Travel Behavior Impacts of Shared Mobility: Analysis of 2017 National Household Travel Survey

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BACKGROUND

Transportation field is undergoing a seismic transformation in response to several disruptive technological innovations. A product of these technological transformations is the adoption of shared mobility systems such as bikesharing (such as CitiBike in New York City), car sharing (such as Zipcar or Car2Go), ridesourcing/ridesharing (such as Uber and Lyft) and ride-splitting (such as dynamic carpooling in urban regions). The emergence of a convenient market place (with smartphone applications or apps being the platform) connecting riders and drivers (or systems) with accurate location information has essentially transformed the transportation-for-hire market and the gig economy. In terms of ridesharing, Uber and Lyft accounted for about 195 million users in just the first three months of 2018 in the US (*1*). Among the shared mobility alternatives, bikesharing offers a sustainable transportation alternative in the urban core regions and could be an effective solution to the last mile problem (*2*). A recent National Association of City Transportation Officials (NACTO) report highlighted that of the 88 million trips made by bikeshare users in the US between 2010-2016, 28 million were trips from 2016 only (*3*). As highlighted in a recent Transit Cooperative Research Program (TCRP) report (*4*), understanding shared mobility adoption and usage provides an unprecedented opportunity to address existing mobility shortcomings in urban regions.

The 2017 National Household Travel Survey (NHTS) data provides the first snapshot of a nationally representative dataset after the emergence and widespread adoption of these newer modes of transportation or services. While the individual trip record in NHTS does not provide information on the use of these modes, we have person level details on bikesharing and ridesharing usage in the previous 30 days. The availability of data on shared mobility service usage provides us an opportunity to examine (a) the impact of the adoption of these modes on travel behavior and (b) the characteristics of individuals adopting these modes. In this broad context, the specific research hypotheses explored in our work include:

1. *Do individuals and households that choose bikesharing and ridesharing exhibit differences in long-term and short-term travel behavior relative to individuals and households that do not choose these modes?*
2. *If detectable differences exist, what are the characteristics of the individuals who choose these modes?*

In our analysis, we identify individuals (and their respective households) adopting shared mobility and categorize them into three classes: (1) households with members that do not use bikesharing or ridesharing, (2) households with members that adopt bikesharing and (3) households with members that adopt ridesharing[1]. Since, examining travel behavior across

[1] We do recognize that there is a small group of households that might use both bikesharing and ridesharing. Given the small sample sizes of this group in the data, we decided not to consider them separately (more details are provided in the data preparation section).

all possible dimensions is quite involved, we focus our attention on one short term indicator (*household vehicle miles travelled*) and one long term indicator (*household vehicle ownership*) for the three classes of households identified above. We examine differences between household vehicle mileage and household vehicle ownership across the three classes by developing pooled models. Household vehicle mileage is examined using log-linear regression model (LR). Household vehicle ownership is studied using ordered logit (OL) model. Based on the model estimation results, we confirm that travel behavior is significantly different across the three classes of households. To offer insights on individuals adopting bikesharing and ridesharing, we explore adoption choice using binary logit (BL) model. The data for the analysis is drawn from four urban regions with reasonable representation (percentage) of shared mobility users from New York, San Jose, Atlanta and Chicago.

SAMPLE FORMATION

The 2017 NHTS data collected detailed information on around one million trips undertaken by 264,234 individuals from 129,696 households sampled from all over the country. The database provides detailed information at the household level, person level, and trip level. For our analysis, four core based statistical areas (CBSA) have been selected including New York-Newark Jersey City (referred to as New York in the rest of the document), San Jose-Sunnyvale-Santa Clara (San Jose), Chicago-Naperville-Elgin (Chicago), and Atlanta-Sandy Springs-Roswell (Atlanta). After removing data with incomplete information, our final estimation sample comprised of 15,392 individuals from 8,955 households across these four regions. The two dependent variables, household vehicles mileage and household ownership, were appropriately aggregated at the household level from the data. The corresponding weights provided in the NHTS data were employed to generate population representative values for the households. The choice of shared mobility adoption was examined at the person level. Hence, we derived two binary variables indicating whether that person use the sharing system or not (separately for bikeshare and rideshare).

