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Environmental Impacts of Transportation Network Company (TNC)/Ride-Hailing Services: Evaluating Net Vehicle Miles Traveled and Greenhouse Gas Emission Impacts within San Francisco, Los Angeles, and Washington, D.C. Using Survey and Activity Data

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Abstract: Transportation Network Companies (TNCs) play a prominent role in mobility within cities across the globe. However, their activity has impacts on vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions. This study quantifies the change in personal vehicle ownership and total miles driven by TNC drivers in three metropolitan areas: San Francisco, CA; Los Angeles, CA; and Washington, D.C. The data sources for this analysis comprise two surveys, one for TNC passengers (N = 8630) and one for TNC drivers (N = 5034), in addition to data provided by the TNC operators Uber and Lyft. The passenger survey was deployed within the three metropolitan areas in July and August 2016, while the driver survey was deployed from October to November 2016. The TNC operator data corresponded with these time frames and informed the distance driven by vehicles, passenger frequency of use, and fleet level fuel economies. The data from these sources were analyzed to estimate the impact of TNCs on travel behavior, personal vehicle ownership and associated VMT changes, as well as the VMT of TNCs, including app-off driving. These impacts were scaled to the population level and collectively evaluated to determine the net impacts of TNCs on VMT and GHG emissions using fuel economy factors. The results showed that the presence of TNCs led to a net increase of 234 and 242 miles per passenger per year, respectively, in Los Angeles and San Francisco, while yielding a net decrease of 83 miles per passenger per year in Washington, D.C. A sensitivity analysis evaluating net VMT change resulting from vehicle activity and key behavioral impacts revealed the conditions under which TNCs can contribute to transportation sustainability goals.

Keywords: shared micromobility; connection; activity data; spatial analysis; temporal analysis; sensitivity analysis

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1. Introduction

Transportation Network Companies (TNCs) have played a prominent role within the portfolio of travel options available to consumers in many urban environments since emerging about a decade ago. With this prominent role have come important questions about the impact that TNCs have had on vehicle miles traveled (VMT) and its associated environmental impacts. The services of TNCs produce considerable VMT during all stages of operation at the regional scale. At the same time, the mobility benefits of TNCs are similar to those provided by the personal automobile. This leads to an important set of substitution effects, where TNC trips replace other trips that would have been made by personal car; and in some cases, can replace the need to have a personal car at all. These substitution effects can lead to a reduction in VMT, both in the form of VMT that no longer occurs and in the form of VMT that would have happened in the absence of TNCs but is instead prevented from occurring. Disentangling these effects into net impacts is a challenging exercise that requires data from multiple sources. These include behavioral data from survey responses that describe how users interact with and respond to the availability of TNC services. They further include activity data of the TNC system itself to produce measures of the VMT and emissions that result from the delivery of TNC services.

This paper reports on a study of TNC impacts on net VMT and associated greenhouse gas emissions (GHG) that were found within three major metropolitan markets in the United States. The study created and assembled several different datasets to support its conclusions. This included a survey of TNC passengers (N = 8630), a survey of TNC drivers (N = 5034), and operator-provided data that described the VMT of TNC vehicles. The operator data included driving from the three phases of TNC driving (Period 1, Period 2, and Period 3), while the driver survey informed the app-off phase of driving. The study covered three major urban markets: Los Angeles, San Francisco, and Washington, D.C. The data were collected mostly during the year 2016, when TNCs had expanded from their early stages and served as major market players within several regions.

Taken together, the data yield insights on the impacts that TNCs have had both on the behavioral change of passengers and how that behavioral change compares to the driving activity that enables it. The net impacts of TNCs on VMT and GHG are derived as a result of these findings and are market-specific. In the sections that follow, we explore a literature review of other research that evaluates related topics. We then present the data and methodology, followed by the results summarizing key findings. We conclude with a discussion of key insights and their broader implications for measuring TNC impacts and policy.

2. Literature Review

As TNCs have rapidly grown in popularity across many U.S. cities, it is important to consider how this mode choice impacts the environment. Oftentimes, the environmental impacts of TNCs are determined by two metrics: VMT and GHGs. This allows for the impacts of TNCs to be compared to other travel modes. These data are typically collected through surveys, activity data, TNC-provided data, and various other sources that indicate how far TNC vehicles are driving with and without a passenger, as well as the estimated vehicle emissions. This section discusses previous research that has been conducted to better understand how TNCs contribute to VMT and GHG emissions.

Among the many concerns about the environmental impact of TNCs is the VMT contribution in the form of deadhead miles. These miles are accrued before and after a ride is given, and while the driver is waiting to accept the next ride and in transit to pick up the next passenger. A study conducted by the San Francisco County Transportation Authority (SFCTA) estimates that 20% of TNC miles are deadhead miles [1]. However, this percentage is lower than the SFCTA estimate of 40% deadhead miles for taxis, which is likely attributed to a less efficient passenger generation process. The California Public Utilities Commission (CPUC) found that about 40% of TNC VMT across the whole state can be attributed to deadheading [2]. However, CPUC notes that it is difficult to account for deadhead miles as many drivers will associate with multiple TNC platforms and have more than one app open at a time when looking to be matched with riders. More recent data collected over an 11-month span from TNCs in California suggest that 30% of the CO_2 emissions from Uber are generated during the deadhead stages of driving [3]. Additionally, one study that conducted a systematic review of the literature found that across various studies, deadheading may account for 28% to 59% of TNC VMT [4].

Similarly, a study in Denver, Colorado found that from over 308 rides using either Uber or Lyft, only about 61% of the VMT was completed with a passenger, indicating that about 40% of the VMT was due to deadhead miles [5]. In this study, Henao actively attempted to reduce VMT by finding a parking space after dropping off a passenger and only accepted rides that were within 15 miles. Another study found that in New York and San Francisco, UberX drivers spend more time with a passenger in the vehicle than taxi drivers in the same city, with UberX drivers spending roughly half of their working time with a passenger in their vehicle [6]. This indicates that there is a significant amount of time where deadhead miles can be accrued.

In general, the literature suggests that TNCs have led to a significant increase in total VMT in cities across the U.S. From 2013 to 2016; TNCs contributed 600 million miles in New York City and accounted for 3.5% of the city's VMT [7]. Another New York study found that between 2013 and 2017, the Manhattan central business district experienced a 36% increase in taxi and TNC mileage [8]. Additionally, Schaller [8] determined that TNC trips tend to be a longer distance than trips made via taxi. In San Francisco, data from 2016 indicated that 6.5% to 10% of intra-San Francisco VMT is from TNCs [1] and from 2010–2016, TNCs were responsible for a 47% increase in VMT [9]. These percentages of VMT from TNCs closely match estimates from a study of six major U.S. cities that found TNC VMT to make up about 1.9% to 12.8% of VMT within the county of the major cities [10]. One study in Denver, Colorado, where the authors collected data as a driver for either Uber or Lyft, found that TNCs contribute about 83.5% more VMT compared to not having TNCs as a travel mode choice [11]. Another study found that 5.7 million VMT are added annually across nine major U.S. cities, including Los Angeles, San Francisco, and Washington, D.C. [12]. It has also been found that switching travel modes to ride hailing doubles VMT because most people shift from non-vehicle modes [13].

As TNCs are a relatively new travel mode option, it is also important to consider how TNCs compare to alternative travel modes and how they may influence TNC usage. For example, one study that analyzed data from the National Household Travel Survey found that people who had access to a household vehicle and were frequent rideshare users (used rideshare four or more times in the last 30 days) had a reduced VMT compared to an occasional or non-user of TNCs with vehicle access [14].

Similar to having an impact on mode choice, TNCs have been found to have an impact on vehicle ownership. An online survey of people in Boston and Philadelphia found that of the approximately 45% of respondents who made vehicle ownership choices after adopting TNCs as a mode of travel, a majority of them decided either not to buy or postpone the purchase of a vehicle [15]. This same study also found that among the same group of participants who made vehicle ownership choices, about 15% of respondents in each city sold a vehicle, while approximately 16% of Boston respondents and 30% of Philadelphia respondents reported that they bought a car.

Vehicle ownership impacts have also been assessed by difference-in-difference models that compare vehicle registration numbers before and after the entry of TNC services. One study in the U.S. found that when TNCs enter various urban U.S. cities, there is a 0.7% increase in vehicle registrations per capita [16]. However, the study also found that despite the increase in vehicles, the fleet average fuel economy does not exhibit a significant difference. Using a similar method, vehicle registration impacts from TNCs have also been studied in Great Britain. The study found that when considering Great Britain as a whole, the entrance of TNCs into the market does not have a statistically significant impact on vehicle registration [17]. However, when looking at a smaller scale, statistically significant changes in vehicle registration were detected. For example, considering just London, the entrance of TNCs was found to be associated with a 2.2% decrease in vehicle registration. In this case, it is important to consider the land use, presence of public transit, and the significant cost of vehicle ownership in London that already contribute to low vehicle ownership levels. Additionally, in the rural areas of Great Britain, where there is more likely to be households with multiple cars, the model predicted a 1.1% decrease in vehicle registration after TNCs were introduced. The authors note that this value may be impacted by a later TNC entrance in these areas, compared to the metropolitan areas, like London, thus delaying the impacts on vehicle registration.

