Investigating the Influence of Alternative Survey Participant Recruitment Strategies on Measurement and Inference of Mobility Patterns

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ABSTRACT
There are growing concerns about the representativeness of survey data in an era of rapidly emerging and evolving technology, low response rates, and increasingly diverse and heterogeneous populations. Because of the complexities and costs associated with conducting surveys using traditional mail and phone methods, researchers and practitioners are adopting new methods to sample respondents. This paper aims to provide a comprehensive assessment of the representativeness of the samples obtained from three survey sampling strategies utilized in the nationwide COVID Future Panel Survey: convenience sampling, email sampling, and online panel sampling. The three subsamples were statistically different from each other for all socio-economic and demographic variables except race, ethnicity, household size, and gender. However, these differences were ameliorated with the application of weights and the three subsamples converged to census distributions on many variables except educational attainment. Weighting was also able to reduce the differences between the subsamples for a variety of mobility variables except transit use frequency. Modeling the influence of survey sample recruitment strategy on measures of mobility shows that it is significant even after controlling for socio-economic and demographic variables in the model specification. It is likely that the survey sample recruitment strategy variable is accounting for unobserved traits such as attitudes and lifestyle preferences. It is therefore recommended to include attitudinal and lifestyle preference questions in transportation surveys so that these traits can be explicitly included in travel model specifications to enhance explanatory power and reduce bias.

Keywords: survey methods, sampling strategies, sample recruitment, online panels, survey weighting, mobility measurement

1. INTRODUCTION

In many fields, surveys of households and individuals serve as the source of information to obtain insights about behaviors, choices, preferences, attitudes, and trends over time. Transportation planning, policymaking, and modeling have long relied on transportation surveys of various types to understand, measure, and quantify activity-travel demand, time use patterns, mobility choices under a variety of scenarios, and attitudes and preferences related to transportation and emerging technologies. Survey data is used to estimate increasingly complex transportation demand forecasting models, understand how travelers feel about different transportation options, modes, policies, and technologies, and gain insights about trends in mobility patterns. Many metropolitan planning agencies as well as national governments conduct travel surveys on a periodic basis to obtain up-to-date information about travel behavior and values. In a few places, data is gathered on a more continuous basis to help monitor trends in mobility patterns on a more frequent basis. In the United States, the National Household Travel Survey (NHTS) that had historically been conducted about every half-dozen years or so has now transitioned to a more frequent data collection protocol, with surveys taking place every other year (*1*). The recent COVID-19 pandemic motivated researchers and practitioners around the world to conduct surveys to gather critical information about changes in mobility patterns, activity-travel demand, and mode choices during and after the pandemic (*2*). Such data has proven crucial to post-pandemic transportation planning and model calibration.

With surveys continuing to serve as a key source of information for transportation planning and modeling, there are growing concerns about the ability to collect representative data in an era of rapidly emerging and evolving technology, low response rates, and increasingly diverse and heterogeneous populations (*3*). The cost of conducting surveys using traditional methods (e.g., mail-out/mail-back surveys, paper-and-pencil surveys, random digit dialing based telephone surveys) has risen sharply due to low response rates, technological tools that allow prospective respondents to screen calls and ignore solicitations, and increases in labor and material costs (*4*). With households and individuals constantly solicited for opinions, feedback, and input from many different entities, it is increasingly difficult to obtain the cooperation of an over-surveyed population that is incessantly experiencing survey fatigue (*5*).

Because of the complexities and costs associated with conducting surveys using traditional mail and phone methods (which yield dismally poor response rates in the current context), researchers and practitioners are adopting a variety of new methods to sample respondents and conduct surveys (*6*). This paper considers three specific methods that are gaining popularity – primarily due to affordable cost and convenience of administration. These methods are easy to execute, quite cost-effective, and often (but not always) considered adequate or good enough for the purposes of collecting data.

The three methods of interest considered in this paper are as follows. The *first* is the use of convenience samples for data collection. Convenience samples are generally comprised of individuals who can be recruited easily and conveniently without considerations of randomness or representativeness in the recruitment process. The *second* is the use of email lists purchased from a commercial vendor. Using new messaging platforms and tools, it is quite easy to blast out hundreds of thousands of email solicitations to individuals, requesting their participation in a survey. Commercial firms have assembled lists of email addresses and sell them for marketing and survey research purposes. The *third* is the use of online survey panels that are assembled by survey research companies. The survey research company is responsible for administering the survey, gathering the data from the agreed-upon number of respondents, and furnishing a reasonably clean data set to the survey research team or agency that has purchased their services. Survey research companies that offer this service have essentially compiled a large pool of professional survey-takers who complete surveys for a modest financial remuneration (*7*).

Within this paper, these three survey modalities will be referred to as alternative *survey sampling strategies* even though they are not all strictly survey sampling strategies per se. While convenience sampling is a sampling strategy, the other two methods do not necessarily constitute established survey sampling strategies (rather, they are more like sample recruitment strategies). Nevertheless, for ease of presentation and articulation in this paper, they will all be referred to as survey sampling strategies.

This paper aims to provide a comprehensive assessment of the representativeness of the samples obtained from each of these survey sampling strategies. Many surveys are unlikely to adopt a multitude of strategies for recruiting survey respondents; rather, only one or two strategies will be used to obtain a survey sample. It is therefore of critical importance to understand the nature of the biases and the level of representativeness associated with each of these increasingly popular survey sampling strategies. Armed with such information, it will be possible for survey researchers and agencies to determine the most appropriate survey sampling strategy (or, strategies) that should be deployed in different survey data collection contexts to meet the objectives of the survey effort.