DESCRIPTIVE ANALYSIS

A brief descriptive analysis of the NHTS 2017 data sample employed in our analysis is presented in Table 1 with information on household vehicle mileage and household vehicle ownership shares for the four urban regions. From the table, following observations can be made. First, in general, Atlanta region accrued the highest average annual VMT followed by San Jose, while Chicago has the lowest VMT. Second, in all regions, households using the rideshare mode accumulated the highest average annual VMT followed by households not using any shared mobility alternative. Third, in terms of vehicle ownership profile, we can observe that in New York region, households with larger fleet size are less likely to use any shared modes. However, in other regions, the vehicle ownership profiles are not as distinctive. In other regions, it is interesting to observe that households with higher vehicle ownership levels are more likely to use shared mobility services. Among different regions considered, in San Jose, households using bikeshare are also likely to have higher percentage of 3 or more vehicles.

MODEL ESTIMATION RESULTS

The proposed research estimates a single model for the three classes of households (no sharing, bikesharing and ridesharing) and four urban regions considered in our study. Within the pooled model, we estimate a partially segmented model for the three household classes. The approach offers two advantages. First, the pooled model allows us to estimate our coefficients employing the full dataset as opposed to estimating parameters based on sub-samples of data. Second, the pooled model allows us to directly identify if any difference exists between the three household classes without requiring any additional statistical tests.

In this section, model frameworks adopted in the study are presented in sequence: (1) ordered logit (OL) model for household vehicle ownership; (2) log-linear regression (LR) model for analyzing household VMT and (3) two binary logit (BL) models at the individual level for bikeshare or rideshare adoption choice.

OL Model (Household Vehicle Ownership)

The OL model results for examining vehicle ownership levels are presented in Table 2. In the OL model, latent household ownership propensity is mapped to the observed vehicle ownership levels using thresholds. A positive (negative) parameter for a variable in the propensity equation indicates a shift toward higher (lower) ownership levels assuming all other variables are constant. From Table 2, we can observe that households in New York, Chicago, and San Jose have lower vehicle ownership propensity relative to Atlanta. Among different regions, New York has the lowest propensity followed by Chicago. In terms of socio-demographic characteristics, several variables are found to have significant impact on household level vehicle ownership decision. Households with larger household size, higher proportion of senior people, and higher number of workers are associated with higher propensity of vehicle ownership. On the other hand, a higher proportion of people working from home has a negative impact on vehicle ownership levels. As expected, households in the rural area are likely to own more personal vehicles relative to households in the urban area. With respect to household income, we observe that low and medium income households are less likely to own more vehicles relative to high income households.

In terms of shared mobility specific attributes, we found that households using bike/ridesharing systems are likely to have lower fleet size relative to those households using no shared mobility alternatives. It is interesting to observe that the impact is more pronounced for households using bikeshare than rideshare alternatives. In order to identify the region specific impacts of shared mobility adoption, interaction of these alternatives with the region specific indicators are also introduced in the model. In the vehicle ownership model, these interaction terms are found to be significant for the New York region. As expected, these impacts are negative in New York region highlighting households in New York that use bikesharing and ridesharing are likely to own fewer vehicles. Overall, the results clearly highlight the potential substitution impact of bikesharing and ridesharing among households. The availability of bikesharing and ridesharing influences households to own fewer vehicles. In our final specified OL model, we also found that households in rural areas using ridesharing are also likely to have higher vehicle ownership propensity. The result indicates the reduction in vehicle fleet due to bikeshare and rideshare are concentrated in urbanized regions. Overall, the results clearly indicate that the three classes of households exhibit distinct vehicle ownership profiles.

LR Model (Household VMT)

The LR model results for examining household VMT is presented in Table 3. From Table 3, we observe that all considered regions in the analysis have lower VMT relative to Atlanta region. With regards to socio-demographic attributes, household size, proportion of male and number of workers are positively associated with annual VMT. On the other hand, proportion of senior people, people worked from home and households with no vehicles are negatively associated with annual VMT. Further, households in rural area are likely to accrue higher VMT compared to households in urban area. Households with income less than 100k are more likely to have lower VMT relative to households with income greater than 100k.