TNCs also directly contribute to environmental concerns through GHG emissions. A study conducted by the Union of Concerned Scientists (UCS) [18] found that non-pooled TNC trips contribute about 47% more emissions than a private vehicle trip. After analyzing responses to a survey of TNC riders in California, the authors indicated that 24% and 36% of non-pooled and pooled TNC riders, respectively, would have otherwise taken the same trip using a travel mode that emits less carbon, such as public transit, walking, or biking. Additionally, they report that under the assumption that 15% of TNC rides are pooled, a TNC trip will pollute 69% more, on average, than the alternative travel mode [18]. The UCS report suggests that increasing the rate of pooling as well as increasing the electrification of TNC vehicles will help reduce the GHG emissions from TNC services.

Another study [19] using data from Austin, New York, Chicago, and California found that if all trips were replaced with TNCs, then there would be about a 20% increase in GHG emission externalities and a 50% to 60% reduction in air pollutant emission externalities. The air pollutant decrease is largely due to the reduction in vehicle cold starts associated with private vehicle driving. It is also noted that TNCs eliminate the need for private vehicles to search for parking and often use newer and more efficient vehicles than private vehicles. However, they determined that GHG emissions from deadheading outweigh all the previously mentioned GHG benefits of TNCs [19].

The current literature shows that TNCs have a varied but noticeable impact on VMT in the U.S. TNC markets. In addition, the usage of TNCs leads to an increase in GHGs relative to other transportation alternatives. This study aims to better understand the relationship between TNCs and their contribution to VMT and GHGs in Los Angeles, San Francisco, and Washington, D.C. In the sections that follow, we present the data, methodological approach, and results of this analysis.

3. Methodology

The key data sets applied in this study consisted of a survey of TNC passengers, a survey of TNC drivers, and operator data describing vehicle driving and the TNC fleet. Collectively, the data were used to disentangle measurements from the two operators and inform the average vehicle miles per passenger, app-off mileage, emissions, and TNC fleet fuel economy.

The three U.S. market boundaries were defined by the respective U.S. Census Core-Based Statistical Area (CBSA). Each CBSA covers almost the entirety of the metropolitan regions of interest and is comprised of whole cities and counties. The counties included in each CBSA are provided in Table 1 below. These markets were selected due to their size, TNC market maturity, and because they were pre-pandemic markets where TNCs offered pooled rides.

Table 1. Counties Included in Target Market CBSAs.

Market and CBSA	**Los Angeles** (Los Angeles–Long Beach–Anaheim, CA)	**San Francisco** (San Francisco–Oakland–Hayward, CA)	**Washington, D.C.** (Washington–Arlington–Alexandria, DC–VA–MD–WV)	
Counties Included	Los Angeles	Alameda	District of Columbia	Prince George's
	Orange	Contra Costa	Arlington	Prince William
		Marin	Calvert	Rappahannock
		San Francisco	Charles	Spotsylvania
		San Mateo	Clarke	Stafford
			Culpeper	Warren
			Fairfax	Alexandria City
			Fauquier	Fairfax City
			Frederick	Falls Church City
			Jefferson	Fredericksburg City
			Loudoun	Manassas City
			Montgomery	Manassas Park City

3.1. Passenger Survey

The passenger survey was developed in collaboration with the National Resource Defense Council (NRDC), Lyft, and Uber. The survey was first released in July 2016 and then again in August 2016. Lyft and Uber assisted in the dissemination of the survey to their passengers by launching the survey via email, with random distribution, over the course of two five-business-day periods. This allowed for the survey to capture data over the course of a week to accurately depict the most recent use of TNC services and various use cases by day. It took respondents an average of 14 min to complete the survey. Sixty-two percent of respondents who started the survey completed it. To incentivize the completion of the survey, respondents who completed the survey had the opportunity to win one of 80 Amazon gift cards worth 50 USD. The number of passengers who completed the survey in the two target markets is provided in Table 2.

Table 2. Passenger Survey Sample Size by Target Market.

Market	**Los Angeles**	**San Francisco**	**Washington, D.C.**
Sample Size	2651	3075	2904

Uber and Lyft determined passenger survey eligibility based on an activity-based definition. The definition was: A passenger used Lyft or Uber at least seven times between 1 June 2015 and 31 May 2016, and at least 50 percent of these trips were within the CBSA of the target city.

This definition was used instead of the billing address associated with a user because operators were concerned that it would not line up with the residential address for a sizeable share of users, particularly younger cohorts. Additionally, the definition ensured that only relatively frequent Uber and Lyft users in the targeted CBSA would be surveyed. Survey responses from passengers who lived outside of the CBSA were excluded from this analysis.

The passenger survey focused on the TNC services provided by Lyft and Uber. Respondents were asked about how Uber and Lyft impacted their travel behavior. The survey topics covered ranged from modal shifts and vehicle holdings to annual VMT, trip purposes, and alternative travel modes if Lyft/Uber is not available for their trip. To preserve passenger identity, de-identified IDs (de-IDs) were generated for each respondent using a series of hashing and encryption. The de-IDs allowed for survey response data to be matched to passenger activity data from the TNC operator. This allowed for a more accurate TNC frequency-of-use measure than respondent reporting. The de-IDs were consistent between Uber and Lyft to capture data from respondents who regularly use both TNCs and prevented Uber and Lyft from knowing which of their customers also used their competitor.

3.1.1. Vehicle Activity Data

At the time of the survey and to this day, TNCs remain effectively a duopoly, which means that reporting aggregate mileage within the markets would have revealed competitive information to the other operator. To prevent this, while meeting the needs of the study, Lyft and Uber provided data detailing the total miles driven per passenger, which was determined as follows:

$$Miles\ per\ Passenger = \frac{Total\ Miles\ Driven}{Passenger\ Population} \tag{1}$$

where

Total miles driven = all miles driven by all drivers in the CBSA during the passenger survey year, including open, fetch, and fare phase miles; and Passenger population = population as defined in the passenger survey (noted above).

The miles per passenger were then determined for the three phases of TNC driving. Several different terminologies are used to describe the phases, presented below:

1. Open phase (Period 1): Drivers are open to receiving a passenger but have not accepted one yet. Distances driven in this phase are always counted as deadheading miles.
2. Fetch phase (Period 2): Drivers travel to pick up an assigned passenger, with no other passenger in the vehicle. Distances traveled in this phase are also counted as deadheading miles when the trip is not being shared by passengers.
3. Fare phase (Period 3): Drivers have an assigned passenger in the vehicle and are transporting this person to their destination.

3.1.2. Response Weighting by Frequency of Use

Lyft and Uber provided population-level distributions of frequency of use to adjust for any bias associated with higher-frequency users being over-represented in the sample. Frequent users of a service may be more likely to respond to a survey about it. At the same time, those using the service may more frequently report more profound impacts. The comparative distributions were used to generate weights to adjust for this bias.

3.1.3. Intersection of Lyft and Uber Passengers and Drivers

Lyft and Uber provided data on total miles driven per passenger; however, many TNC passengers use both Lyft and Uber. The mileage per passenger measure included passengers that use both TNC companies. Using the activity data provided by Lyft and Uber, an estimation of the number of passengers that use both Lyft and Uber in each market was determined relative to the whole sample. This proportion of passengers was assumed to represent the population of each target market. The mileage per passenger ratios were then adjusted according to a weighting factor applied to the original miles per passenger measure from each operator.

Many gig drivers will register with both Lyft and Uber. This means that when the driver is waiting for a rider during the open phase (Period 1), their mileage can be counted by both TNC companies, overestimating the mileage per driver. To account for this issue, it was necessary to discount some of the open phase mileage. Based on the percentage of open miles driven in each market, which was provided by the two TNC operators, a ratio of open miles driven on Uber as compared to Lyft was calculated. Then, a sensitivity analysis of mileage overlap was conducted from 0 percent to 30 percent, in 5% increments. This sensitivity analysis and information from other researchers in the area led to an assumption of a 5% overlap of open miles.

3.2. Driver Survey

A driver survey was developed with Lyft and Uber and deployed to drivers in the target markets in late October to early November 2016. It took the drivers an average of 8 min to complete. As an incentive, drivers could enter a drawing to win one of 60 Amazon gift cards worth 50 USD. The number of drivers sampled in each market is provided in Table 3 below.

Table 3. Driver Survey Sample Size by Target Market.

Market	Los Angeles	San Francisco	Washington, D.C.
Sample Size	2568	1300	1166

The survey was designed to gather information on driver travel behaviors, including app-off driving. Drivers were asked to provide their home zip code as well as the area where they typically collect passengers. They were also asked when they log into the Lyft/Uber apps to better estimate mileage that is not captured by the TNC apps.

3.2.1. App-Off Driving

App-off driving includes the miles driven by the driver to or from the passenger market that is not recorded by the TNC app. This can be from a driver traveling to a passenger market before turning the app on or traveling away from it after turning the app off. The estimation of the percentage of app-off miles was determined for each target market based on responses in the driver survey, which were translated into an estimated percentage of app-off driving for each market. The percentages were used to scale the miles per passenger within the respective target market.