The analysis in this paper utilizes data from the COVID Future Survey, a national panel survey conducted in 2020 and 2021 to measure the impacts of the COVID-19 pandemic on traveler behaviors, mobility choices, activity modalities, and perceptions and preferences. The COVID Future Survey adopted all three survey sampling strategies described above, yielding a composite sample that includes respondents recruited via a convenience sampling approach, email messages sent to a list purchased from a commercial vendor, and an online survey panel commissioned by a survey research company. Each of the subsamples is then weighted to control for a series of socio-economic and demographic variables and ensure population representativeness (with respect to those variables). The weighted subsamples are then compared with respect to measures of mobility and activity participation (and transitions over time) with a view to assess the extent to which inferences about mobility drawn from different subsamples differ (or not) after weighting is performed.

The rest of this paper is organized as follows. The next section offers a detailed description of the COVID Future Survey data set and weighting methodology. The third section presents a detailed comparison of unweighted and weighted survey subsamples with respect to socio-economic and demographic variables, while the fourth section offers a similar comparison with respect to activity-mobility characteristics. The fifth section presents econometric models of select activity-mobility variables with a view to identify the significance of the effect of sampling strategy on measures of activity-mobility after controlling for relevant socio-economic, demographic, and contextual variables. It also includes a comparison of trends in mode choice over time, to examine differences and similarities in trends depicted by the different subsamples. Finally, the sixth section offers conclusions and implications for survey design and sampling strategies in different contexts and applications.

2. SURVEY DESCRIPTION

The COVID Future Survey was carried out during the pandemic years to study changes in mobility, attitudes and perceptions, and activity participation modalities. The first wave of the survey was comprised of two components. The first component was administered between April and June of 2020, at the height of the pandemic when many jurisdictions in the United States locked down and implemented stay-at-home orders to limit the spread of contagion. This component of the data set is referred to as Wave 1A. The survey research team reached out to friends, family, colleagues, and acquaintances via email messaging, social media channels/contacts, and professional listservs of the transportation and urban planning fields. As the respondents were recruited via these convenient mechanisms, this sample may be considered a convenience sample. Through Wave 1A, a total of 1,127 survey responses were obtained.

A slightly modified and larger scale version of the survey was conducted between June and October 2020. This wave of the survey, dubbed Wave 1B, employed a dual sampling strategy to recruit respondents. First, a large email database of 350,000 email addresses was purchased from a commercial vendor. An additional 100,000 email addresses were randomly drawn from the rest of the United States, and a sample of 39,000 email addresses from the Greater Phoenix metropolitan region of Arizona was also contacted for potential participation in the survey. This recruitment strategy yielded a total of 2,946 survey responses. Second, Wave 1B also involved recruiting respondents through an online survey panel aggregated by an established survey research company, yielding an additional 5,262 responses that largely aligned with sampling quotas conveyed by the research team. Thus, the Wave 1B subsample comprises a total of 8,208 respondents (2,946 + 5,262).

Following the administration of the first wave, subsequent waves were administered to all Wave 1 respondents through email communications. In order to ensure appropriate spacing between Wave 1 and Wave 2, the second wave was administered between November 2020 and April 2021. The third wave was administered during October – November 2021. All respondents from Wave 1 received invitations for responding to Waves 2 and 3. A total of 3,093 individuals responded to Wave 2 while a total of 2,860 individuals responded to Wave 3 (*2, 8*). The stayer sample numbered 1,933 individuals who responded to *all three waves* of the survey.

A robust weighting methodology was employed to ensure that the survey samples obtained in the three waves were representative of the general population on a host of socio-economic and demographic variables at the census division level. These samples were weighted to provide geographic representativeness across a broad array of socio-economic and demographic characteristics for each of the nine census divisions in the United States. Sample size limitations prevented controlling for socio-economic and demographic variables at a finer geographic resolution. The weighting was done using the PopGen iterative proportional updating (IPU) algorithm (*9*). To meet the objectives of this study, three survey subsamples recruited through different means – convenience sample, email sample, and online panel – were each weighted separately to represent the population. The selected control variables included gender, age, education, race/ethnicity, household size, household income, and vehicle ownership. The American Community Survey (ACS) 2021 summary files of the US Census Bureau served as the source of information for marginal control distributions on the variables of interest.

3. COMPARISON OF SOCIO-ECONOMIC AND DEMOGRAPHIC VARIABLES

This section focuses on a comparison of socio-economic and demographic variables across the three subsamples. The three subsamples are convenience sample (CS), email sample (ES), and online panel (OP). These three subsamples are compared *both* for unweighted *and* weighted statistics and distributions. The summary of this comparison is presented in Table 1. The table shows several socio-economic and demographic attributes with several categories for each of the variables. The first section of the table presents the comparison for unweighted statistics and the second section presents the comparison for weighted statistics. The chi-square (χ^2) p-value is indicative of the level of statistical significance for differences in statistical distributions across the survey subsamples. The last column of the table presents the ACS 2021 statistics for the variables shown in the table.