In terms of the shared mobility specific attributes, households using bikeshare as trip alternatives are likely to have lower annual VMT while households using rideshare, surprisingly, are likely to accrue higher annual VMT. The interaction term between New York and rideshare reveals positive impact on annual VMT. Households in the rural areas using ridesharing system are likely to have lower annual VMT reported. For the households with income less than 100k, bikeshare users (households) are likely to have higher annual VMT. Finally, in Chicago households with higher proportion of senior people using ridesharing are likely to have higher annual VMT. The results clearly indicate that the three classes of households exhibit distinct vehicle mileage profiles.

BL Model (Rideshare and Bikeshare Adoption Choice)

The estimation results of shared mobility adoption models are presented in Table 4 – rideshare model results are presented in 2nd and 3rd column panels while bikeshare models results are presented in 4th and 5th column panels. With regards to different regions considered, people living in the New York regions are less likely to adopt rideshare relative to other regions, while people living in the Atlanta region are less likely to adopt bikeshare compared to New York, San Jose and Chicago regions. In terms of trip maker's characteristics, males are likely to use bikeshare more relative to females, however, gender does not have any significant impact on rideshare adoption. From Table 4, we can observe that senior people are less likely to adopt ridesharing alternative compared to young individuals (under 65 years old). The variables indicating Ethnicity is white and employment status as employed have positive impact on the adoption of both shared alternatives.

Vehicle availability of the trip maker is defined based on availability of personal vehicle for making trips. In defining availability, we compute the ratio of number of vehicles to the number of drivers and if the ratio is ≥1, then we set vehicle availability to 1. As expected, the vehicle availability variable shows negative impacts on both shared mobility options. With respect to household characteristics, trip makers living in zero and one vehicle ownership households are likely to adopt shared mobility alternatives relative to those living in higher vehicle ownership households. The impacts are more pronounced for households with zero vehicle. Relative to low income households, individual living in medium and high income households are likely to adopt rideshare more. At the same time, trip makers of high income households are more likely to adopt bikeshare relative to low and medium income households. From Table 4, we can observe that people living in rural areas are less likely to adopt shared mobility alternatives compared to households from urban areas. People living in own residences are less likely to adopt ridesharing options, while it does not have any significant impact on bikesharing.

Elasticity Analysis

From the model results, it is not possible to identify the magnitude of impacts of the variables on the household vehicle ownership and annual VMT. Therefore, to provide a better understanding of the impacts of exogenous factors, we compute disaggregate level impact in both short-term and long-term effects based on some variables found significant in the final model specifications. Specifically, we consider six different synthetic households based on several hypothetical conditions and compute the annual predicted VMT and probability of vehicle ownership for three different household classes including household using no sharing, using bikesharing and ride sharing. The synthetic households considered are as follows:

1. <u>Household 1:</u> Household is a low income household, with 2 workers, no senior individuals (above 65 years old) and located in rural area of New York region.
2. <u>Household 2:</u> Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in rural area of New York region.

3. Household 3: Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in urban area of New York region.
4. Household 4: Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in urban area of Chicago region.
5. Household 5: Household is a high income household, with 2 workers, 2 senior individuals (above 65 years old) and located in urban area of Chicago region.
6. Household 6: Household is a high income household, with 2 workers, 2 senior individuals (above 65 years old) and located in urban area of San Jose region.

Figure 1 and 2 represents the predicted VMT and predicted probabilities of different vehicle ownership levels for these six different hypothetical households. Several observations can be made. First, we can observe that urban region has significant impact on mileage and ownership dimensions. Second, the VMT profiles highlight the lower mileage of bikeshare users across urban regions. Third, for vehicle ownership, the probability of owning more vehicles is higher for no sharing households in general. Finally, the results also highlight the important role of income on vehicle ownership across the three classes of households. For example, low income households in New York that adopt bikesharing or ridesharing are unlikely to own more than 1 vehicle relative to households that do not adopt sharing.