3.3. GHG Emissions and Fuel Economies

Lyft and Uber provided data to determine the distribution of fuel economies within the TNC vehicle fleet. The harmonic mean fuel economy in each target market was determined using these data: 28 miles per gallon (mpg) in Los Angeles, 28 mpg in San Francisco, and 25 mpg in Washington, D.C. The fuel economy of personally owned or sold vehicles reported in the passenger survey was determined by the make, model, and year of the vehicle as recorded by the survey respondents. It was assumed that personal vehicles suppressed by TNC usage had a fuel economy of 31 mpg, equivalent to the average fuel economy in the Lyft and Uber vehicle fleets. The fuel economies and VMT data were then converted into GHG impacts by fuel economy factors provided by the U.S. Environmental Protection Agency (EPA).

3.4. Study Limitations

The methodological approach of this study used a variety of behavioral and activity data sets together in an effort to generate a comprehensive analysis of the major components of impact that TNCs can have on net VMT and GHG emissions. The study is still subject to caveats and limitations that are regularly associated with these data types. Survey responses were used to determine behavioral effects, and such responses constitute self-reported behavioral change. Respondents in the passenger survey were asked to assess impacts as a result of the TNCs specifically, and this can have advantages given that the respondent is generally most knowledgeable as to why and whether certain behavioral changes occurred. At the same, the instrument required that respondents also provide the measurement, which will have some degree of estimation and imprecision. The study also focused on three metropolitan regions. While these regions are distinct from each other in several ways, they are also not comprehensive of urban environments within and outside the U.S. The results that follow characterize the impacts identified during a pre-pandemic era of TNC use within these regions. Many dynamics of these regions and this period arguably extend appropriately within the post-pandemic era and across similar regions. Nonetheless, the targeted regions are not comprehensive or completely generalizable to other regions, land use environments, or circumstances. In the sections that follow, we present the results and analysis derived from this collection of data and report the findings as they relate to net VMT and GHG impacts from TNCs.

4. Results and Analysis

The following sections present findings from the passenger survey sections including (1) sociodemographics, (2) impacts of Lyft and Uber on vehicle ownership, and (3) impacts on VMT and GHG emissions.

4.1. Sociodemographics—Passenger Survey

The seven sociodemographic attributes presented include gender, age, race/ethnicity, income, education, household size, and households with children. The passenger survey demographics provided in the following sections are compared to data from the 2016 five-year estimates from the American Community Survey (ACS) for each CBSA. This allows for a greater understanding of how the population of TNC passenger respondents compares to the greater population in the target markets. The TNC passenger survey respondents were 18 years and older, which is the same age range covered by most ACS distributions. The ACS data comprise the 2016 five-year estimates in the San Francisco, Los Angeles, and Washington, D.C. CBSAs. One-year estimates, which are preferred when available, were not obtainable for the smaller jurisdictions of the Washington, D.C. CBSA. For consistency, the five-year estimates were used across the study.

4.1.1. Gender

In all three target markets, there were more female passenger respondents than male respondents (Table 4), while the ACS showed a gender split that was fairly even. This suggests that females disproportionately rode TNCs in the target markets or that women were more likely to take the passenger survey. The largest gender gap existed in Washington, D.C., where 61 percent of the respondents identified as female and only 39% as male.

Table 4. Passenger and ACS Survey Gender and Age Distributions.

Demographic Attribute	Los Angeles		San Francisco		Washington, D.C.	
	Passenger Survey	ACS 2016	Passenger Survey	ACS 2016	Passenger Survey	ACS 2016
Gender	N = 3003	N = 13,310,447	N = 2589	N = 4,679,166	N = 2859	N = 6,011,752
Male	46%	51%	46%	51%	39%	51%
Female	54%	49%	54%	49%	61%	49%
Age Category	N = 2962	N = 10,344,691	N = 2573	N = 3,739,464	N = 2823	N = 4,609,735
18 to 19 years	1%	3%	0%	3%	0%	3%
20 to 29 years	38%	20%	32%	17%	38%	18%
30 to 39 years	31%	18%	37%	19%	40%	20%
40 to 49 years	16%	18%	16%	18%	12%	19%
50 to 59 years	9%	17%	8%	17%	7%	18%
60 to 69 years	4%	12%	4%	13%	3%	12%
70 to 79 years	1%	7%	2%	7%	1%	6%
80 years and over	0%	4%	1%	5%	0%	4%

4.1.2. Age

At least two-thirds of passenger survey respondents were 40 years old or younger, which skewed younger than the general population in all three target markets (Table 4). According to the ACS 2016 data, 17% to 20% of the population in the target markets were 20 to 29 years old, but this age group represented about one-third of the passenger survey respondents. During this period, about one-third of people in the general population were over 50 years old. In contrast, less than 20% of passenger survey respondents in the evaluated markets fell into this category.

4.1.3. Race/Ethnicity

In all three markets, the greatest proportion of passenger respondents were white. They were over-represented within CBSA populations by 17% to 19% (Table 5). The percent of Asian passenger survey respondents closely matched the general population. However, Hispanic/Latino and African American survey respondents were under-represented compared to the general population. Relative to the general population, the largest margin of under-representation for Hispanics/Latinos was in the Los Angeles market (23% lower) and in Washington, D.C. for African Americans (12% lower).

Table 5. Passenger and ACS Survey: Race/Ethnicity, Household Income, and Education Distributions.

Demographic Attribute	Los Angeles		San Francisco		Washington, D.C.	
	Passenger Survey	ACS 2016	Passenger Survey	ACS 2016	Passenger Survey	ACS 2016
Race/Ethnicity	N = 2826	N = 13,189,366	N = 2454	N = 4,577,530	N = 2689	N = 6,011,752
White	49%	30%	59%	41%	64%	47%
Black or African American	5%	6%	3%	7%	13%	25%
American Indian or Alaska Native	0.4%	0.2%	0.4%	0.2%	0.2%	0.2%
Asian	16%	15%	21%	24%	10%	10%
Native Hawaiian or Pacific Islander	1%	0.3%	1%	1%	0%	0.1%
Hispanic or Latino	22%	45%	8%	22%	6%	15%
Two or more races	7%	2%	8%	4%	6%	3%
Other	0%	0.3%	0%	0.4%	0%	0.3%
Household Income	N = 1461	N = 2,929,987	N = 1157	N = 1,061,817	N = 1198	N = 1,422,996
Less than 15,000 USD	11%	8%	4%	5%	4%	4%
15,000 to 34,999 USD	13%	17%	4%	10%	7%	8%
35,000 to 49,999 USD	11%	12%	5%	8%	7%	7%
50,000 to 74,999 USD	12%	16%	8%	13%	10%	13%
75,000 to 99,999 USD	12%	12%	9%	12%	10%	12%
100,000 to 149,999 USD	15%	16%	18%	19%	21%	21%
150,000 to 199,999 USD	9%	8%	15%	12%	17%	14%
200,000 USD or more	16%	10%	37%	20%	25%	20%
Education	N = 2927	N = 10,171,409	N = 2557	N = 3,642,378	N = 2832	N = 4,609,735
Currently in or less than high school	2%	20%	0%	12%	0%	10%
High school degree or equivalency	12%	21%	4%	17%	4%	20%
Some college or associate's degree	23%	30%	10%	28%	9%	25%
Bachelor's degree	43%	20%	52%	27%	46%	24%
Graduate or professional degree	21%	10%	34%	17%	41%	21%

4.1.4. Income

The passenger survey respondents generally reported higher household incomes than the population in their respective CBSA (Table 5). The greatest difference was in the San Francisco market, where 71% of passenger survey households had incomes of 100,000 USD or more, compared with 52 percent in the CBSA. In Los Angeles and Washington, D.C., the difference between households in the survey earning 100,000 USD or more and the general population was less than 10%.

4.1.5. Education

The majority of passenger survey respondents had obtained a higher level of education than the general population (Table 5). In each market, the percentage of people who completed a bachelor's degree or greater was roughly double the percentage in the general population. The finding that the survey (user) population is generally more educated than the general population by considerable margins is consistent with findings from several other studies [20,21].

4.1.6. Summary of Passenger Survey Sociodemographic Results

In all three markets, the sociodemographics of the passenger survey respondents were different from the general population. The passenger survey respondents had a higher tendency of being younger, more often white, and female compared to the distribution of these demographics within each CBSA. Additionally, the respondents had higher household incomes and had completed a higher level of education than the associated general population. Over 65% of respondents in all three markets were under the age of 40 and at least 60% had completed a bachelor's degree or more, in terms of education level. In general, these results are fairly similar to the sociodemographic findings in other shared mobility studies.

4.2. Impacts of Lyft and Uber on Vehicle Ownership

The presence of Lyft and Uber can impact the personal vehicle ownership of riders as TNC services provide another automotive mode of travel. "Vehicle holdings", which include vehicles that are owned or leased, can be reduced by personal vehicle shedding or personal vehicle suppression. Vehicle shedding occurs when a TNC rider decides that they no longer need to own or lease a private vehicle that they have. The rider decides to sell, donate, or dispose of the vehicle. Another effect, vehicle suppression, occurs when a TNC rider decides they no longer need to acquire a personal vehicle. In this case, the respondent decides to avoid vehicle ownership, which unlike vehicle shedding is an easier inaction of not acquiring a vehicle. Both impacts on vehicle holdings reduce the number of vehicles on the road and eliminate the cost associated with owning or leasing a vehicle, due to access to another form of automotive mobility. They also eliminate the driving that those vehicles would have done. At the same time, the presence of Lyft and Uber may induce the acquisition of a new vehicle. For example, if someone wanted to become a driver for Lyft and/or Uber they may need to purchase a new vehicle to meet the vehicle requirements of the TNC companies. In the following sections, we describe in greater detail the impacts of TNCs on vehicle holdings, including frequency of TNC usage, vehicle suppression, vehicle shedding, and vehicle acquisition for each target market.