The comparison of the unweighted statistical distributions yields several interesting insights. Although the gender distributions are not statistically different from one another, it can be said that the online panel is clearly comprised of a larger percent of females (from a qualitative standpoint). A review of the age distributions shows that they statistically differ at the 0.05 significance level. As expected, the convenience sample is largely comprised of employed individuals who are of working age. The online panel subsample is rather uniformly distributed across all age groups. The email sample, on the other hand, is clearly skewed towards the older age groups with more than one-half of the subsample aged 55 years or over. This is rather consistent with the general tendency for older individuals to respond at a higher rate to surveys than individuals in other age brackets (*10*). Older individuals generally exhibit a higher level of civic participation and are able to spare the time necessary to respond to surveys, thus contributing to the unweighted age distribution seen in the table for the email sample.

As mentioned earlier, the convenience sample (CS) is drawn largely from the social and professional networks of the survey research team. As such, it is not surprising that this subsample exhibits a high level of educational attainment, a very high employment rate, and a substantially higher income profile than the other subsamples. The online panel respondents tend to be less educated, lower income, and less employed than the other two subsamples. This suggests that individuals who sign up to be professional survey takers are generally of a lower socio-economic status and become members of the online survey panel to derive some income (*11*). With respect to education, employment, and income, the email sample generally falls in between the convenience sample and the online panel, largely consistent with expectations and the age profile of the subsample (*12*).

All three subsamples are predominantly white, more so than the general population, with the online panel depicting a greater proportion of nonwhite individuals. In terms of home ownership, the email sample depicts the highest rate of home ownership, with the convenience sample and the online panel depicting similar patterns of home ownership. Given the age distribution of the respondents in the email sample (older), it is not surprising that this group depicts a higher rate of home ownership (*13, 14*). Vehicle ownership distributions differ at the 0.10 significance level, suggesting that the patterns are rather consistent with one another. The email subsample, comprising older individuals to a greater degree, depicts a greater proportion falling into the category of owning three or more vehicles (*15*).

Overall, unweighted subsamples differ significantly from one another on all of the socio-economic and demographic variables considered in this table, with the exception of ethnicity, race, and household size. In other words, each of these sample recruitment strategies results in biased respondent samples that need to be weighted appropriately to draw statistically valid inferences about the population as a whole. The weighted statistical distributions generally mirror the census distributions, suggesting that weighting is capable of compensating for socio-economic and demographic biases that may arise.

TABLE 1 Distributions of Socioeconomic and Demographic Variables

Variable	Attribute	Unweighted					Weighted					ACS 2021 (%)
		χ2 p-value	CS n = 1,127 (%)	ES n = 2,946 (%)	OP n = 5,262 (%)	All n = 9,335 (%)	χ2 p-value	CS n = 1,127 (%)	ES n = 2,946 (%)	OP n = 5,262 (%)	All n = 9,335 (%)	
Gender*	Male	0.55	41.1	41.8	34.9	37.8	0.83	52.6	48.8	48.8	49.1	49.0
	Female		58.9	58.2	65.1	62.2		47.4	51.2	51.2	50.9	51.0
Age* (years)	18 - 24	0.00	6.1	2.3	12.1	8.3	0.92	14.2	11.7	11.8	11.7	11.7
	25 - 34		28.7	9.5	19.0	17.2		12.9	17.7	17.4	17.6	17.4
	35 - 44		22.5	12.9	18.6	17.3		19.1	17.2	17.0	17.1	17.0
	45 - 54		18.9	16.0	14.1	15.3		20.4	15.4	15.7	15.6	15.7
	55 - 64		16.7	23.4	16.5	18.7		9.8	16.7	16.4	16.4	16.6
	65+		7.1	35.8	19.8	23.3		23.6	21.3	21.7	21.5	21.6
Education*	< High school	0.00	0.3	0.9	2.7	1.8	0.03	7.5	10.3	10.5	10.5	10.7
	High school or GED		0.4	6.0	21.2	13.9		9.9	27.2	26.9	26.9	27.3
	Some college		8.6	25.8	34.7	28.7		38.0	29.3	29.7	29.6	29.5
	≥ Bachelor's degree		90.8	67.3	41.4	55.6		44.6	33.3	32.9	33.0	32.5
Employment	Employed	0.00	86.4	55.9	49.3	55.9	0.15	61.2	62.1	49.8	54.1	64.2
	Not employed		13.6	44.1	50.7	44.1		38.8	37.9	50.2	45.9	35.8
Ethnicity	Hispanic	0.29	6.7	7.8	12.7	10.4	0.46	10.9	16.9	15.0	14.7	16.9
	Not Hispanic		93.3	92.2	87.3	89.6		89.1	83.1	85.0	85.3	83.1
Race*	White	0.22	84.5	85.6	77.0	80.6	0.98	64.5	63.4	63.6	63.7	63.6
	Nonwhite		15.5	14.4	23.0	19.4		35.5	36.6	36.4	36.3	36.4
Household Income*	Less than $50,000	0.00	13.0	22.2	46.6	34.8	1.00	29.9	29.9	29.9	29.9	31.4
	$50,000 to $149,999		54.4	54.5	45.2	49.3		48.9	48.9	48.9	48.9	47.8
	$150,000 or more		32.7	23.4	8.1	15.9		21.2	21.2	21.2	21.2	20.8
Household Size*	1	0.74	19.3	18.1	18.9	18.7	1.00	16.9	16.9	16.9	16.9	16.9
	2		42.8	45.1	33.7	38.4		33.0	33.0	33.0	33.0	33.0
	3		15.0	15.0	20.0	17.8		18.7	18.7	18.7	18.7	18.7
	4 or larger		23.0	21.8	27.4	25.1		31.4	31.4	31.4	31.4	31.4
Housing Tenure	Own	0.01	57.1	78.3	57.3	63.9	0.07	55.0	64.5	62.8	62.7	67.2
	Rent		35.0	18.2	37.2	30.9		27.7	28.0	31.3	30.8	28.5
	Other		7.9	3.4	5.5	5.1		17.3	7.5	5.8	6.5	4.4
Vehicles Available*	0	0.10	9.5	3.5	8.7	7.1	1.00	8.9	8.9	8.8	8.9	8.9
	1		31.8	28.7	42.9	37.1		23.1	23.2	23.1	23.1	23.1
	2		41.5	43.4	34.9	38.4		37.8	37.8	37.8	37.8	37.8
	3 or more		17.2	24.4	13.5	17.4		30.2	30.2	30.2	30.2	30.2