CONCLUSIONS

Given the burgeoning growth in rideshare and bikeshare systems and their growing rate of adoption for trip making, it is important to understand the impact of sharing systems on household trip. So, we proposed a framework to examine (a) the impact of the adoption of these modes on travel behavior and (b) the characteristics of individuals adopting these modes. In our analysis, we identify individuals (and their respective households) adopting shared mobility and classify the population into three classes: (1) households with members that do not use bikesharing or ridesharing, (2) households with members that adopt bikesharing and (3) households with members that adopt ridesharing. We examine differences between household vehicle mileage and household vehicle ownership across three classes by developing pooled models. Household vehicle mileage is examined using log-linear regression models. Household vehicle ownership is studied using ordered logit models. The model estimation results clearly highlight significant differences in vehicle ownership and annual VMT across the three household classes. The results also identified the impact of several variables including household income, household location and region on the differences in household vehicle ownership and annual VMT across three classes. The model applicability is further augmented by generating probability plots for various scenarios. The plots clearly highlight the important role of household location and household income on annual mileage and vehicle ownership across the three classes of households.

After confirming the differences across the three classes of households, we investigate the adoption of bikeshare and rideshare at the individual level to answer - who are individuals who are likely to choose these shared modes. The results highlight how potential adopters are young employed urban residents, predominantly Causcasian usually with high income and 0 or 1 vehicles in the household.

To be sure, the study is not without its limitations. While the individual trip record in NHTS does not provide information on the use of these modes, we have person level details on bikesharing and ridesharing usage in the previous 30 days. For some respondents it is possible that the adoption of bikesharing or ridesharing is an anomaly. Thus, such inaccuracies in household classification can affect model findings.

REFERENCES

[1] Statista: The Statistics Portal. Ridesharing services in the U.S.- Statistics & Facts. https://www.statista.com/topics/4610/ridesharing-services-in-the-us/. Accessed September. 25, 2018.
[2] Jäppinen, S., T. Toivonen, and M. Salonen. Modelling the potential effect of shared bicycles on public transport travel times in Greater Helsinki: An open data approach. Applied Geography, Vol. 43, 2013, pp. 13-24.
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[4] Feigon, S., and C. Murphy. TCRP Research Report: Shared mobility and the transformation of public transit. Transportation Research Board, Washington, D.C., 2016. https://www.trb.org/Main/Blurbs/174653.aspx/.

Table 1 Summary Statistics of Dependent Variables across Different Regions

<table>
<tr><th>Region</th><th>Dependent Variable</th><th>Value</th><th>No Share</th><th>Bike Share</th><th>Ride Share</th></tr>
<tr><td rowspan="5">New York</td><td>Annual VMT per household</td><td></td><td>27046.321</td><td>18049.189</td><td>46098.082</td></tr>
<tr><td rowspan="4">Vehicle Ownership (%)</td><td>0.000</td><td>22.03</td><td>55.70</td><td>41.97</td></tr>
<tr><td>1.000</td><td>34.00</td><td>35.38</td><td>29.04</td></tr>
<tr><td>2.000</td><td>27.29</td><td>4.94</td><td>17.37</td></tr>
<tr><td>≥3.000</td><td>16.68</td><td>3.98</td><td>11.62</td></tr>
<tr><td rowspan="5">Chicago</td><td>Annual VMT per household</td><td></td><td>26132.860</td><td>21065.933</td><td>37265.640</td></tr>
<tr><td rowspan="4">Vehicle Ownership (%)</td><td>0.000</td><td>11.76</td><td>5.90</td><td>11.65</td></tr>
<tr><td>1.000</td><td>36.50</td><td>46.89</td><td>38.36</td></tr>
<tr><td>2.000</td><td>29.82</td><td>45.17</td><td>31.52</td></tr>
<tr><td>≥3.000</td><td>21.92</td><td>2.05</td><td>18.47</td></tr>
<tr><td rowspan="5">Atlanta</td><td>Annual VMT per household</td><td></td><td>32874.018</td><td>142115.438[2]</td><td>53133.637</td></tr>
<tr><td rowspan="4">Vehicle Ownership (%)</td><td>0.000</td><td>5.13</td><td>19.98</td><td>6.62</td></tr>
<tr><td>1.000</td><td>33.28</td><td>27.55</td><td>32.06</td></tr>
<tr><td>2.000</td><td>36.82</td><td>10.28</td><td>41.72</td></tr>
<tr><td>≥3.000</td><td>24.77</td><td>42.19</td><td>19.60</td></tr>
<tr><td rowspan="5">San Jose</td><td>Annual VMT per household</td><td></td><td>38954.671</td><td>19425.505</td><td>44358.096</td></tr>
<tr><td rowspan="4">Vehicle Ownership (%)</td><td>0.000</td><td>3.31</td><td>0.00</td><td>7.39</td></tr>
<tr><td>1.000</td><td>30.06</td><td>26.88</td><td>26.55</td></tr>
<tr><td>2.000</td><td>36.00</td><td>24.73</td><td>36.52</td></tr>
<tr><td>≥3.000</td><td>30.62</td><td>48.39</td><td>29.54</td></tr>
</table>