4.2.1. Total Vehicle Holdings

The respondents were classified as members of households or as individuals based on their response to several questions about their household structure. Namely, if members of the household shared income and made vehicle purchase decisions with other co-habitants, then they were asked subsequent questions as a household. If they shared only living costs (as is generally the case with roommates), then they were asked vehicle questions as individuals. Within these contexts, the passenger survey asked respondents to report their vehicle holdings. Those who owned or leased vehicles were then asked to report the make, model, year, total annual driving, and changes in driving those vehicles, as a result of TNCs. The distribution of these vehicle holdings was then compared to population data from the 2016 ACS five-year estimates.

One important note on this comparison is that the ACS classifies individuals living with roommates slightly different from the scheme used in this survey. These individuals are classified as non-family households, whereas the passenger survey classifies these respondents as individuals because they make their travel and vehicle purchase decisions as individuals. This difference in classification means that a greater proportion of one-person households are represented in the passenger survey as compared to the general population.

Table 6 compiles the passenger survey and ACS household vehicle holding metrics for each of the target markets. In all three markets, the passenger survey respondents reported having fewer vehicles per household than households of the same size within the respective general population. However, both the survey and general population data show that as household size increases, the percentage of households with zero vehicles decreases. By itself, these data do not confirm that the presence of Lyft or Uber reduces vehicle ownership. However, they do indicate that households with fewer or no cars are more likely to use TNC services than the general population.

Table 6. Household Vehicle Holdings According to the Passenger Survey and ACS 2016 for Each Target Market.

Household Size	Distributed Vehicles in Household		Households with Zero Vehicles		Total Households of Given Size		Vehicles per Household		Percentage of Households with Zero Vehicles	
	Passenger Survey	ACS 2016 Estimated	Passenger Survey	ACS 2016 Estimated	Passenger Survey	ACS 2016 Estimated	Passenger Survey	ACS 2016 Estimated	Passenger Survey	ACS 2016 Estimated
Los Angeles										
1	930	1,019,856	420	192,487	1258	1,054,906	0.74	0.97	33%	18%
2	1244	2,122,087	94	78,728	842	1,218,745	1.48	1.74	11%	6%
3	595	1,495,403	50	35,285	367	723,957	1.62	2.07	14%	5%
4 or More	1244	3,077,150	57	51,202	608	1,301,249	2.05	2.36	9%	4%
Total or Average	4013	7,714,496	621	357,702	3075	4,298,857	1.31	1.79	20%	8%
San Francisco										
1	672	395,858	605	125,647	1217	456,210	0.55	0.87	50%	28%
2	991	888,802	202	50,239	861	527,692	1.15	1.68	23%	10%
3	360	568,660	37	16,681	241	280,694	1.49	2.03	15%	6%
4 or More	640	967,773	26	15,061	332	409,444	1.93	2.36	8%	4%
Total or Average	2663	2,821,093	870	207,628	2651	1,674,040	1.00	1.69	33%	12%
Washington, D.C.										
1	716	548,664	772	123,940	1454	580,435	0.49	0.95	53%	21%
2	975	1,173,155	217	46,938	901	655,746	1.08	1.79	24%	7%
3	332	748,289	56	21,271	255	361,170	1.30	2.07	22%	6%
4 or More	507	1,277,044	43	23,191	294	553,315	1.72	2.31	15%	4%
Total or Average	2530	3,747,152	1088	215,340	2904	2,150,666	0.87	1.74	37%	10%

Comparing the data from the three CBSAs, it is evident that the San Francisco and Washington, D.C. passenger survey data were very similar across all vehicle holding metrics. It is interesting to note, however, that the Washington, D.C. population-level data more closely matched that of Los Angeles in the categories of vehicles per household and the percentage of households with zero vehicles. This may be due to a large portion of the Los Angeles and Washington, D.C. CBSAs including areas outside the downtown areas where there is greater car dependence. Out of the three cities, Los Angeles had the highest vehicle ownership per household from both the passenger survey and the ACS.

4.2.2. Frequency of TNC Use

Frequent users of Lyft or Uber may be more likely to take an operator-provided passenger survey and may be more likely to experience greater impacts due to their TNC usage. This can introduce an overestimation bias into the results, where enthusiastic, high-impact respondents would over-represent the true impact within the population. To account for this potential bias, the frequency of Lyft and Uber use for each respondent was determined and used to develop weights. However, because passengers used both systems and the passengers were separately surveyed by each operator, a few complications had to be navigated. First, it was important to combine respondent usage of both TNCs. The research team used the de-IDs accompanying the operator-provided data to match a persons' TNC activity data with their survey data with a 97% match rate. The de-IDs were developed such that an encryption and hash function prevented each operator from identifying passengers from the other operator. If a survey respondent did not match any activity data provided by the TNC operators, then their response to the passenger survey question of this nature was used instead.

The combined frequency of TNC use values for each survey respondent were binned into ranges to better understand their distribution. As discussed in the methodology, for respondents to be included in the study, they had to use Lyft or Uber at least seven times a year, with at least half of those trips occurring in the target market. The data were further refined for the vehicle impact analysis, such that only passengers that used Lyft and Uber combined at least 20 times per year had their reported impacts considered. This threshold is established as a conservative benchmark of active use, where the impacts of respondents using TNCs less than this frequency of use are not considered large enough to substantively impact their vehicle holdings. The TNC impacts on vehicle holdings were assumed to be zero for those using TNCs less frequently than this threshold. However, such users are still engaged in mode substitution through TNC use, and the impact on the TNC mileage for these less frequent users was still considered. Thus, it was still necessary to calculate weights for all the frequency-of-use ranges.

Using the operator-provided data on the frequency of TNC use in each target market, weights were calculated as the general population percentage divided by the sample percentage for each frequency range. A weight greater than 1 applied to bins where the sample population was under-represented, while a weight less than 1 applied to sample population frequency bins that were over-represented relative to the general population. Weights were initially calculated for each frequency range for Lyft and Uber users separately as the TNC frequency distributions were provided by each operator separately. The weight for each operator was then averaged to produce the final weight for each frequency range. The weights for each operator within frequency ranges were similar and all but one of the factors were less than 2, indicating that the sample representation of the population was not highly misaligned or distorted. Figure 1 shows the distribution of final weighting factors for each frequency category in all three markets. These weights are used in the following analyses of vehicle holdings.

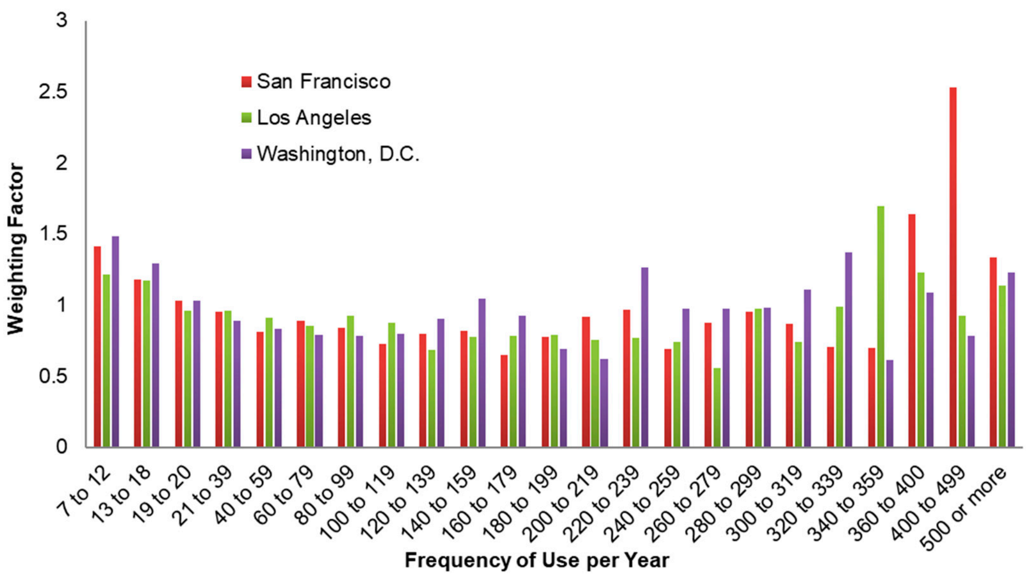

Figure 1. Distribution of weights by frequency of use.

To execute a more conservative analysis of TNC impacts on vehicle holdings, no more than one vehicle shed, suppressed, or acquired was counted per person. For example, if a respondent indicated that they shed a vehicle because of their TNC usage and would acquire a new vehicle if TNCs went away, then only one vehicle was considered for the vehicle shedding analysis. This avoided a double counting of respondents reporting that they would re-acquire a vehicle that they had discharged. This had largely inconsequential effects on the overall vehicle holdings analysis as many respondents reported no more than one change in their vehicle holdings.

4.2.3. Vehicle Shedding

The passenger survey asked a series of questions to determine if TNC usage induced vehicle shedding. The majority of survey respondents did not shed a vehicle as a result of using TNCs, but there is a subset of respondents who reported that they made the decision to shed a vehicle.