Note: * Variables controlled during weighting; CS=Convenience Sample; ES= Email Sample; OP= Online Panel; ACS = American Community Survey

A few noteworthy findings may be discerned from the table in the context of weighted distributions. First, for the variables not controlled in the weighting process, the distributions still differ from one another, but the differences diminish – even to the extent of becoming statistically insignificant in several instances. This happens for employment and housing tenure, both of which were significantly different for the unweighted subsamples, but not so for the weighted samples. All of the controlled variables show no statistically significant difference across the survey subsamples, with the exception of education. This particular variable is still statistically different across the survey subsamples simply because the convenience sample included a very tiny number of individuals at the low end of the educational spectrum. Despite the application of a robust weighting methodology, the sample sizes in those categories for the convenience sample were simply too small for the weighting process to produce weights that could replicate the census distributions. As such, while the weighting process did improve the percent of individuals in the weighted convenience sample falling into these lower education categories, it was not able to fully correct the large bias in the unweighted sample. This suggests that the bias associated with a convenience subsample that is largely drawn from professional and social networks may not be fully overcome even through a robust weighting scheme. Nevertheless, the results in this table suggest that weighting is a reasonably effective way of correcting for socio-economic and demographic biases associated with different survey recruitment and sampling strategies.

4. COMPARISON OF MOBILITY AND ACTIVITY PARTICIPATION VARIABLES

While it is possible to correct for survey biases by weighting subsamples with respect to census distributions on socio-economic and demographic variables, the same cannot be said of mobility and activity participation variables (*16*). It is generally not feasible to include measures of mobility and activity participation in survey weighting processes because there are no census distributions for such variables. Table 2 presents a comparison of distributions for several mobility and activity participation variables across the three subsamples. To ensure that COVID effects do not impact the comparisons presented in this analysis, all mobility and activity participation variables are depicting pre-COVID patterns of behaviors.

A comparison of unweighted statistical distributions shows that the subsamples differ substantially for travel and activity participation variables. The online panel (which depicts lower levels of educational attainment, employment, and income) shows a lower level of driver's license holding. They also have significantly less access to a bike, are more likely to choose the private automobile for commuting, and least likely to choose transit for commuting. The convenience sample, which is largely comprised of individuals derived from professional and social networks of transportation professionals, exhibits a higher level of transit use, the lowest level of private vehicle use, and the highest level of "other mode" (walking, bicycling, ridehailing, and micromobility modes) use for commuting.

Although not statistically significantly different at the 0.05 level (but significantly different at the 0.11 level), there are key differences in work-from-home frequency across the subsamples *who have the option to telecommute*. The convenience sample shows the highest level of hybrid work modality (frequent or occasional), consistent with the nature of the social and professional networks from which the convenient sample respondents were recruited. As these individuals are largely transportation professionals and individuals within their networks, it is likely that they are largely office workers who have some flexibility with respect to work location even in the pre-COVID era (*17*). The email sample and the online panel tend to be more similar to one another in terms of distributions of pre-COVID work-from-home frequency.

