Supplementary Information for

The Value of Car Ownership and Use

Data Collection

Case Study City Selection

For this study, we selected four U.S. metropolitan areas that represented a diversity of geographic region within the U.S. and level of "car dependence" measured in terms of household car ownership and commuter car use and traffic (INRIX, 2018). Due to the variation in governance, culture, and urban form found in different geographic regions, we selected one city each from the East Coast (Washington, D.C.), West Coast (Seattle, WA), South (Dallas, TX), and the Interior (Chicago, IL). In terms of car dependence, Dallas, TX has the highest average number of cars and lowest percentage of zero-car households of any of the cities select, with these numbers also being above and below the U.S. national average, respectively (see Table 1). On the other hand, Chicago, IL has the lowest average number of cars per household and the highest percent of households that do not own a car among the cities selected.

Because our study considered ridehailing as an alternative to private car ownership and use, we wanted to ensure that respondents in each of our target metropolitan areas was likely to be familiar with such services. Therefore, all four of our selected cities are among the top or middle tier of cities in terms of number of ridehailing trips (Table 1).

Table 1. Characteristics of case study metropolitan areas

	Chicago, IL	Dallas, TX	Seattle, WA	Washington, D.C.
Household car ownership:				
Average # cars per household	2.08	2.29	2.25	2.17
Zero-car households (%)	6.14	1.71	3.69	5.45
Commute mode share:				
Drive alone (%)	70.0	80.9	67.6	66.4
Carpool (%)	7.62	9.61	10.5	9.18
Traffic rank (2018)	3	21	6	2
City rank in terms of number of ridehailing trips	Top 8	Top 8	Mid 11	Top 8
Previous research on ridehailing	Shabanpour, Golshani, & Mohammadian, 2018	Lavieri & Bhat, 2019	Dias, et al., 2017	

Sources: Household car ownership and commute mode share data from American Community Survey (2017a); traffic rank from INRIX (2018); rank in terms of number of ridehailing trips from Schaller (2018) based on data from the U.S. National Household Travel Survey (2017).

Sample

Respondents for our online survey were recruited by a professional panel company, Qualtrics. Quota sampling was used to ensure statistical representativeness of each metropolitan area sample by age, household income, and household car ownership. However, there was difficulty in reaching respondents in the lowest income bracket and those whose household owned three or more cars; therefore, these quotas were relaxed towards the end of data collection. We collected a total of 4,937 responses from which 915 individuals were screened out by quota questions or failed to complete all sections of the survey. . This left us with a final sample size of 4,022 responses, with 1,017 from Washington, D.C., 1,006 from Chicago, 1,001 from Seattle, and 998 from Dallas.

Table 2. Sociodemographic breakdown of our sample (S) compared to the population (P) for each city

		Washington, D.C.		Chicago, IL		Dallas, TX		Seattle, WA	
		P	S	P	S	P	S	P	S
Gender	Male	48.9	42.0	48.9	36.7	49.2	38.2	50.0	42.4
Age	18-29	21.3	23.3	21.8	21.1	22.5	22.0	21.5	19.0
	30-39	19.8	19.9	18.3	18.7	19.8	20.1	19.8	21.8
	40-49	18.5	20.4	17.5	18.3	19.1	18.8	17.7	17.4
	50-59	17.8	17.2	17.7	18.4	17.5	18.1	17.4	17.4
	60+	22.6	21.2	24.7	23.6	21.1	21.0	23.6	24.5
Annual household income	Less than $25K	10.8	9.5	19.0	13.1	17.2	14.5	14.2	11.4
	$25K - $50K	13.3	12.2	19.9	16.1	21.8	18.1	17.6	15.8
	$50K - $75K	14.6	14.2	16.8	17.6	18.2	18.9	16.8	17.4
	$75K - $100K	12.7	13.8	12.8	14.9	12.6	14.1	13.6	14.6
	$100K - $150K	20.2	21.8	16.0	18.7	15.6	18.1	18.4	20.5
	$150K - $200K	12.0	13.6	7.4	9.7	7.0	7.9	9.0	10.1
	$200K or more	16.4	14.8	8.2	9.8	7.6	8.2	10.3	10.3
Household car ownership	0	5.6	7.2	6.3	7.3	1.9	2.9	3.9	6.0
	1	23.0	35.4	24.4	26.7	20.3	25.2	21.5	31.0
	2	39.1	39.7	40.6	43.5	44.5	48.4	40.9	42.8
	3 or more	32.2	17.7	28.7	22.5	33.3	23.4	33.7	20.3
Household size	1	27.0	14.6	28.7	14.4	24.8	12.4	27.8	17.2
	2	30.6	26.4	30.4	32.5	30.9	33.1	34.2	33.8
	3	16.8	23.6	15.7	18.2	16.8	19.3	15.9	21.0
	4 or more	25.7	23.9	25.1	22.9	27.5	20.4	22.1	16.8
Education level	High school diploma or less	29.2	13.0	37.0	17.6	38.8	17.0	29.4	12.4
	Assoc. degree or some college	24.6	25.2	29.0	26.0	30.4	29.7	32.3	31.1
	College degree	24.5	27.9	21.3	33.7	20.6	33.9	24.6	35.7
	Advanced degree	21.8	33.9	12.7	22.7	10.2	19.5	13.7	20.9
Unemployed (%)		8.4 (3.1)	11.0	16.3 (3.6)	14.9	8.2 (3.3)	16.3	10.0 (3.3)	14.8