The question structure that a passenger survey respondent received to evaluate vehicle shedding was determined by their classification as an individual or belonging to a household (Figure 2). If the respondent reported that they got rid of vehicle "partially" or "definitely" due to Lyft and Uber, then they were asked a series of questions to gather information on the make, model, year, and annual miles associated with the shed vehicle. In order to confirm that the vehicle was shed as a result of Lyft and Uber, the survey asked if they still would have gotten rid of the vehicle if Lyft and Uber did not exist. Only those who responded "no" to the final question were counted in the vehicle shedding analysis.

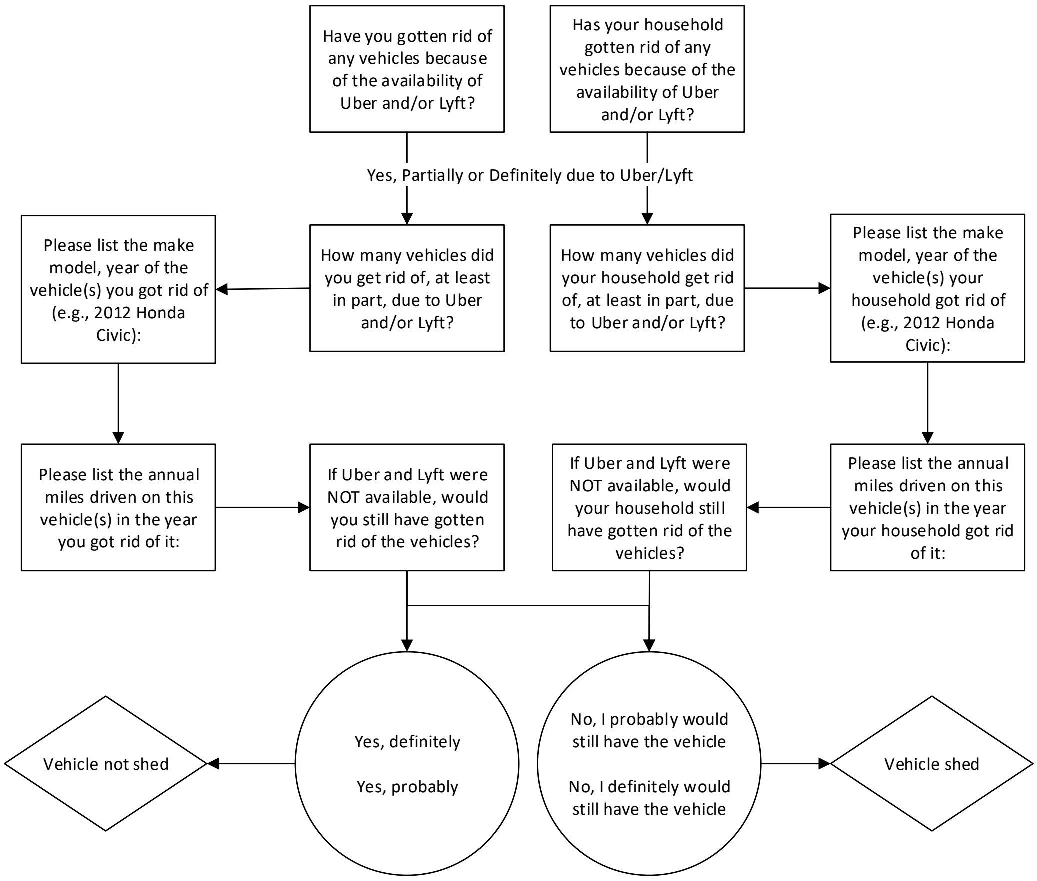

Figure 2. Personal vehicle shedding question structure.

The weighted results of the passenger survey vehicle shedding analysis are provided in Table 7. This table only accounts for the respondents who verified that they "probably" or "definitely would" still own the vehicle if Lyft and Uber were not present in the market. Additionally, the table shows the percentage of passengers who reported a shed vehicle within each market. After applying the weights to the survey values, non-whole numbers were rounded to the nearest whole number. These rounded values were used for the total and percentage calculations.

Table 7. Personal Vehicle Shedding from Weighted Sample.

Vehicles Shed	Partially Due to Lyft/Uber	Definitely Due to Lyft/Uber	Total Due to Lyft/Uber	Would Still Be Held If Not for Lyft/Uber	Vehicles Shed per Passenger
Los Angeles	80	60	140	80	2.6%
San Francisco	141	58	199	83	3.1%
Washington, D.C.	124	31	155	49	1.7%
Total (3 Markets)	345	149	494	212	2.5%

4.2.4. Vehicle Suppression

The impacts of Lyft and Uber on vehicle suppression were analyzed in a similar manner to vehicle shedding. As with vehicle shedding, the question structure that a respondent received was determined by their classification as an individual or belonging to a household (See Figure A1). The survey first asked if the respondent would acquire a car if Lyft or Uber no longer existed in their market. Respondents who indicated that they "probably" or "definitely" would acquire a car were further questioned on the circumstance of the acquired vehicle(s). As noted earlier, if the respondent had previously indicated that they shed a vehicle, then any reporting of vehicle suppression was not considered to prevent double counting of the same vehicle. On the contrary, those that had not reported a vehicle shed and reported that they were "less likely" or "much less likely" to acquire a new vehicle in the next few years were counted for vehicle suppression.

Table 8 displays the weighted results of the vehicle suppression assessment. Lyft and Uber had the greatest impact on vehicle suppression in Los Angeles, with 9.2% of vehicles being "probably" or "definitely" suppressed per respondent in that market. Comparatively, the suppression rate in San Francisco and Washington, D.C. was 7.8% and 6.4%, respectively. Lyft and Uber having more impactful vehicle suppression effects within Los Angeles is consistent with the region's car-dependent environment and with the fact that TNCs are more accessible than other shared modes of travel.

Table 8. Personal Vehicle Suppression from Weighted Sample.

Vehicles Suppressed	Partially Due to Lyft/Uber	Definitely Due to Lyft/Uber	Total Due to Lyft/Uber	Total Sustained Suppression Due to Lyft/Uber	Vehicles Probably or Definitely Suppressed per Passenger
Los Angeles	348	196	544	284	9.2%
San Francisco	254	66	320	207	7.8%
Washington, D.C.	236	100	336	186	6.4%
Total (3 Markets)	838	362	1200	677	7.8%

The data indicate that Lyft and Uber had a greater impact on vehicle suppression than on vehicle shedding. As discussed previously, it is easier not to acquire a new car than it is to get rid of a currently owned vehicle. This inaction results in displaced VMT that would otherwise have occurred if Lyft and Uber did not exist.

Los Angeles had an especially notable suppression rate of 26 percent among zero-car households. In San Francisco and Washington, D.C., the suppression rate for zero-car households was 15 percent and 12 percent, respectively. The results suggest that Lyft and Uber prevented the acquisition of new cars and in particular, contributed to sustaining zero-car households.

4.2.5. Vehicle Acquisition

Generally, shared mobility impacts are focused on the reduction in personal vehicles; however, it is possible someone may have acquired a vehicle as a result of Lyft and Uber. One reason someone may acquire a personal vehicle is to enable them to drive for Lyft or Uber. While the driver survey addressed more driver-specific behavior questions, the passenger survey also asked respondents if they had ever been a Lyft or Uber driver to provide potential insight into their reason for the acquisition. Two follow-up questions were asked of respondents to determine how important Lyft and Uber were in the decision to acquire a new vehicle and how many vehicles were acquired (See Figure A3 for question structure).

Vehicles acquired were only counted if the respondent indicated that they "partially" or "definitely" acquired a vehicle due to Lyft and Uber and indicated that the TNCs were "very important" or "somewhat important" to the decision. Using the same criteria and weighting as the vehicle shedding and suppression analyses, Table 9 displays the results of vehicle acquisition activity from the survey.

Table 9. Personal Vehicle Acquisition from Weighted Sample.

Vehicles Acquired	Partially Due to Lyft/Uber	Definitely Due to Lyft/Uber	Total Due to Lyft/Uber	Lyft and Uber Somewhat or Very Important for Acquisition	Personal Vehicles Acquired per Passenger
Los Angeles	17	17	34	29	0.9%
San Francisco	5	10	15	13	0.5%
Washington, D.C.	12	10	22	19	0.7%
Total (3 Markets)	34	37	71	61	0.7%

The passenger survey did not specifically ask the respondents the reason for their vehicle acquisition; however, it should be noted that 18 of the respondents reported that they were a driver for Lyft or Uber. In all three markets, the acquisition rate per passenger was less than 1%. Lyft and Uber do contribute to vehicle acquisition, but at a lower rate than vehicle shedding and suppression.

With the three vehicle impacts calculated, it is a useful juncture to review the unweighted trends of impacts to vehicle holdings as compared to TNC frequency of use. The plot of these impacts by frequency more empirically shows the need for weighting along this dimension. Figure 3 shows that the rate of both vehicle shedding and suppression increases as the frequency of TNC use increases. This fits the expected pattern, as the more an individual uses TNC services to fulfill their automotive needs, the less likely they are to need a personal vehicle. Vehicle acquisition, however, stays relatively low across all frequencies, most likely because a personal vehicle decreases the utility of TNCs.

