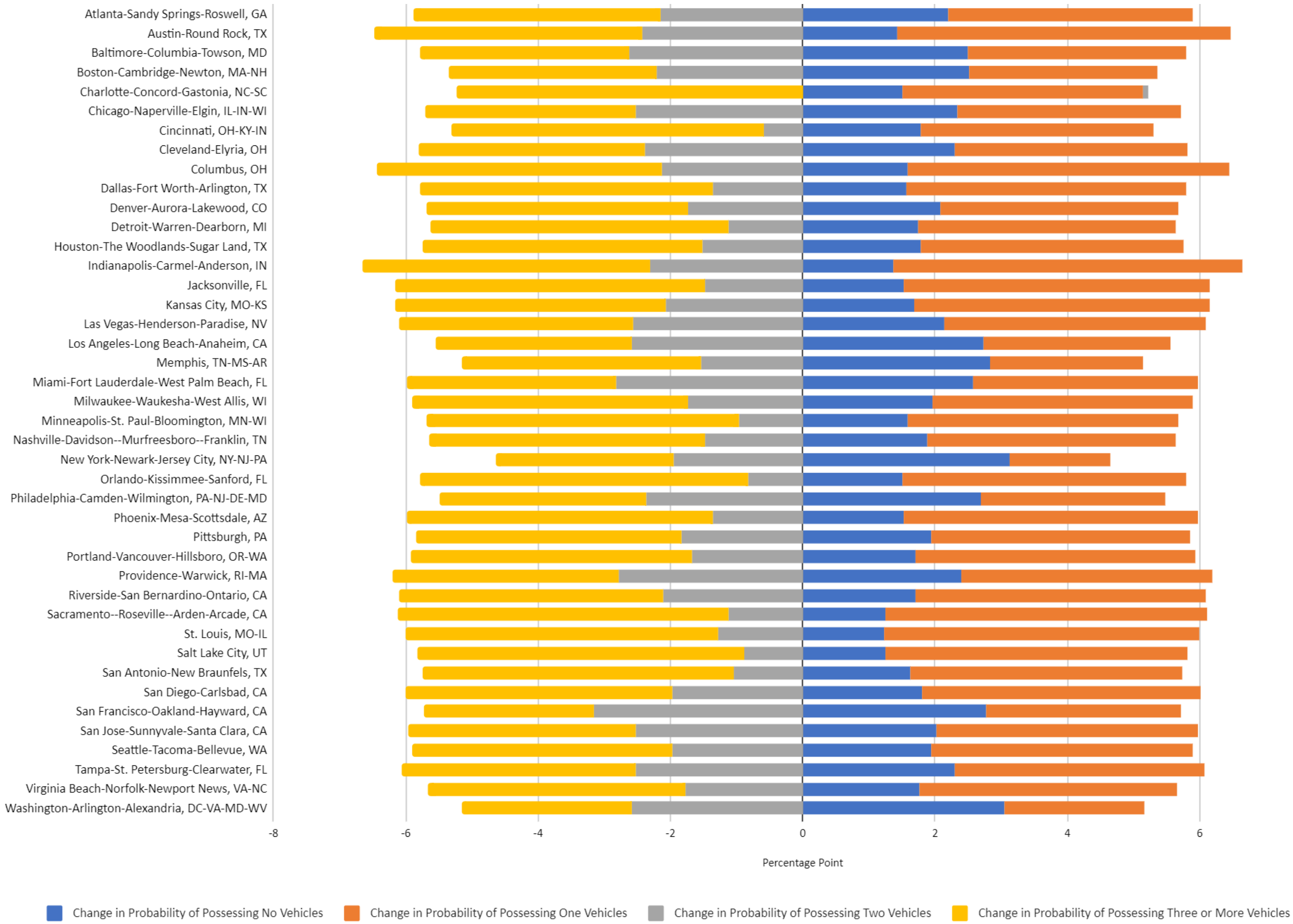

Figure 4. Simulated Changes in Probabilities of Possessing Vehicles for Regular Users by CBSA

Notes: This figure presents the simulated changes in probabilities of possessing vehicles at different levels as an average regular user converts to an average highly frequent user in different CBSAs.