TABLE 2 Pre-COVID Mobility and Activity Participation Characteristics

		Unweighted					Weighted				
Variable	**Attribute**	**χ2** p-value	**CS** n = 1,127 (%)	**ES** n = 2,946 (%)	**OP** n = 5,262 (%)	**All** n = 9,335 (%)	**χ2** p-value	**CS** n = 1,127 (%)	**ES** n = 2,946 (%)	**OP** n = 5,262 (%)	**All** n = 9,335 (%)
Drivers' License	Yes	0.00	98.0	96.6	87.5	91.6	0.55	92.1	90.8	87.6	88.6
	No		2.0	3.4	12.5	8.4		7.9	9.2	12.4	11.4
Regular Bike Access	Yes	0.00	67.3	53.7	42.2	48.9	0.11	60.9	50.4	46.6	49.4
	No		32.7	46.3	57.8	51.1		39.1	49.6	53.4	50.6
Private Vehicle Use Frequency	Every day	0.06	43.9	64.6	55.0	56.7	0.51	45.7	59.3	55.8	55.4
	Frequent		43.9	29.2	32.4	32.8		39.4	29.2	31.4	31.4
	Occasional		6.0	2.6	3.1	3.3		6.5	4.8	3.2	3.6
	Never		6.2	3.7	9.5	7.3		8.4	6.7	9.6	9.5
Transit Use Frequency	Every day	0.00	15.6	4.9	4.0	5.7	0.01	16.5	5.9	4.1	5.6
	Frequent		26.4	9.6	15.3	14.9		22.1	12.3	15.3	14.3
	Occasional		26.6	18.7	15.8	18.0		17.4	15.7	17.0	16.7
	Never		31.4	66.8	64.9	61.4		44.0	66.2	63.6	63.4
Online Grocery Shopping Frequency	Every day	0.23	0.1	0.0	0.7	0.4	0.53	0.0	0.0	0.7	0.4
	Frequent		6.5	7.0	15.6	11.8		12.6	10.4	15.6	12.6
	Occasional		10.3	7.6	10.5	9.5		4.7	9.7	9.9	9.3
	Never		83.1	85.4	73.3	78.3		82.7	79.8	73.8	77.7
Commute Mode Choice (*)	Private vehicle	0.00	54.1	74.2	77.6	72.4	0.52	65.6	74.0	78.4	74.2
	Transit		22.3	10.3	8.7	11.6		13.4	11.8	8.8	10.8
	Work-from-home		7.5	10.3	8.8	9.1		11.5	7.1	8.5	8.7
	Other mode		16.0	5.2	4.8	6.9		9.6	7.1	4.4	6.3
Airplane Travel for Business (*)	Very frequent	0.01	0.7	1.1	1.3	1.1	0.94	0.5	0.9	1.5	1.2
	Frequent		38.3	29.2	20.9	26.5		23.8	25.6	23.6	24.4
	Occasional		24.9	16.2	12.8	16.0		18.3	15.1	12.8	14.5
	Never		36.1	53.5	64.9	56.4		57.4	58.4	62.1	59.8
Work-From-Home Frequency (**)	Every day	0.11	10.5	21.4	21.8	18.8	0.83	21.7	17.2	21.1	20.1
	Frequent		58.0	48.0	49.0	51.0		42.7	50.4	48.0	47.2
	Occasional		26.2	21.5	16.9	20.8		26.4	21.7	19.0	21.4
	Never		5.3	9.0	12.2	9.4		9.2	10.8	12.0	11.2

Note: CS: Convenience Sample; ES: Email Sample; OP: Online Panel. Frequent = a few times per month *or* a few times per week; Occasional = a few times per year. (*): n = 942, 1743, 2679 and 5364 for CS, ES, OP & All respectively. (**): n = 676, 840, 1081 and 2597 for CS, ES, OP & All respectively.

Overall, it can be seen that unweighted subsamples recruited through different strategies show significant differences with respect to mobility and activity participation variables. Virtually all of the measures included in Table 2 are statistically different across the three subsamples (at the ~0.1 level), except for online grocery shopping frequency. However, what is noteworthy and encouraging is that the weighted subsamples resemble one another more closely with a number of statistically significant differences becoming insignificant after weighting. That is, regardless of the sampling recruitment strategy that is adopted, the weighted samples provide statistically identical measures of mobility and activity participation characteristics. The only variable that remained statistically different across the three subsamples is that of transit use frequency. This may be because transit use is heavily influenced by service quality and coverage, attitudes and perceptions related to transit and the environment, and the geographic and cultural context in which the travelers are located (*18, 19*).

5. MODELS OF ACTIVITY-MOBILITY CHARACTERISTICS

To further investigate the influence of sampling strategy on metrics of activity-mobility characteristics derived from sample surveys, this section presents a series of statistical and econometric models in which the influence of the sampling strategy is assessed while controlling for socio-economic and demographic variables that significantly explain activity-travel choices. The paper presents four distinct models: (1) Ordered probit model of vehicle ownership; (2) Ordered probit model of transit use; (3) Ordered probit model of online grocery shopping; (4) Multinomial logit model of commute mode choice. The entire Wave 1 dataset was used to estimate the three ordered probit models while a workers-only dataset was used to estimate the multinomial logit model. All variables represent pre-COVID activity-travel choices to control for any effects that the pandemic may have had in shaping these measures of behavior.

Model estimation results are presented in Table 3. In general, the models offer reasonable interpretations with respect to the influence of socio-economic and demographic variables on the endogenous variables of interest. For the sake of brevity, an exhaustive description of the influence of socio-economic and demographic variables is not provided here. A few key highlights are offered for illustrative purposes. Vehicle ownership is higher for those in the oldest age group (>55 years), as evidenced by the negative coefficients for other age groups. The youngest group depicts a positive coefficient for vehicle ownership, primarily because they continue to reside at home with individuals in the oldest age group (which serves as the base alternative), thus increasing overall household vehicle ownership. The likelihood of frequent transit use decreases with age, while the frequency of online grocery shopping appears to be highest for those in the middle age groups of 25-34 and 35-44 years. Older workers tend to favor the car for their commute and are found to work from home more so than their younger counterparts. As household vehicle ownership increases, the frequency of transit use decreases as does the frequency of online grocery shopping; these findings are entirely consistent with expectations as higher levels of vehicle availability will naturally be associated with greater levels of automobile use and in-person engagement in activities (*20*). Those in single family houses exhibit lower levels of transit use, presumably because they are in lower density areas less served by transit (*21*).