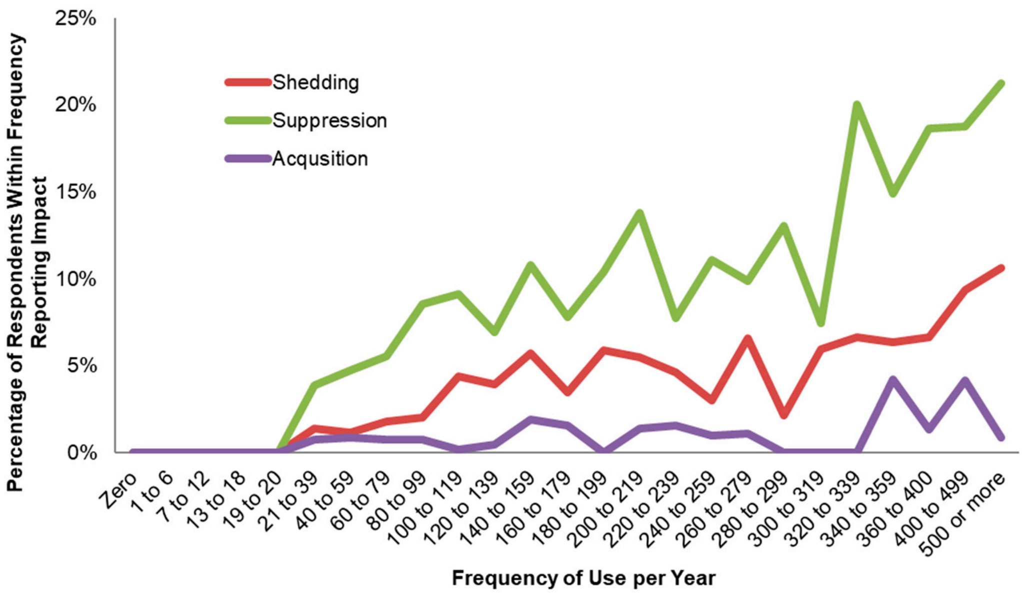

Figure 3. Percentage of respondents reporting vehicle impact as a function of usage frequency (unweighted).

4.2.6. Summary of Vehicle Ownership Impact Findings

The results from the vehicle shedding, suppression, and acquisition analyses are compiled in Table 10 to show the weighted net change in vehicle holdings within the three markets. The net change in each market was calculated by considering vehicle shedding and suppression as a reduction in vehicles, indicated as negative, while vehicle acquisitions were considered as additions to the total number of vehicles. Though most respondents did not change in vehicle holdings in either direction, there was a decrease of over 200 personal vehicle holdings in each of the target markets. Los Angeles experienced the greatest change in net personal vehicles per passenger at −10.9%, followed by San Francisco at −10.4%, and lastly, Washington, D.C. with the smallest change at −7.4%. These values will be further considered in the context of VMT and emissions in the following section.

Table 10. Personal Vehicle Impacts within Weighted Sample.

Market	Personal Vehicles Shed	Personal Vehicles Suppressed	Personal Vehicles Acquired	Net Personal Vehicle Change	Net Personal Vehicle Change per Passenger
Los Angeles	−80	−284	29	−335	−10.9%
San Francisco	−83	−207	13	−277	−10.4%
Washington, D.C.	−49	−186	19	−216	−7.4%
Total (3 Markets)	−212	−677	61	−828	−9.6%

4.3. Impacts of TNC Services on Vehicle Miles Traveled and Greenhouse Gas Emissions

The analysis calculating the net impact of TNCs on VMT considers the VMT accrued while a passenger is in the vehicle, the TNC miles driven without a passenger, as well as the collective impacts due to the behavioral change of TNC users. As discussed in the vehicle holdings analysis, many TNC users shed a vehicle or suppressed the acquisition of a vehicle because their mobility needs were being fulfilled by TNCs. Other behavioral changes impacting VMT included changes in personal vehicle use and changes in the use of other shared vehicle modes. Estimates of these behavioral changes were gathered through responses to the passenger survey. The four behavioral changes considered for the net VMT impacts from Lyft and Uber are defined as follows:

- Change in Personal Vehicle Use: This accounts for the change in personal vehicle driving. For example, someone may take a Lyft or Uber to a social event instead of driving their personal vehicle. If TNCs were not available and the person had otherwise driven their personal vehicle, then much of the VMT would have occurred anyway. Respondents to the passenger survey were also able to report that TNCs led to an increase in personal VMT, if they felt that their use of TNCs increased the amount of driving they did in their personal vehicles.
- Change in the Number of Vehicles Owned or Leased (Vehicle Shedding): Vehicle shedding occurs when a TNC user decides to sell or get rid of a personal vehicle due to their use of Lyft or Uber services. The miles that would have been driven on the vehicle discharged no longer occur.
- Change in the Number of Vehicles That Would Have Been Acquired (Vehicle Suppression): The use of Lyft or Uber may fulfill the vehicle needs of a user such that they no longer need to acquire a personal vehicle. If Lyft and Uber were not available, then these passengers would have needed to acquire a personal vehicle. However, the suppressed vehicle is not acquired, not driven, and therefore does not add to personal VMT.
- Change in the Use of Other Shared Vehicle Modes (e.g., taxi, carsharing, car rental, etc.): Lyft and Uber are common substitutes for taxis or other short-term use, shared vehicle modes of travel. In such circumstances, the VMT from the Lyft or Uber ride would have occurred in a similar manner even if TNCs did not exist in the market.

Thus, using Lyft or Uber instead of other shared vehicle modes does not add to or reduce total VMT.

The VMT impacts from the behavioral changes listed above and the TNC-generated VMT are combined to estimate the net VMT impacts from Lyft and Uber. As described in the vehicle holdings analysis, the frequency-of-use weights are applied to adjust for the potential bias associated with people who may be more or less inclined to take the survey depending on how often they use Lyft or Uber. This weighting method does not account for any demographic dissimilarities between the survey sample and the general population. Lyft and Uber did not have population-level demographic data of their users. However, the frequency of use likely has the greatest effect on user impacts from TNCs given that the use of the service is most directly connected to its impacts.

The VMT calculations from Lyft and Uber mileage and the behavioral change data can be further analyzed to determine GHG emissions. The additional data needed to complete the GHG analysis are the personal vehicle make, model, and year of respondents as collected in the passenger survey. The personal vehicle data were then used to reference a fuel economy factor in the U.S. EPA fuel economy database. A market-wide average fuel economy was used for the TNC fleets within each city. Using fuel economy and VMT, gasoline consumption can be calculated and converted to GHG emissions. The following sections first describe the VMT impacts from each of the behavioral changes, followed by the VMT generated by the Lyft and Uber vehicles, and finally the conversion of that VMT to GHG emissions. The results section is concluded with a sensitivity analysis quantifying how changes in vehicle suppression and operator-generated mileage impact net VMT (and by extension emissions).

4.3.1. Change in Personal Vehicle Use

The passenger survey asked respondents if their personal vehicle usage changed as a result of their usage of Lyft and Uber. The most commonly reported change was a decrease in the usage of their personal vehicle; however, some respondents indicated that they increased their personal vehicle usage. A series of questions were developed to assess the circumstances of the change in personal vehicle usage (see Figure A3 for question structure). The respondents had to indicate for every vehicle they owned or leased if Lyft or Uber caused them to drive the vehicle more, less, or no change. If there was a reported change in driving, then they were asked to approximately quantify the change in miles per year. Only responses of more or less personal vehicle driving due to Lyft and Uber were considered.

The data from this section of the survey were used to determine the distribution of change in personal vehicle miles traveled (PVMT) due to Lyft and Uber. Figure 4 displays the distribution of change in PVMT in all three markets, where about 30 percent of respondents indicated that they drove less. Washington, D.C. had the lowest percentage of respondents reporting a decrease in driving at 27 percent, followed by Los Angeles at 30 percent, and San Francisco with 33 percent of respondents. A majority of this subsample reported driving 1 to 500 miles less as a result of Lyft and Uber. Across all markets, the weighted average decrease in miles driven per year was calculated to be 607 miles per year.

The distribution of change in PVMT for the respondents who indicated an increase in personal vehicle usage is shown in Figure 5. This subsample of respondents is much smaller than the number of individuals who reported a decrease in PVMT. The portion of respondents who reported an increase in Los Angeles, San Francisco, and Washington, D.C. was 3 percent, 2 percent, and 1 percent, respectively, within each market. The variance in the number of additional miles driven was greater than that of the reported decrease in miles. The average weighted increase in miles driven per year was 1311 per person across these smaller subsamples within all three markets.

The collective findings of Figures 4 and 5 suggest that the presence of TNCs can cause users to experience a change in their personal vehicle travel behavior. The net effect of these impacts was calculated by subtracting the magnitude of increased mileage from the magnitude of decreased mileage. The weighted average net change in PVMT across the three markets was a decrease of 153 miles per year. There was a net decrease in PVMT of 194 miles per year within Los Angeles, 164 miles per year in San Francisco, and 100 miles per year in Washington, D.C. It is important to note that this decrease was representative of a subsample of the greater respondent data and that the majority of survey respondents indicated no change in PVMT.