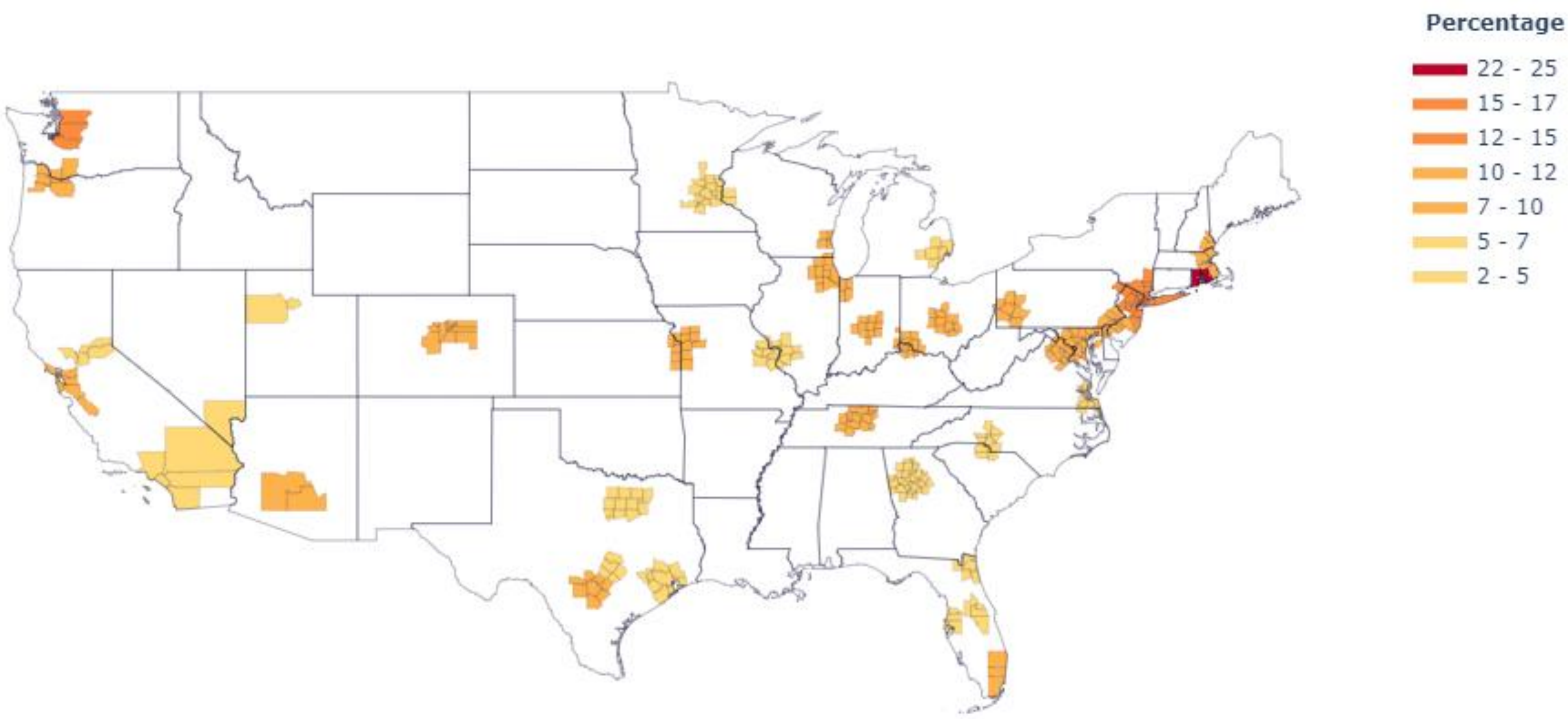

Figure 5. Simulated Percentage Decrease in The Number of Vehicle Holdings for Average Regular Users by CBSA

Notes: This figure presents the simulated percentage decreases in the number of vehicle holdings as an average regular user converts to an average highly frequent user in different CBSAs.

Table A1. Maximum Likelihood Estimates of Model Parameters

	Number of Owned Vehicles		Weekly Ride	
	Estimate	Std. Err.	Estimate	Std. Err.
Rent Percent / 100	–0.362***	(0.068)	0.120	(0.087)
Log(Population Density)	0.084**	(0.034)	–0.049	(0.048)
Log(Housing Density)	–0.292***	(0.031)	0.234***	(0.039)
Log(Worker Density)	0.071***	(0.025)	0.051	(0.037)
Age / 10	0.174***	(0.051)	–0.571***	(0.070)
$(\text{Age} / 10)^2$	–0.021***	(0.005)	0.030***	(0.007)
Drivers	1.457***	(0.036)	–0.228***	(0.029)
Rail	–0.227***	(0.026)	0.166***	(0.035)
Male	0.143***	(0.026)	0.080**	(0.033)
Work	0.071**	(0.032)	0.164***	(0.047)
Home Owner	0.311***	(0.036)	–0.189***	(0.043)
White	–0.064	(0.062)	0.091	(0.071)
Black	–0.119	(0.074)	–0.005	(0.091)
Asian	–0.201**	(0.079)	–0.171*	(0.093)
High School	0.021	(0.132)	–0.289	(0.178)
Some College	0.138	(0.131)	–0.196	(0.167)
College	0.0003	(0.132)	0.022	(0.166)
Graduate	–0.121	(0.132)	0.008	(0.167)
$15,000 to $24,999	0.275***	(0.073)	0.011	(0.109)
$25,000 to $34,999	0.436***	(0.072)	–0.208*	(0.113)
$35,000 to $49,999	0.533***	(0.070)	0.038	(0.096)
$50,000 to $74,999	0.651***	(0.069)	0.187**	(0.091)
$75,000 to $99,999	0.721***	(0.073)	0.336***	(0.094)
$100,000 to $124,999	0.807***	(0.076)	0.451***	(0.097)
$125,000 to $149,999	0.860***	(0.081)	0.584***	(0.102)
$150,000 to $199,999	0.866***	(0.082)	0.689***	(0.102)
≥ $200,000	1.135***	(0.085)	1.092***	(0.100)
Weekly Ride < 1	–0.472***	(0.074)		
Weekly Ride = 1~2	–0.665***	(0.099)		
Weekly Ride > 2	–1.105***	(0.147)		
Netizen			0.324***	(0.081)
τ_0, ξ_0	–0.373	(0.230)	1.184***	(0.312)
τ_1, ξ_1	2.000***	(0.235)	1.856***	(0.312)
τ_2, ξ_2	3.792***	(0.239)	2.589***	(0.313)
ρ	0.232***	(0.040)		

Notes: Asymptotic standard errors (in parentheses) are clustered by households. ***, **, and * indicate the significance level of 1%, 5%, and 10%, respectively.