Table 2 Ordered Logit Model Results

Variables	Estimate	t-stat
Threshold between zero and one cars	-1.595	-8.547
Threshold between one and two cars	0.738	4.070
Threshold 2 between two and more than two cars	2.761	14.110
Region (Base: Atlanta)		
New York	-1.121	-13.150
Chicago	-0.417	-4.040

[2] For Atlanta region, across the bikesharing groups, we don't have much household. As a result, this number does not express anything significant

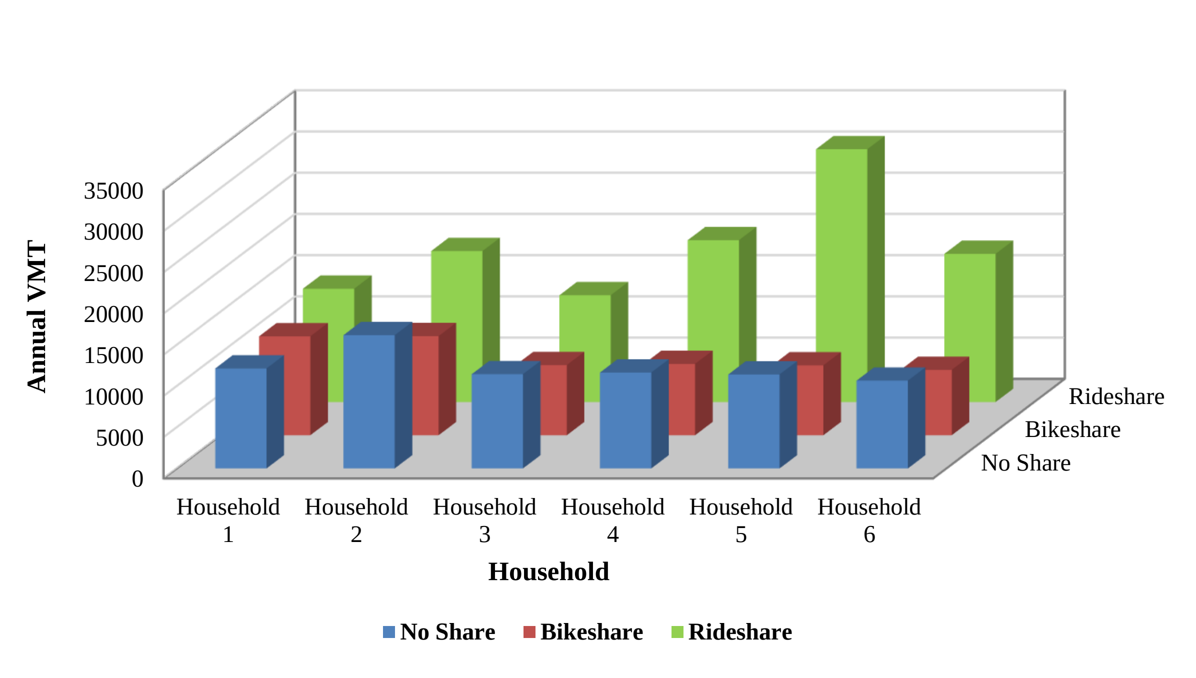
San Jose	-0.173	-1.690
Socio-demographic Attributes		
Household Size	0.509	12.130
Proportion of people above 65 years in a household	0.949	8.530
Number of workers in a household	0.791	12.090
Proportion of people worked from home	-0.418	-2.010
Household location (Base: urban area)		
Rural area	1.258	7.350
Household income (Base: high income (>150k))		
Low income household (<35k)	-1.979	-13.030
Medium income household (>35k-150k)	-0.669	-6.490
Shared Mobility Specific Attributes		
Bikeshare (household using bikeshare)	-0.552	-1.280
Rideshare (household using rideshare)	-0.752	-5.130
New York*bikeshare	-1.204	-2.340
New York*rideshare	-0.766	-3.740
Household in rural area*rideshare	0.539	1.250