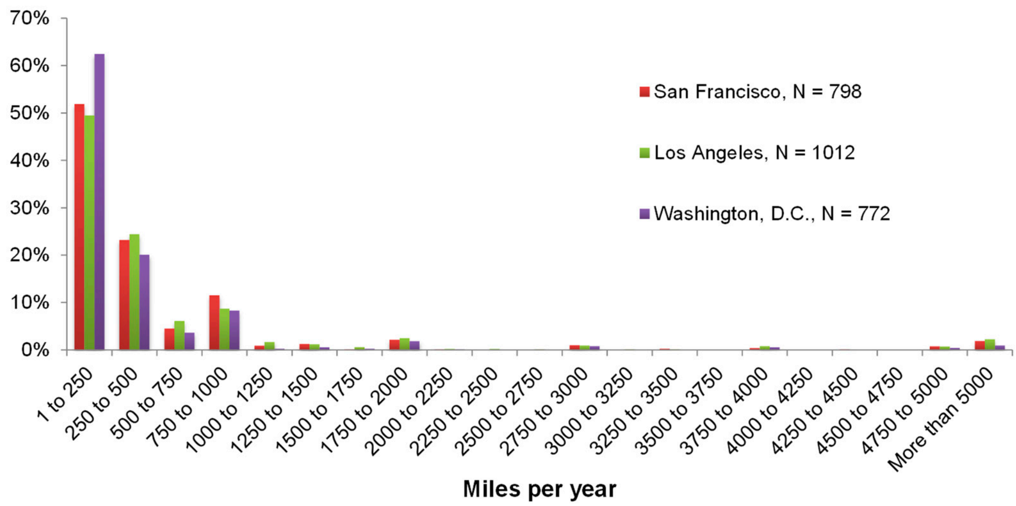

Figure 4. Distribution of weighted annual VMT decrease in personal vehicles due to Lyft and Uber.

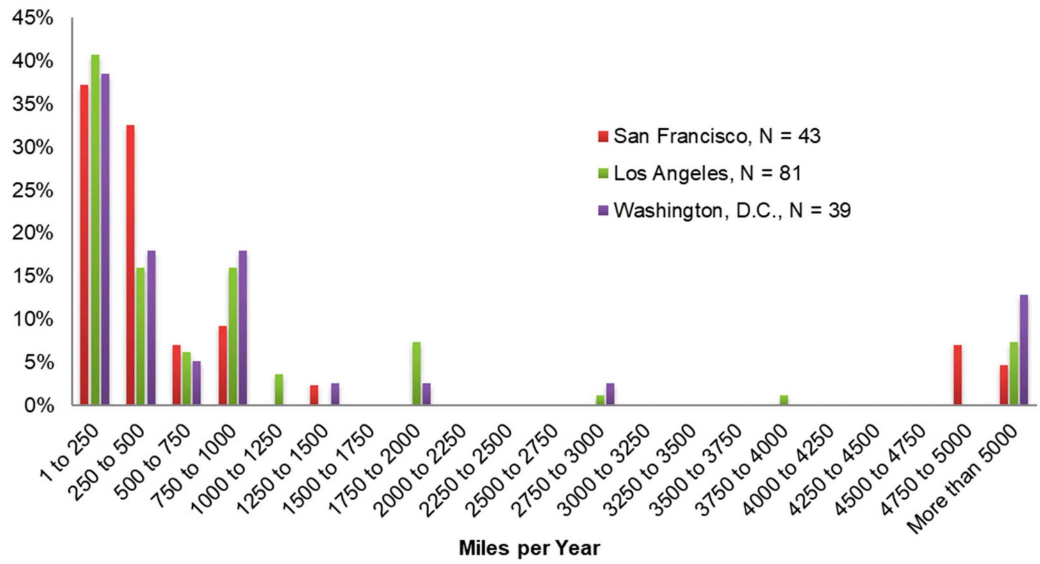

Figure 5. Distribution of weighted annual VMT increase in personal vehicles due to Lyft and Uber.

4.3.2. Change in the Number of Vehicles Owned or Leased (Vehicle Shedding)

Vehicle shedding results in the reduction in PVMT. Although a small percentage of vehicles were shed across the three target markets, it led to substantial reductions in PVMT. Survey respondents reported an estimate of miles driven on shed vehicles during the year before a vehicle was shed. From these data, a distribution of weighted annual mileage was developed for all the vehicles shed (Figure 6), which were appropriately applied to the vehicle mileage to understand how the TNCs impacted PVMT.

Within the subsample of respondents who reported a vehicle shed, the weighted average annual miles driven on a vehicle before shedding was 5205 miles in Los Angeles, 6308 miles in San Francisco, and 5845 miles in Washington, D.C. When these impacts were averaged over the entire sample of respondents within each market, the weighted mileage reduction per person was 141 miles in Los Angeles, 197 miles in San Francisco, and 103 miles in Washington, D.C.

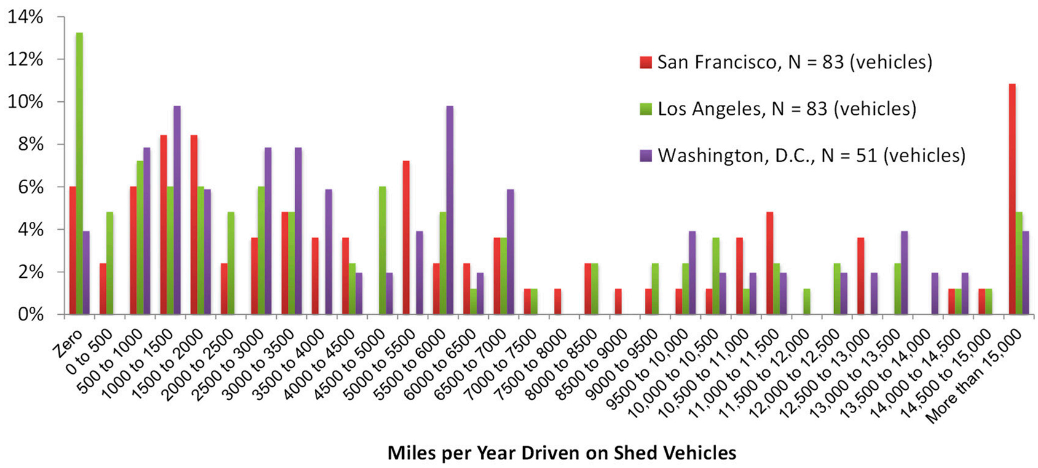

Figure 6. Distribution of weighted annual miles driven by vehicles shed.

4.3.3. Change in the Number of Vehicles That Would Have Been Owned (Vehicle Suppression)

Out of all the vehicle holding impact categories, Lyft and Uber have the greatest impacts on vehicle suppression. The vehicle suppression data were gathered through the passenger survey question structure provided in Figure A1 in the Appendix A. The PVMT analysis for vehicle suppression accounted for the mileage that would have accrued if a vehicle had been acquired, as reported in the passenger survey. The hypothetical mileage estimation for vehicle shedding was not considered if the respondent had already reported vehicle shedding or if they reported the suppression of two vehicles. Additionally, a limit on the unweighted estimation of mileage suppression was defined at 20,000 miles per year. The results for the distribution of weighted annual miles suppressed are displayed in Figure 7.

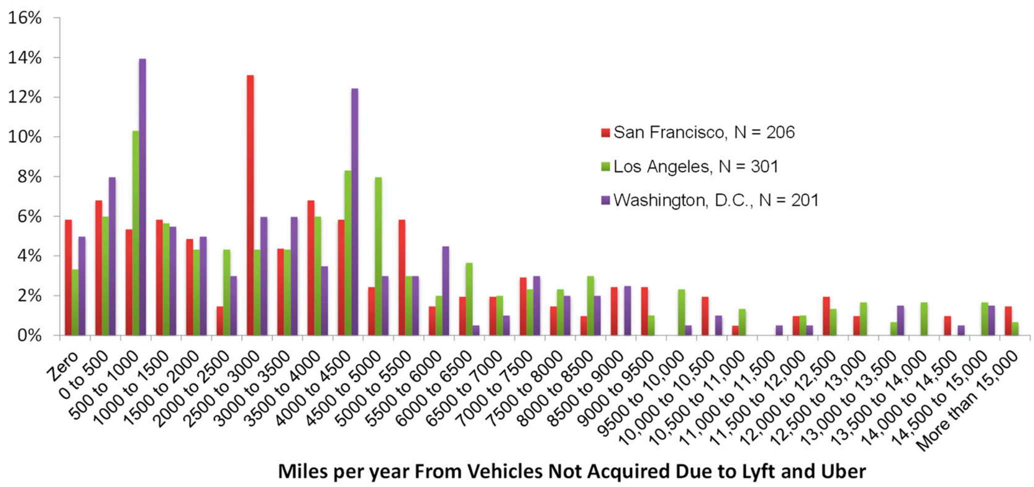

Figure 7. Distribution of weighted annual VMT reduction from personal vehicle suppression.

Most of the vehicles suppressed were estimated to contribute relatively low annual mileage. This comes as no surprise as TNCs would more likely fulfill the needs of a vehicle that is driven lower than average. The average weighted mileage attributed to suppressed vehicles was determined for Los Angeles, San Francisco, and Washington, D.C. to be 5097 miles per year, 5286 miles per year, and 4375 miles per year, respectively.