Sources: Age, income, household car ownership, household size, and education level from the American Community Survey (2017b-g); unemployment data for June 2020 (and 2019 annual average) are from U.S. Bureau of Labor Statistics (2020).

Table 2 includes details on the representativeness of each of our metropolitan area samples. Across our cities, we find that we are overrepresenting individuals with high educational attainment (advanced degrees) compared to those who attained no more than a high school diploma. We also find that our sample reflects the higher unemployment rate during the COVID-19 pandemic compared to the average in previous years (see next section).

Study Timeframe during COVID-19

Participants completed our online survey from June 10 to July 2, 2020. Therefore, this study was conducted while the COVID-19 pandemic was ongoing in each of the four cities. Figure 1 includes the number of new COVID-19 cases per day for each of the four counties containing our metropolitan areas: Dallas County, TX, Cook County, IL, King County, WA, and Washington, D.C. The data collection period is marked in grey. In addition, Figure 2 shows aggregate changes in travel by public transit, driving, and walking according to various sources. Generally, these show that driving and walking were close to if not above pre-pandemic levels by the time of the survey, while public transit use remained significantly lower in all cities.

Figure 1. Timeline of survey data collection versus new COVID-19 cases by metropolitan area

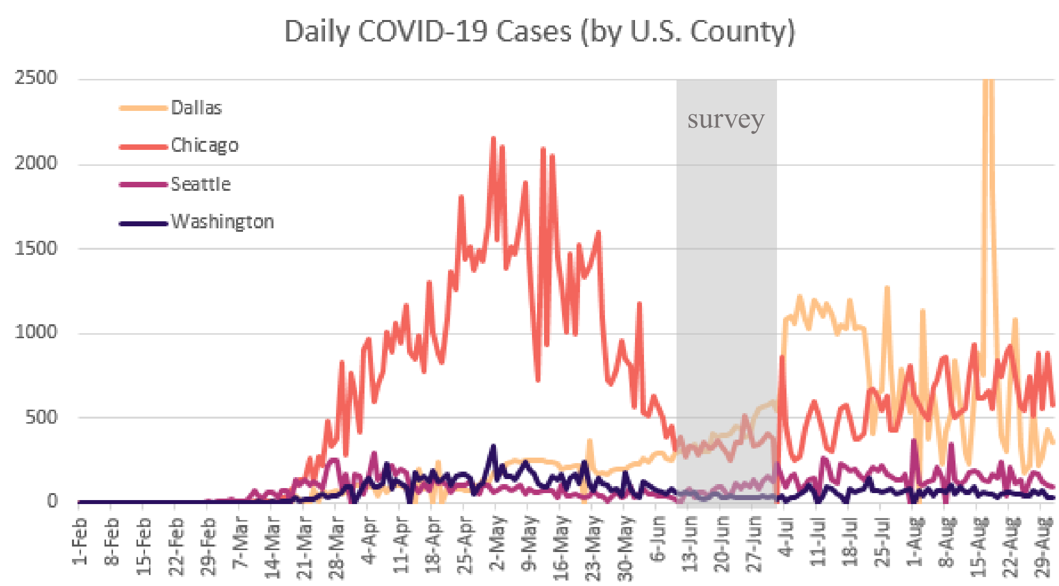
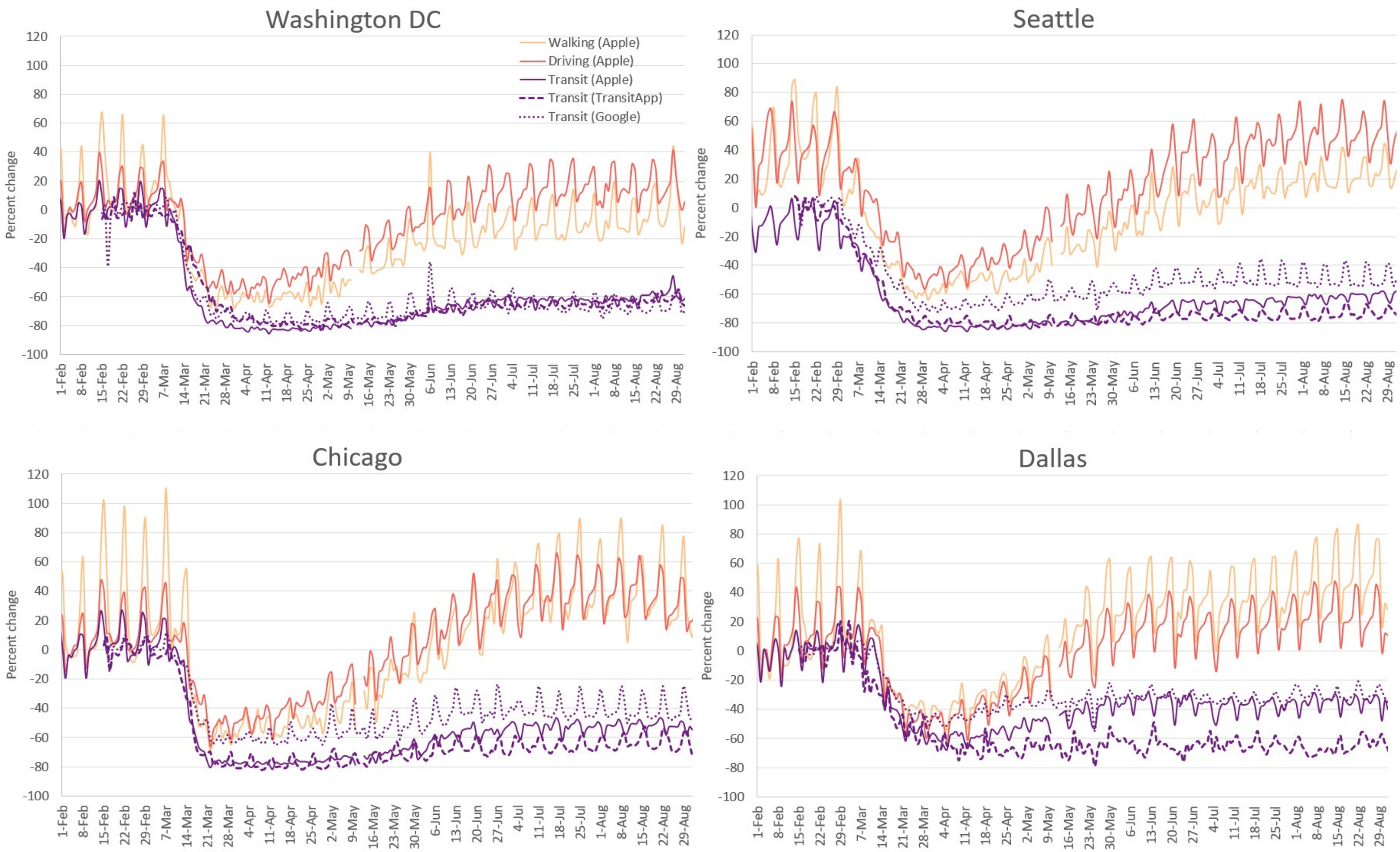


Figure 2. Aggregate travel trends by mode during COVID-19 in four U.S. metropolitan areas



Notes: Data from Apple Maps represent daily volume of direction requests by mode compared to baseline volumes from January 13, 2020. Data from Transit App shows actual use of the app compared to projected use of the app based on 2019 numbers (adjusted for annual growth rate). Data from Google Maps provides number of visits per day at transit stations compared to the median value for the corresponding day of the week during the 5-week period from January 3 to February 6, 2020; data are only from users opted into location history for their Google Accounts. No demographic information accompanies any of this data, so we cannot assess their representativeness of the metropolitan area populations.