Table 3 Linear Regression Model Results

Variables	Estimate	T-stat
Constant	9.047	157.184
Region Specific Constant (Base Atlanta)		
New York	-0.276	-6.706
Chicago	-0.258	-6.146
San Jose	-0.326	-4.797
Socio-demographic Attributes		
Household Size	0.116	9.699
Proportion of male in household	0.440	10.266
Number of workers in a household	0.334	18.288
Proportion of people above 65 years in a household	-0.040	-0.909
Proportion of people worked from home	-0.169	-2.374
Household vehicle (at least 1 vehicle)		
Household with no vehicle	-0.781	-20.886
Household location (Base: urban area)		
Household in rural area	0.346	4.594
Household income (Base: high income (>100k))		
Household income (<100k)	-0.287	-9.536
Share Specific Attributes		
Bikeshare (household using bikeshare)	-0.296	-2.554
Rideshare (household using rideshare)	0.088	1.901
New York*rideshare	0.037	0.594
Household in rural area*rideshare	-0.394	-1.989
Household income (<100k)*bikeshare	0.286	1.738
Chicago*rideshare*proportion of senior people	0.933	2.729

Table 4 Binary Logit Model Results

	Rideshare		Bikeshare	
Variable	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Constant	-3.113	-12.690	-5.958	-13.020
Region Specific Constant				
New York (Base: San Jose, Chicago and Atlanta)	-0.318	-3.300	--	--
Atlanta (Base: San Jose, Chicago and New York)	--	--	-0.791	-2.160
Trip maker's Characteristics				
Male (Base: Female)	--	--	0.753	2.950
Age > 65 years (Base: Age≤65)	-1.387	-8.250	--	--
White (Base: All other race)	0.296	3.010	0.501	2.020
Worker (Base: Non-worker)	0.708	6.120	0.680	2.130
Vehicle is available to the person	-0.315	-2.390	-0.618	-1.960
Household Characteristic				
Household vehicle (Base: More than 1 vehicle)				
0 vehicle household	1.433	7.530	1.604	4.230
1 vehicle household	0.736	6.240	1.175	3.630
Household income (Base: Low income (<35k))				
Medium income household (≥35k to 150k)	1.173	7.300	--	--
High income household (>150k)	2.367	13.420	0.593	2.080
Household location (Base: urban area)				
Household is rural area	-0.485	-1.430	-1.761	-2.870
Household residence status (Base: rented and other)				
Household owned	-0.664	-6.300	--	--



Note - Hypothetical Households are:

Household 1: Household is a low income household, with 2 workers, no senior individuals (above 65 years old) and located in rural area of New York region.

Household 2: Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in rural area of New York region.

Household 3: Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in urban area of New York region.

Household 4: Household is a high income household, with 2 workers, no senior individuals (above 65 years old) and located in urban area of Chicago region.

Household 5: Household is a high income household, with 2 workers, 2 senior individuals (above 65 years old) and located in urban area of Chicago region.

Household 6: Household is a high income household, with 2 workers, 2 senior individuals (above 65 years old) and located in urban area of San Jose region.