TABLE 3 Model Estimation Results for Select Activity-Mobility Characteristics

Variable	Attribute	Model 1		Model 2		Model 3		Model 4					
		Ordered Probit		Ordered Probit		Ordered Probit		Multinomial Logit					
		Vehicle Ownership		Transit Usage Frequency		Online Grocery Shopping Freq		Commute Mode Choice (base = Other)					
								Car		Transit		WFH	
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant		--	--	--	--	--	--	0.85	5.33	-2.08	-11.08	-0.34	-1.32
Gender	Female	0.10	3.90	-0.25	-9.23	-0.21	-6.45	0.32	3.84	0.21	1.88	0.22	1.83
Age	18 to 24 years	0.20	3.85	0.57	10.13	0.39	6.35	-2.34	-18.35	-1.57	-7.13	-2.87	-10.93
	25 to 34 years	-0.23	-6.00	0.38	9.09	0.49	10.26	-0.83	-8.49	-0.39	-3.12	-1.71	-9.71
	35 to 44 years	-0.36	-9.48	0.29	7.08	0.50	10.61	--	--	--	--	-0.28	-2.37
	45 to 55 years	-0.12	-3.26	0.21	4.99	0.22	4.54	--	--	--	--	--	--
Education	Some college	0.11	3.95	0.15	3.36	--	--	--	--	--	--	--	--
	Bachelor's or higher	--	--	0.43	9.45	--	--	--	--	0.37	3.19	--	--
Employment	Employed	0.27	8.86	0.12	3.52	0.09	2.23	--	--	--	--	--	--
	Full-time	--	--	--	--	--	--	1.06	13.48	1.24	8.75	--	--
Student Status	Student	0.15	2.22	0.25	3.57	--	--	--	--	--	--	--	--
Race	White	0.12	4.06	-0.09	-2.81	-0.13	-3.50	--	--	--	--	0.27	2.07
	Black	--	--	--	--	--	--	--	--	0.56	3.86	--	--
Ethnicity	Hispanic	0.12	2.96	--	--	--	--	--	--	--	--	--	--
Household Size	One	--	--	--	--	--	--	0.34	3.21	--	--	0.36	2.50
	Two	0.84	23.64	--	--	--	--	0.21	3.09	--	--	--	--
	Three	1.21	28.24	--	--	0.18	4.34	--	--	--	--	--	--
	Four or more	1.42	33.57	0.07	2.17	0.32	8.13	--	--	--	--	--	--
Household Vehicle Ownership	Zero	--	--	--	--	--	--	-3.32	-12.67	0.48	3.08	-0.48	-2.21
	One	--	--	-0.89	-17.40	-0.30	-5.38	--	--	--	--	--	--
	Two	--	--	-1.14	-20.33	-0.57	-9.31	--	--	--	--	--	--
	Three or more	--	--	-1.19	-18.80	-0.87	-12.09	--	--	--	--	--	--
Household Income	$50,000 or less	--	--	--	--	--	--	--	--	--	--	-0.22	-1.78
	$50,000 to $149,999	0.55	18.69	0.11	3.12	0.10	2.78			--	--	--	--
	$150,000 or more	0.79	18.58	0.35	7.33	0.31	5.80	-0.31	-3.99	--	--	--	--
Housing Type	Single family house	0.43	13.23	-0.12	-3.39	--	--	--	--	--	--	--	--
	Apartment	--	--	--	--	--	--	-0.32	-3.67	0.38	3.35		
Work modality	Work-from-home	-0.26	-8.42	0.28	8.49	0.34	9.02	--	--	--	--	--	--
Home Internet	Yes	0.17	3.34	-0.17	-2.94	0.27	3.92	--	--	--	--	--	--
Housing Tenure	Own	0.28	8.98	-0.11	-3.21	0.12	3.22	--	--	--	--	--	--
Transit Service Level	High	-0.24	-7.75	0.48	14.61	--	--	--	--	1.31	13.61	--	--

TABLE 3 (Continued) Model Estimation Results for Select Activity-Mobility Characteristics

		Model 1		Model 2		Model 3		Model 4					
		Ordered Probit		Ordered Probit		Ordered Probit		Multinomial Logit					
		Vehicle Ownership		Transit Usage Freq		Online Grocery Shopping Freq		Commute Mode Choice (base = Other)					
								Car		Transit		WFH	
Variable	**Attribute**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
Population Density	High (>2900/km^2)	-0.40	-13.10	0.56	17.74	0.30	8.59	-0.75	-9.78	--	--	-0.62	-4.87
Sampling Strategy	Email	--	--	-0.38	-8.72	--	--	0.50	3.75	--	--	0.42	1.91
	Online panel	-0.30	-10.93	-0.43	-10.23	0.36	9.88	0.85	6.62	--	--	0.62	2.86
Interaction Effects	Male & CS	--	--	--	--	-0.38	-3.95	--	--	--	--	--	--
	Graduate & CS	-0.17	-3.86	--	--	-0.22	-3.17	-0.54	-3.61	--	--	-0.54	-2.06

Goodness of fit statistics

Model 1; sample size = 9,335; final log likelihood = -9236.15; initial log likelihood = -11465.2; r-square = 0.19
Model 2; sample size = 9,335; final log likelihood = -8180.06; initial log likelihood = -9790.41; r-square = 0.16
Model 3; sample size = 9,335; final log likelihood = -5774.76; initial log likelihood = -6443.47; r-square = 0.10
Model 4; sample size = 6170 (workers only); final log likelihood = -5131.49; initial log likelihood = -8553.44; r-square = 0.40; AIC = 10336.97; BIC= 10585.89

Note: Coef = coefficient; t-stat = t-statistic; Freq. = Frequency; WFH = work from home; "--" = not applicable. Base category corresponds to all complementary/omitted categories in each set of attributes.