Survey Design

We undertook an online survey with two distinct types of discrete choice experiments: single binary discrete choice (SBDC) (Loomis et al., 1998) and best-worst scaling (BWS) (Louviere et al., 2013). In the following sections, we provide details on the experimental design, analytic approach, and results for each of these choice experiments. While our data collection protocol prohibits us from publishing the raw data records, the full questionnaire, analysis code, and results are available at: https://github.com/jcmoody6/car-value.

Single Binary Discrete Choice (SBDC)

Experimental Design

The single binary discrete choice (SBDC) experiment asked respondents to make a single choice from two options: keep access to a transportation option or forego access in return for a specific amount of compensation. Different scenarios were created to measure the value of private car ownership and use compared to ride-hailing:

1. Value of ride-hailing: Given all your travel needs and options, choose whether to give up access to **ride-hailing** for one year and receive a compensation amount, or keep access to ride-hailing and receive no compensation.
2. Value of car ownership and use: Given all your travel needs and options, choose whether to give up access to your **primary car** for one year and receive a compensation amount, or keep access to your car and receive no compensation.
3. Value of car ownership: You are given access to a **new, free, ubiquitously available ride-hailing service** that can serve all of the trips that you currently make by your primary vehicle without any additional inconvenience. Choose whether to give up access to your **primary car** for one year and receive this free service and a compensation amount, or keep access to your car and receive no compensation nor free ride-hailing.

Then from the difference between scenarios 2 and 3, we can isolate the value of car use.

Each respondent was randomly presented with four compensation amounts randomly selected from a pre-determined set for each scenario (Table 3). For one set of scenarios, all respondents were asked to recall their typical travel behavior in a year pre-COVID-19 (for example, 2019). For a second set of scenarios, all respondents were asked to answer for a month during COVID-19 (for example, June 2020) with the monetary amounts adjusted to be approximately 1/12 those provided for the typical year. Compensation amounts were determined prior to the start of data collection through a review of existing literature on costs of car ownership and use and a pilot survey with 200 responses conducted in February 2020 on Amazon's MechanicalTurk platform.

Table 3. Compensation amounts used in the SBDC scenarios

Scenario	COVID period	Set of possible compensation amounts ($)
Scenario 1. Value of ridehailing	Typical year pre-COVID	25; 50; 100; 250; 500; 750; 1,000; 2,500; 5,000; 7,500; 10,000; 12,500
	Month during COVID	2; 4; 8; 20; 40; 60; 80; 200; 425; 650; 800; 1,000
Scenarios 2 and 3. Value of car ownership and use	Typical year pre-COVID	100; 500; 1,000; 2,000; 3,000; 4,000; 5,000; 7,500; 10,000; 15,000; 20,000; 25,000; 30,000; 40,000; 50,000; 75,000
	Month during COVID	10; 40; 80; 150; 250; 300; 400; 625; 800; 1,250; 1,500; 2,000; 2,500; 3,000; 4,000; 6,250

Analytic Approach

SBDC questions are compatible with economic theory and random utility models. Therefore, we can use a logistic regression to measure the surplus that individual consumers obtain from access to different transportation options and the monetary value that they attach to them. Specifically, we represent the utility that a consumer experiences from a transportation option t by $U(t)$. In our SBDC questions, utility is only affected by a change in access to the transportation option, with quantities restricted to 1 and 0, i.e., a consumer can either access a good within a defined time period (t^1) or not (t^0). We assume that $U(t^1) \geq U(t^0)$ or that customers derive a non-negative utility from accessing the transportation option (and would otherwise not use it.

Following Brynjollfson, Eggers, and Collins (2018), we estimate two logistic regression models to estimate the willingness to accept compensation (WTAC) for access to the transportation options in each of our scenarios. The first logistic regression (our base model) contains only the compensation amount and a random intercept term. The second logistic regression (our model with socio-demographics) includes additional predictors in the choice whether or not to give up access to the transportation option for a year—such as characteristics of the respondent, his/her household, and the built environment. Both models include panel effects to control for the fact that each respondent in our survey answered four choices for each scenario and therefore the error terms of these choices may be correlated with one another.

