Online supplement to

"A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services"

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METHODOLOGY TO CALCULATE PSEUDO-ELASTICITIES

The parameters on the exogenous variables do not directly provide a sense of the absolute magnitude of the effects of variables. To obtain such order-of-magnitude effects, cardinal values are assigned to each of the ordinal levels of ride-sourcing and car-sharing to compute the "pseudo-elasticity" effects of exogenous variables on the expected total number of instances per month of each of ride-sourcing and car-sharing use, as well as the expected total number of instances per month of ride-sourcing *plus* car-sharing use. For the computations, it is assumed that an individual uses these services no more than once a day. The cardinal value assignments for the ordinal frequency levels in the model are as follows: (1) I never do this = 0 instances per month, (2) I do this, but not in the past 30 days = 0.333 instances per month, (3) I did this 1-3 times in the past 30 days = 2 instances per month, (4) I did this one day per week = 4 instances per month, (5) I did this two or more days per week (say 4 instances per week) = 16 instances per month. With these assignments, and using the notation c_m for the cardinal value assignment corresponding to ride-sourcing level *m*, the marginal expected value of the frequency of ride-sourcing use per month for individual q $(\tilde{f}_q)$ is:

$$E(\tilde{f}_q) = \sum_{m=1}^{5} c_m \times \Pr[f_q = m] \tag{1}$$

Similarly, using the notation d_n for the cardinal value assignment corresponding to car-sharing level *n*, the marginal expected value of the frequency of car-sharing use per month for individual q $(\tilde{g}_q)$ is:

$$E(\tilde{g}_q) = \sum_{n=1}^{5} d_n \times \Pr[g_q = n] \tag{2}$$

and the expected value of the total number of ride-sourcing plus car-sharing instances per month is:

$$E(\tilde{f}_q + \tilde{g}_q) = \sum_{m=1}^{5} \sum_{n=1}^{5} \left[(c_m + d_n) \times \Pr\left[f_q = m, g_q = n\right]\right] \tag{3}$$

With the equations above, it is possible to compute the aggregate-level "pseudo-elasticity effects" of exogenous variables. For variables that have an interaction effect with another variable, the elasticities are computed for all sub-groups characterized by the main and interaction effects. For example, for car-sharing, consider the main effects of smartphone ownership and the interaction effect with whether the individual belongs to a single-person household. To examine the joint effects of smartphone ownership and family structure, four multinomial sub-groups are developed: (1) no smartphone ownership, non-single, (2) no smartphone ownership, single, (3) smartphone ownership, non-single, and (4) smartphone ownership, single. The elasticity effects are computed for these variables with respect to the first sub-group (no smartphone ownership, non-single) as the base instance. Based on the results in Table 2, there is no ride-sourcing propensity difference between the first two sub-groups listed above; so, in this case, both of the first two sub-groups constitute the base. Also, for the ride-sourcing frequency, there are no interaction effects; so the elasticity effects for the last two sub-groups should be the same as well. A similar approach is adopted for other cases of interaction effects.

In the current analysis, based on the above discussion, we have two types of exogenous variable effects: discrete variables and a count variable. The discrete variables include binary variables (education level and driver's license holding) and multinomial variables (employment, age, and other variables obtained as interaction variables). But because the binary variables are simply one type of a multinomial variable, we will discuss the methodology we use to compute elasticity effects only for one of the multinomial variables (the employment variable) within the class of discrete variables. For these variables, we first predict the expected value of frequency for each of ridesourcing (equation 1), carsharing (equation 2), and the combination (equation 3), assigning the base value of "0" for all dummy variables characterizing the multinomial exogenous discrete variable (that is, assigning zero values for all the four employment categories). All other exogenous variables are at their values in the original data. Then, we sum the expected frequency of use of each of the ridesourcing, carsharing, and combination in the sample in the base case (label the resulting vector of three values in this base case as BASE). Subsequently, the same procedure as above is undertaken but after changing the value of the "employed part-time" dummy variable for each individual from the value of zero to the value of one, and obtaining the expected frequency of use for each of ridesourcing, carsharing, and the combination (label the resulting vector of three values as "PTIME"). Next, the same procedure as above is implemented, but now starting with the base data and changing the value of the "employed full-time" dummy variable for each individual from the value of zero to the value of one (label the resulting vector of three expected values as FTIME). Finally, we get the corresponding vector for the "employed self-employed" dummy variable (label the resulting vector as SEMP). Subsequently, to obtain an aggregate-level elasticity of the "employed part-time" dummy variable, we compute the change between the PTIME and BASE vectors as a percentage of the BASE vector, yielding the three elasticity values (one for ridesourcing, one for carsharing, and a third for the combination). Similarly, to obtain an aggregate-level elasticity of the "employed full-time" dummy variable, we compute the change between the FTIME and BASE vectors as a percentage of the BASE vector, once again yielding three elasticity values. The same is done for "employed-self". Finally, we compute the mean and standard errors of the aggregate-level elasticity effects as computed above across 200 bootstrap draws taken from the sampling distributions of the estimated parameters.

For the one count variable (number of vehicles), the procedure is simpler. We simply change the count variable (number of vehicles) for each individual by the value of one, and compute the percentage change in the expected frequencies of use.