Higher transit level of service (referring to residing in cities with extensive transit coverage and service, including New York City, Boston, Chicago, Seattle, and San Francisco) is associated with greater frequency of transit use and lower levels of vehicle ownership, along with a higher probability of using transit for commuting. Residing in areas with higher population density is associated with greater levels of transit use, lower levels of vehicle ownership, and a lower probability of using the car for commuting. Once again, these findings are entirely consistent with expectations (*22*).

The key variables of interest in this context are those shown at the end of Table 3. These variables represent the sampling strategy employed, with convenience sampling serving as the base alternative and email recruitment and online panel explicitly included in the model specifications. It is found that those recruited via email sampling exhibit lower levels of transit usage frequency than those in the convenience sample even after controlling for a host of socio-economic and demographic variables. Arguably, this finding is not surprising given that the email sample is older, lives in single family detached houses, and owns their homes at higher rates than the convenience sample and the online panel. They also exhibit the highest levels of vehicle ownership as seen earlier in Table 1. It appears that the email sample is more inclined towards a car-oriented lower-density lifestyle, and it is this unobserved lifestyle preference/inclination that is reflected and captured via the effect of the email sampling variable, suggesting that an email sampling strategy is likely to yield a respondent sample that is more automobile-oriented.

The online panel variable is found to be statistically significant in several models of endogenous variables. Model estimation results show that online panel respondents exhibit lower levels of vehicle ownership and transit use frequency and higher rates of online grocery shopping frequency, presumably due to their comfort with navigating online services and applications (*23*). Online panel members were found to exhibit lower levels of income, education, and employment. As online survey takers are likely to be tech-savvy and very adept at using online platforms and services, it is not surprising that their online grocery shopping frequency tends to be higher than groups recruited via other means (*24*). Thus, the online panel variable is capturing the effect of "being tech-savvy", which is an unobserved trait not captured by any of the other observed variables in the model specification. For mode choice, the online panel depicts a higher rate of work from home, once again reflecting a penchant for a more home-based online activity participation modality. The model specification also includes a couple of interaction effects to reflect that males in the convenience sample are less likely to shop online frequently for groceries and those who are college graduates in the convenience sample are less likely to use car as their commute mode or work from home (compared to transit and other modes). The latter group is also less likely to reside in households with higher vehicle ownership and to shop online frequently for groceries.

As mentioned earlier, the COVID Future Survey was a panel survey that collected information from the same respondents at multiple points in time. The panel survey data set allows the examination of transitions in behavior for the same set of individuals through the period covered by the panel. To further compare the three subsamples, changes in the distributions of commute mode choice are examined specifically for the worker subsamples of each recruitment method (who responded to all three waves of the survey). This transition is shown in Table 4. While it is feasible to examine transition matrices (either in tabular form or via Sankey diagram), such transition matrices and diagrams are not included for the sake of brevity. Table 4 depicts the univariate distribution of commute mode choice for each of the three subsamples in each of the three periods. The commute mode choice variable is selected for this examination because of the widespread interest in this variable in transportation modeling and planning processes and because of the effect that COVID-19 had on commuting.

It is found that the convenience sample is especially different from the other two samples. The email sample and the online panel depict similar patterns of change; for example, both samples exhibit a drop in private vehicle mode share of about 25-30 percentage points. The corresponding drop for the convenience sample is nearly 40 percentage points. Similarly, the shift to work from home for the convenience sample is dramatically larger than that for the other samples. While the percent of those working from home increases by 30-40 percent for the email sample and the online panel, the corresponding increase for the convenience sample (of mostly transportation professionals) is nearly 85 percentage points – reflecting the professional office nature of their occupation. In all cases, the subsamples stated that they expect to rebound to some degree – but not entirely back to pre-COVID percentages – in the post-COVID period (note that these percentages reflect what respondents stated that they expected to do in a post-COVID era, since actual post-COVID era behaviors could not be measured or observed within the duration covered by the panel survey).

TABLE 4 Change in Commute Mode for Stayer Sample of COVID Future Panel Survey

Mode	Pre-COVID	During COVID	Post-COVID
	Convenience Sample (n = 166)		
Private Vehicle	45.8	6.6	37.4
Transit	31.3	0.0	22.8
Work-from-home	5.4	90.4	21.7
Other	17.5	3	18.1
	Email Sample (n = 212)		
Private Vehicle	69.4	40.1	64.6
Transit	9.9	1.4	7.1
Work-From-Home	16.0	56.1	22.6
Other	4.7	2.4	5.7
	Online Panel (n = 400)		
Private Vehicle	76.0	52.6	73.4
Transit	9.7	2.8	6.3
Work-from-home	11.0	41.3	16.3
Other	3.3	3.3	4.0
	All (n = 778)		
Private Vehicle	67.7	39.5	63.3
Transit	14.4	1.8	10.0
Work-from-home	11.2	55.7	19.2
Other	6.7	3.0	7.5

6. STUDY IMPLICATIONS AND CONCLUSIONS

In an era of low survey response rates and high survey administration costs, transportation surveys are increasingly adopting a variety of sample recruitment strategies to boost respondent sample sizes. Among the variety of methods being deployed, three methods are of particular interest in the current context as they are being increasingly adopted for transportation surveys. This includes the use of convenience samples, the use of commercially available email lists (for administering surveys via email), and the use of online survey panels aggregated by survey research companies. All three methods are considered efficient, cost effective, and potentially beneficial from the standpoint of realizing desired/large respondent sample sizes.