Base Model

For our base model, we model the choice to give up access to a transportation option, t (choice = 1) in exchange for a given compensation amount C ($) or to keep access to the transportation option and forgo the money (choice = 0). We model the binary choice variable as a function of a random intercept and the logarithmic transformation of the compensation amount, *log(C)*, using a logistic regression where p_i is the probability that individual *i* gives up transportation option *t*:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_{0,i} + \beta_c \log(C) + \varepsilon_i$$

We estimate the mean of the random intercept $\beta_{0,i}$ and β_c using the *pglm* package in R (Croissant, 2020b) and then solve for the median WTAC for access to *t* by setting p_i equal to 0.5 and solving for *C*:

$$\log\left(\frac{0.5}{1-0.5}\right) = \overline{\beta_{0,\iota}} + \widehat{\beta_c} \log(C)$$

$$\log(1) \text{ or } 0 = \overline{\beta_{0,\iota}} + \widehat{\beta_c} \log(C)$$

$$-\frac{\overline{\beta_{0,\iota}}}{\widehat{\beta_c}} = \log(C)$$

$$C = e^{\frac{-\overline{\beta_{0,\iota}}}{\widehat{\beta_c}}}$$

This provides a point estimate of the compensation amount associated with indifference between giving up and keeping access to the transportation option for the entire sample. We estimate this separately for each of the SBDC scenarios to measure the WTAC for ridehailing, car ownership and use together, and car ownership separately.

Model with Socio-demographics

Next, we want to understand. We have a vector of socio-demographic characteristics $\boldsymbol{x_i}$ for each individual *i* in our sample. Including these as predictors in our logistic regression, we can estimate:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_{0,i} + \beta_c \log(C) + \boldsymbol{\beta_x x_i} + \varepsilon_i$$

Estimating this model, we get a set of coefficients that are general, but since each individual has their own socio-demographic characteristics, when plugging in *p = 0* we solve for an individual-specific "indifference compensation" that we call C_i:

$$\log\left(\frac{0.5}{1-0.5}\right) = \overline{\beta_{0,\iota}} + \widehat{\beta_c} \log(C) + \widehat{\boldsymbol{\beta_x}} \boldsymbol{x_i}$$

$$C_i = e^{-\frac{\overline{\beta_{0,\iota}} + \widehat{\boldsymbol{\beta_x}} \boldsymbol{x_i}}{\widehat{\beta_c}}}$$

The result is no longer a point estimate, but instead a distribution of C_i at the indifference point $p = 0.5$ for every individual i. We can take the median (or mean) of this distribution across individuals to get a point estimate similar to the median WTAC calculated in the base model. However, this result now accounts for the socio-demographics of the individuals that make up our sample. One benefit of having this individual-specific indifference compensation amount is that we can compare these values across subsamples of our data. For example, we can look at how the median or mean C_i among urban residents differs from the value for suburban or rural residents, controlling for the other sociodemographic characteristics of these groups.

The results for the base model and the model with socio-demographics are reported in the manuscript for all pre-COVID (typical year) scenarios. The results for the base model only are presented for the month during-COVID scenarios.

Benchmarking the Single Binary Discrete Choice (SBDC) Measures with Best-Worst Scaling (BWS)

In addition to the single binary discrete choice experiments, we also conducted choice experiments based on the best-worst scaling (BWS) or maximum difference scaling approach (Finn and Louviere, 1992) following the benchmarking method used by Brynjolfsson, Collis, and Eggers (2019). We employ case 1 or object case BWS choice tasks, which ask respondents to select the best (most important) and worst (least important) options from a set of alternatives (Mühlbacher et al. 2016; Louviere et al., 2013).[1] Collecting more information for each respondent, both within the choice set and across sequential choice sets, makes this approach more efficient than SBDC which elicits only one decision. Furthermore, individuals are required to make a tradeoff when deciding which good they perceive as most and least valuable, which helps mitigate or even eliminate hypothetical bias with respect to the ordinal ranking of the choices.

Experimental Design

Before the BWS portion of the survey began, respondent were randomly assigned to either a pre-COVID scenario (typical year in 2019) or a during COVID scenario (one month like June 2020). Then each respondent answered 10 randomly selected questions. For each question, respondents were asked to select the best and worst option among a set of three options: a mobility option, a non-mobility or other option taken from Brynjolfsson, Collis, and Eggers (2019), and a monetary amounts.

[1] There are more complex best-worst scaling experimental designs that not only present choice options, but also a list of their attributes and levels. These include case 2 or "profile case" BWS and case 3 or "multiprofile case" BWS.

The options for the pre-COVID typical year scenario are given in Table 4. Because we examined the value of foregoing access to specific mobility goods or services for one year, the monetary options were also expressed as losses (e.g., earning a specific amount of money less for one year) in order to be comparable. The price sensitivity we are measuring is therefore closer to WTP than WTA.