Figure 1 VMT Plots across Different Groups for Different Scenarios

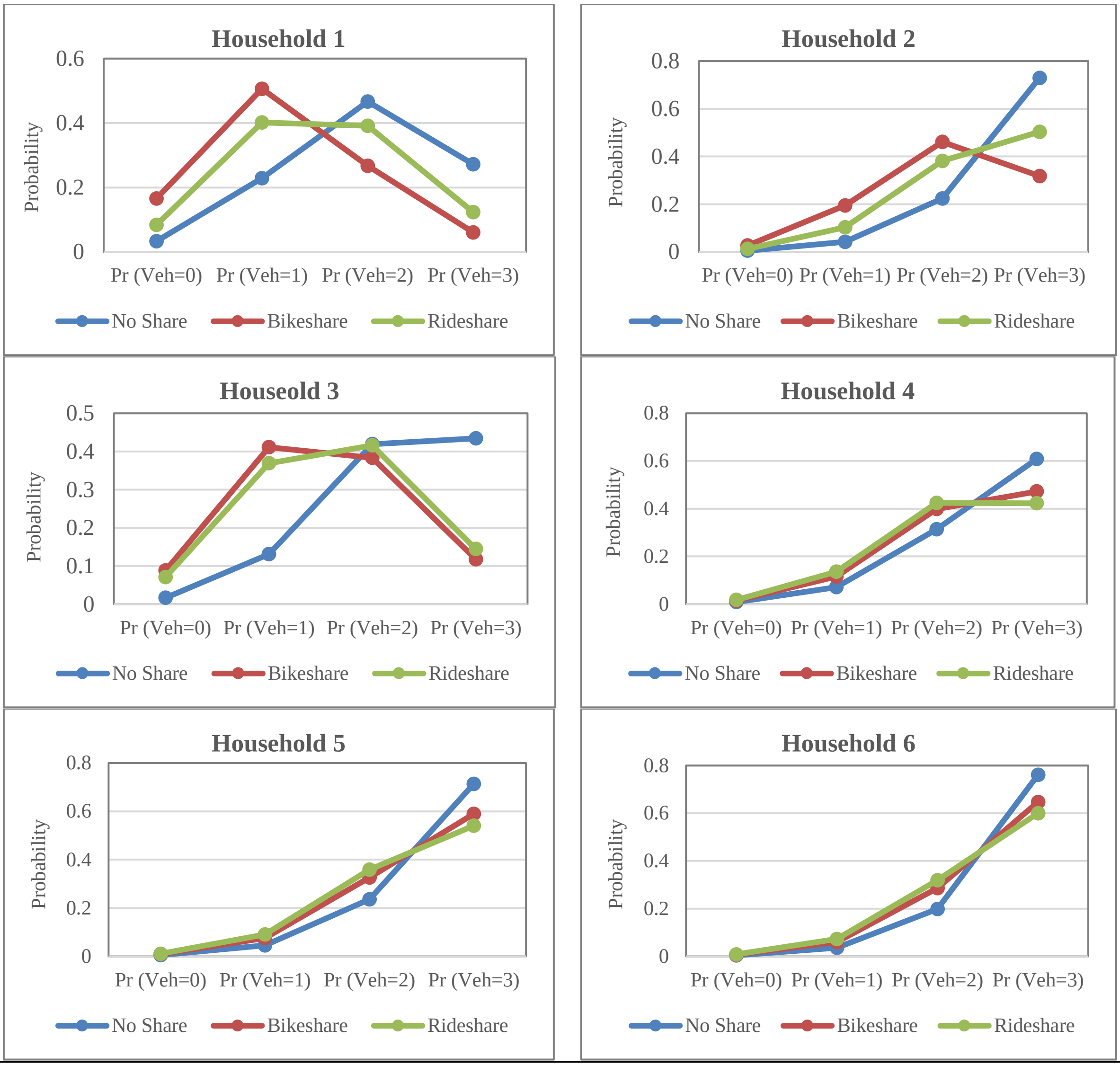


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Figure 2 Probability Plots of Vehicle Ownership across Scenarios