This paper aims to assess and compare these three methods with respect to differences and biases in sample characteristics that result from the adoption of each of the methods. In general, it is very difficult to perform such a comparison because any single survey will generally adopt just one single administrative modality to conduct the survey. It is therefore difficult to perform a controlled comparison of these three survey methods while controlling for other survey features (such as content and length of survey). A unique opportunity to perform such a comparison presented itself in the context of the COVID Future Panel Survey, a multi-wave nationwide longitudinal survey conducted in 2020 and 2021. Respondents were recruited via all three methods noted previously, i.e., convenience sampling, email messaging to a large database of email addresses purchased from a commercial vendor, and use of an online survey panel assembled by a commercial survey research company. The survey sample has a total of 9,335 respondents, with 1,127 in the convenience sample, 2,946 in the email sample, and 5,262 in the online panel. The same survey was administered to all three survey subsamples.

The assessment is conducted through three primary types of analyses. First, the comparison of socio-economic and demographic characteristics shows that the convenience sample tends to be of working age and depict higher levels of employment, income, and education. This is primarily because the convenience sample is largely a professional and social network of transportation professionals who are well educated and employed in the transportation profession. The online panel, on the other hand, is lower income, less educated, and exhibits lower levels of employment. The only variables for which the three subsamples were not statistically different from one another included race, ethnicity, household size, and gender (although the online panel clearly had a numerically larger percent of female respondents).

Second, the analysis involved comparing pre-COVID activity-mobility characteristics across the three subsamples (to eliminate any COVID effects). It is found that the subsamples differ significantly from one another on a host of mobility and activity-travel participation variables considered in this study. Online panel members show lower levels of driver's license holding, higher levels of regular access to a bicycle, and higher levels of online grocery shopping. On the other hand, the convenience sample of largely transportation professionals depicts the highest level of transit use frequency, driver's license holding, regular access to a bicycle, commuting by transit and other modes, and airplane travel for business. These findings are entirely consistent with expectations, given the nature and source of the convenience sample. The bottom line is that the three subsamples differed substantially with respect to measures of mobility and activity-travel modality, suggesting that the method of sample recruitment does influence measurement of travel behavior. However, what is particularly encouraging is that weighting the subsamples on socio-economic and demographic variables does compensate and overcome these differences quite substantially. When *weighted* distributions of mobility characteristics are compared across survey subsamples, it is found that statistical differences fade away for all mobility measures except for transit use frequency; this is because the convenience sample is so unique in comparison to the email sample and the online panel that transit use patterns in the weighted convenience sample continue to show a different pattern. Given that the convenience sample is largely comprised of transportation professionals, this finding is not surprising.

Finally, econometric models of vehicle ownership, transit use frequency, online grocery shopping frequency, and commute mode choice show that, even after controlling for a host of socio-economic and demographic variables in the model specification, the survey sample recruitment strategy has a significant effect on measures of mobility that serve commonly as endogenous variables of interest in the field of travel behavior research. Model estimation results show that the email sample is less likely to use transit frequently when compared with the convenience sample and online panel respondents. The online panel is more likely to engage in online grocery shopping frequently and work from home, and less likely to own a larger number of vehicles or use transit frequently. In general, these individuals appear to be more home-bound (less mobile) and more tech-savvy, thus enabling greater activity engagement (work and shopping) through online modalities.

This paper has helped uncover the unique characteristics of survey respondent samples recruited through different means. The findings suggest that extreme care should be exercised in the recruitment and use of convenience samples as they may exhibit substantial biases with respect to socio-economic, demographic, and mobility characteristics. While weighting the survey sample to match census distributions compensates to some degree, a few significant differences may remain for variables where the convenience sample exhibits very uniquely different patterns. When it comes to email sample recruitment, the respondent sample appears to be older, higher income individuals, with a lifestyle that is more automobile-oriented, residing in single family detached houses in lower density areas. This is not necessarily a serious concern as weighting the sample appears to be able to correct for these biases and provide a more representative distribution of sample characteristics. The online panel is biased in the other direction, comprised of individuals who are younger and exhibit lower levels of income, educational attainment, vehicle ownership, and employment status. Once again, however, weighting the sample to match census socio-economic and demographic distributions is found to compensate for these biases for the most part, enabling the drawing of population-wide inferences regarding activity-travel characteristics. In other words, the use of online panels for travel surveys appears to be a cost-effective robust approach for survey sample recruitment, especially given the dismally low response rates associated with mail and email-based solicitations.

The study shows that the survey respondent sampling strategy variable is significant in explaining a host of mobility characteristics and choices even after controlling for socio-economic and demographic variables. This means that the survey method variable is capturing the effects of unobserved traits including attitudes and lifestyle preferences that are not adequately captured by socio-economic and demographic variables. Weighting survey samples compensates for biases in socio-economic and demographic variables, but does not necessarily compensate for biases in unobserved traits such as attitudes and lifestyle preferences (because there are no census distributions for such variables). It would therefore be of considerable value to include attitudinal and lifestyle preference questions in transportation surveys on a consistent and routine basis so that these traits can be explicitly included in travel model specifications, helping to enhance explanatory power, reduce omitted variable bias, and account for biases in unobserved traits that may arise from the choice of sample recruitment strategy.

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