In the following sections, we present only the analysis and results from the pre-COVID scenario. Therefore, these results are estimated from a randomly selected subsample of 2,014 individuals who each answered 10 BWS questions.

Table 4. Choice set for best-worst scaling choice experiments

Mobility	Other	Monetary
1. No access to personal car	1. No toilets in the home	1. Earning $100 less
2. No access to bus	2. No TVs in the home	2. Earning $200 less
3. No access to train	3. No access to all e-mail services	3. Earning $500 less
4. No access to exclusive ride-hailing services (e.g., UberX or Lyft Classic)	4. No access to online maps	4. Earning $1,000 less
5. No access to pooled ride-hailing services (e.g., UberPOOL or Lyft Shared)	5. No access to a smart phone	5. Earning $2,000 less
6. No access to personal bike	6. No access to a personal computer or laptop	6. Earning $5,000 less
7. No access to airline travel	7. No meeting with friends in person	7. Earning $10,000 less
8. No access to bike or scooter share		8. Earning $15,000 less
9. No access to car rental or car sharing (e.g., Zipcar)		9. Earning $20,000 less

Analytic Approach

There are two approaches for analyzing responses to case 1 BWS questions: the counting approach and the modeling approach. The counting approach calculates several types of scores on the basis of the number of times each item is selected as the best or worst item among all the questions across respondents (Finn and Louviere, 1992; Lee, Soutar, and Louviere, 2007). For aggregate statistics, one can count the total number of times that each option is chosen as best and worst across all questions (choice sets) and individuals. Dividing these counts by the number of times the option appeared in the choice sets provides metrics of proportion best and proportion worst (see Table 4). Once can also calculate the difference in the best and worst counts (best minus worst, B-W). This B-W score has been shown to correlate well with revealed preferences and predict real behavior comparably with more sophisticated regression models (Louviere and Islam, 1006; Louviere et al., 2013).

In addition to the counting approach, one can use a discrete choice modeling approach to analyze responses based on utility maximization theory. There are three discrete choice models that are commonly used to assess case 1 BWS data: the maxdiff or paired model, the marginal model, and the marginal sequential model (Marley and Louviere, 2005; Flynn et al., 2007; Louviere, Flynn, and Marley, 2015). All three models are based on utility maximization theory, assuming that respondents derive utility for each item in a choice set C. From the m items in the choice set, the respondent selects item i as the best item and item j as the worst item, where $i \neq j$. The three models generally assume that the utility for the item selected as the worst is the negative of the one selected as the best.

Table 5. Best-worst scaling summary statistics ordered by difference in the best and worst counts; mobility options indicated with grey fill

Option	Proportion best	Proportion worst	Best – worst
No toilets in the home	0.057	0.704	-1869
No access to a smart phone	0.115	0.481	-1048
No access to a personal computer or laptop	0.129	0.475	-980
Earning $20,000 less	0.172	0.553	-835
No access to all e-mail services	0.136	0.419	-827
Earning $15,000 less	0.174	0.538	-822
Earning $10,000 less	0.173	0.533	-792
No meeting with friends in person	0.168	0.374	-594
Earning $5,000 less	0.196	0.460	-591
No TVs in the home	0.184	0.358	-501
Earning $2,000 less	0.191	0.392	-469
No access to personal car	0.235	0.409	-392
Earning $1,000 less	0.208	0.368	-358
Earning $500 less	0.258	0.311	-119
No access to online maps	0.232	0.255	-68
Earning $200 less	0.263	0.284	-45
Earning $100 less	0.286	0.250	81
No access to airline travel	0.622	0.143	1066
No access to pooled ride-hailing services	0.690	0.129	1262
No access to car rental or car sharing	0.689	0.127	1264
No access to exclusive ride-hailing services	0.695	0.129	1269
No access to bus	0.689	0.114	1312
No access to personal bike	0.700	0.105	1339
No access to train	0.723	0.107	1347
No access to bike or scooter share	0.728	0.105	1370

The models differ in how they assume that respondents select the best and worst items from the choice set. The maxdiff model assumes that respondents make their selections of best and worst items based on the greatest utility difference among the options.[2] The marginal model assumes that respondents simultaneously select item i as the best item and item j as the worst item from m possible items. Therefore, the model assumes that the utilities for items i and j are the maximum and minimum, respectively, among the utilities of all m items. Finally, the marginal sequential model assumes that

[2] In other words, the model assumes that respondents select items i and j such that the utility difference between i and j is the greatest utility difference among $m \times (m-1)$ possible utility differences, where $m \times (m-1)$ is the number of possible pairs in which item i is selected as the best item and item j is selected as the worst item from m items.

respondents first select item i as the best item from m items and then select item j as the worst item from the remaining $m-1$ items.

Under these assumptions, the probability of selecting item i as the best and item j as the worst from a choice set C for each model can be expressed using a conditional logit model with the systematic component of utility V, as follows:

$$P(\text{best}=i, \text{worst}=j) = \frac{e^{(V_i - V_j)}}{\sum_{k,l \in C, k \neq l} e^{(V_k - V_l)}} \quad (1)$$

$$P(\text{best}=i, \text{worst}=j) = \frac{e^{(V_i)}}{\sum_{k \in C} e^{(V_k)}} \frac{e^{(-V_j)}}{\sum_{k \in C} e^{(-V_k)}} \quad (2)$$

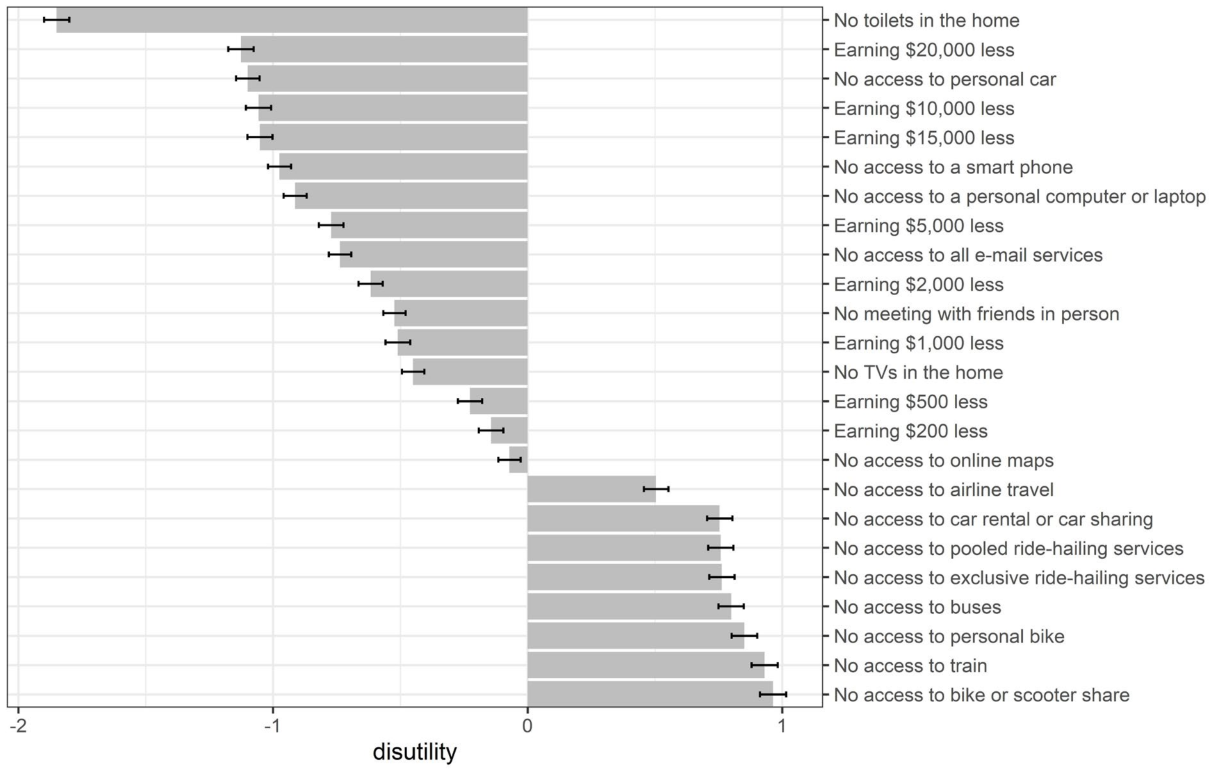
$$P(\text{best}=i, \text{worst}=j) = \frac{e^{(V_i)}}{\sum_{k \in C} e^{(V_k)}} \frac{e^{(-V_j)}}{\sum_{l \in C-i} e^{(-V_l)}} \quad (3)$$

In this study, we choose to estimate our case 1 BWS conditional logit using the maxdiff model described in equation (1). We estimate the utility parameters (coefficients) using the *mlogit* package in R (Croissant, 2020a) following an example by Aizaki (2019). This estimation leads to interval-scaled scores that represent the disutility of not having access to a good (or earning an amount less in income) for one year (see Figure 3).

Results

From Figure 3, we see that individuals rank losing access to personal car for a year between earning \$10,000 and \$20,000 less for a year. When it comes to access to other mobility options, including airline travel, car rental, ride-hailing, public transit, and bikes/scooters are valued at less than \$100 for a year. This finding agrees with results from Brynjolfsson, Collis, and Eggers, who found that, among a sample of U.S. respondents, access to airline travel for a year was valued between \$5 and \$10, access to public transportation for a year was valued at \$1 and \$5, and access to ride sharing services and Uber were valued at less than \$1 for a year (2019).

Figure 3. Disutility of losing an option for a year based on BWS maxdiff model estimation; all results are relative to earning $100 less per year set to disutility = 0.



To translate estimated disutilities into monetary amounts, we can estimate an equation of best fit between the loss of the monetary amounts provided and their estimated disutility as in Figure 4. We can then use this equation to calculate the monetary equivalent of the disutilities estimated for the mobility and other goods included in the BWS model. These results are presented in Table 6, which provides an estimate for the value of one year of access to a personal car of $16,890 with a standard error of around $100.

Figure 4. Exponential equation of best fit between monetary loss and estimated disutility from the BWS maxdiff model

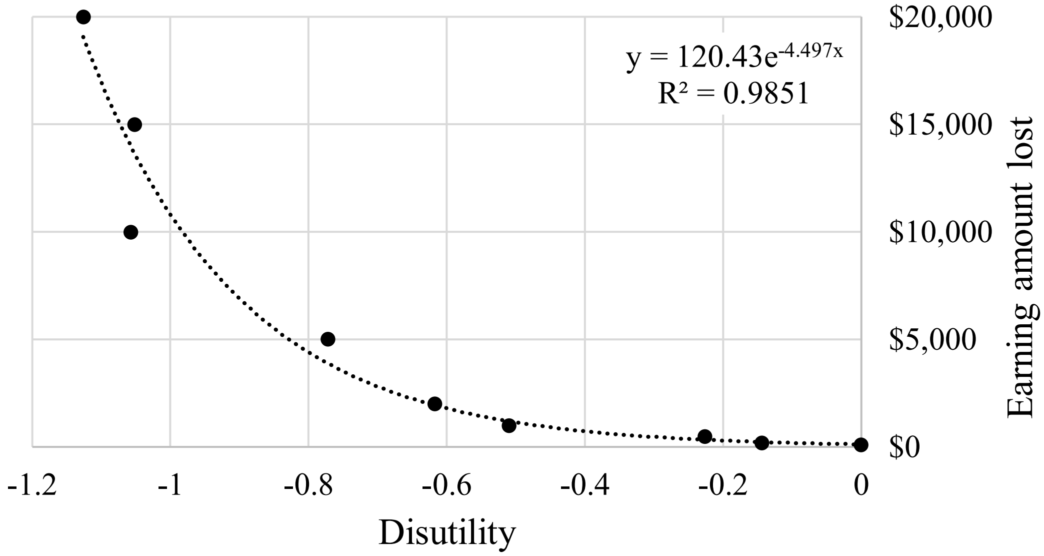


Table 6. Estimated disutilities and their extrapolated monetary amounts from the BWS experiment

Option	Disutility estimate	Standard error	Calculated value ($)
No toilets in the home	-1.850	0.049	494,664
No access to personal car	-1.099	0.046	16,890
No access to a smart phone	-0.975	0.045	9,649
No access to a personal computer or laptop	-0.913	0.045	7,326
No access to all e-mail services	-0.737	0.044	3,316
No meeting with friends in person	-0.523	0.044	1,267
No TVs in the home	-0.450	0.044	911
No access to online maps	-0.072	0.044	166
No access to airline travel	0.504	0.049	12
No access to car rental or car sharing	0.754	0.050	4
No access to pooled ride-hailing services	0.758	0.050	4
No access to exclusive ride-hailing services	0.763	0.050	4
No access to buses	0.799	0.050	3
No access to personal bike	0.851	0.050	3
No access to train	0.930	0.051	2
No access to bike or scooter share	0.963	0.051	2

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