4.3.4. Change in the Use of Other Shared Vehicle Modes (e.g., Taxi, Carsharing, Car Rental, etc.)

The use of Lyft and Uber can also substitute for trips that would have alternatively been fulfilled by a taxi. Additionally, Lyft and Uber can replace trips that would have otherwise been taken using a rental car or one-way carsharing. A question structure was developed for the passenger survey to assess changes in shared vehicle modes. Respondents were asked to report their average miles per trip and frequency of use per year to estimate the mileage attributed to these modes.

The substitution of a taxi with a TNC results in roughly the same VMT, given that both modes involve deadheading and fetch distances. Rental cars and carsharing accrue fewer deadhead miles, since these modes are driven by the user. However, both modes can involve the repositioning of vehicles to manage supply and demand. To account for the VMT substitution, only additional miles that occurred because of the substitution were added to the personal VMT total. Deadheading was approximated by adding 45 percent of the reported taxi mileage to the PVMT count [1], and vehicle re-positioning was approximated by adding 5 percent of the carsharing and rental car miles to the PVMT total. Additionally, respondent VMT estimations that were attributed to other shared vehicle modes were bounded by their total Lyft and Uber trip mileage. Since the trip VMT, excluding deadheading, is similar across all the vehicle modes, it was assumed that the actual miles substituted would not be greater than the mileage recorded by Lyft and Uber combined. Deadhead miles were not considered in the upper bound determination, as these miles are non-fare-earning miles and are not recorded by the TNC companies; they were added after the VMT constraint was applied.

The distribution of weighted mileage reductions from taxis, rental cars, and carsharing, as a result of Lyft and Uber usage, is displayed in Figure 8. Over 25 percent of respondents in each target market reported that their usage of other vehicle modes was "about the same". The majority of the remaining respondents reported a reduction of less than 500 miles per year. No more than 14 people within each market reported an increase in the other vehicle mode mileage. The net VMT reduction per year attributed to other vehicle modes was 85 miles in Los Angeles, 57 miles in San Francisco, and 79 miles in Washington, D.C. Approximately 70 percent, 20 percent, and 10 percent of the reductions were due to taxis, rental cars, and carsharing, respectively.

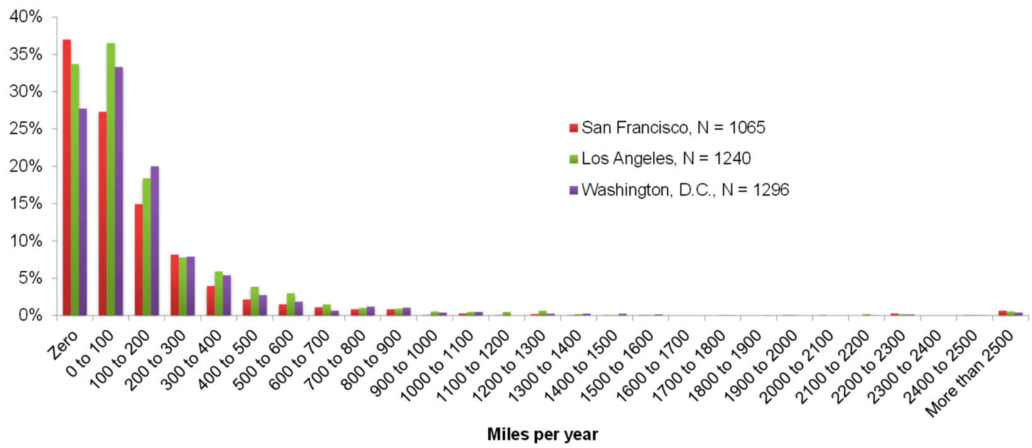

Figure 8. Distribution of weighted miles of estimated reduction in taxi, rental car, and carsharing use.

4.3.5. Summary of Average VMT Change Impacts

The magnitude of impact from the four behavioral changes varied among the target markets. The change in weighted average VMT per passenger for one year is provided in Table 11, with values rounded to the nearest tenth. The values were initially determined by the passenger survey data and weighted according to data reflecting TNC activity data. Negative values are used to indicate a decrease in VMT.

Table 11. Summary of Average Changes in VMT (Miles per Passenger per Year).

VMT Change Due to Behavioral Change	Los Angeles	San Francisco	Washington D.C.
Average Change Due to PVMT	−194.2	−163.9	−100.2
Average Change Due to Vehicle Shedding	−140.5	−197.5	−102.7
Average Change Due to Vehicle Suppression	−511.1	−424.5	−303.8
Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift	−85.0	−56.9	−78.5
Average Change in Weighted VMT per Passenger per Year	−930.8	−842.7	−585.2
N	3075	2651	2904
Standard Deviation	2753	2909	2150
Sample Mean Margin of Error	127.9	145.5	102.8
Average Change in Weighted VMT per Passenger per Year and 99% Confidence Interval About the Sample Mean	−931 (−1059, −803)	−843 (−998, −697)	−585 (−688, −482)

Table 11 shows that the largest impact on VMT came from the vehicle suppression impacts from Lyft and Uber. With the exception of changes in the use of other shared vehicle modes, these impacts were derived from a minority of the passenger survey respondents. The bottom section of Table 11 shows the number of people surveyed in each market (N), the standard deviation, the sample mean margin of error, and the 99% confidence interval for the average change in weighted VMT.

The results indicate that Uber and Lyft have induced behavioral changes within the target markets that have led to a reduction in miles traveled. The next section describes the final component of the net VMT calculation, the VMT contributed by Lyft and Uber vehicles.

4.3.6. Miles Driven by Lyft and Uber Vehicles

The vehicle annual miles driven per passenger in each target market were provided by Lyft and Uber. These values were determined by dividing the total VMT during the study year of all Lyft and Uber vehicles in a given target market by the total number of passengers that qualified to take the passenger survey in that market, to produce an average number of TNC miles per passenger. Additional processing accounted for an overlap in passengers and the double counting of miles driven by drivers who used both TNC platforms (as described in Section 3.2.1). However, this processing did not account for app-off driving that may have occurred while drivers were driving to the target market.

During the open phase, or Period 1, of TNC driving, the driver app is open and the driver is actively waiting to receive a notification for their next passenger. The mileage driven during this time is recorded on the driver app, but if a driver uses both Lyft and Uber, then the miles accrued during this time are recorded by both apps, leading to a double counting of miles. Lyft and Uber agreed that this phenomenon does occur during the open phase but not during the fetch phase, or Period 2. It is assumed that once a driver accepts a passenger on one app, they will usually turn off the other app. Thus, miles during the fetch phase are only recorded by the operator through which the passenger requested a ride.

To properly discount the double-counted miles, an estimation was generated using a factor from a study conducted by the California Air Resources Board (CARB) in March 2019. The study found that 18 percent of mileage driven during the open phase was double-counted by TNC operators [22]. For this analysis, the estimate was rounded up to 20 percent and varied within a sensitivity analysis (see Table 12 below) exploring the influence of this percentage on the results.

Next, the TNC mileage needed to be adjusted to account for passengers that may have used both Lyft and Uber. As each operator divided the mileage of all their vehicles by the total number of qualified riders in a given market, it was possible that a rider using both services would be counted as a qualified rider for both operators. To correct for this, the passenger survey was used to determine the percentage of Lyft passengers that also used Uber, as well as the percentage of Uber passengers that also used Lyft. These percentages were then multiplied by the associated operator-provided mileage to estimate mileage generated by riders who used both Lyft and Uber. These two estimates were then added together to determine the combined Lyft and Uber mileage within each market.

Table 12. Combined Estimated Miles per Passenger per Year by Operator Given Baseline Assumptions.

CBSA	Combined Miles per Qualified Passenger during Survey Year + Unmeasured Driving
Los Angeles	1173
San Francisco	1077
Washington, D.C.	502

Lastly, the VMT per passenger was adjusted to include the app-off mileage driven by TNC drivers. This adjustment was informed by the driver survey, which asked drivers to approximate how many miles they drove for Lyft and Uber and then to estimate what percent of those miles were driven with the TNC apps off. It was determined that an average of 19 percent of miles were driven app-off in Los Angeles, 19 percent in San Francisco, and 18 percent in Washington, D.C. These percentages were then used to determine the total VMT per passenger in each target market.

Table 12 shows the estimated mileage per qualified passenger in the three target markets resulting from these calculations. These estimates include the miles driven to pick up a passenger, drive the passenger to their destination, open miles, and app-off TNC-related miles.

The TNC operators provided the open phase mileage in the form of a percent of the total miles driven, with an average of 34 percent. The range of open phase miles was 24 to 46 percent across all markets and both operators. To assess how changing the percent of double-counted open miles affects the overall determination of VMT per passenger per year, a sensitivity analysis was conducted with overlapping percentages ranging from 0 to 40 percent. The results of the overlapping miles percentage sensitivity analysis are provided in Table 13.

Table 13. Sensitivity of Miles per Passenger per Year Estimate to Percentage of Open Miles Overlap between Uber and Lyft.

CBSA/Percent of Open Miles Overlap	0%	5%	10%	15%	20%	25%	30%	35%	40%
Los Angeles	1257	1236	1215	1194	1173	1152	1131	1110	1089
San Francisco	1148	1130	1112	1095	1077	1059	1042	1024	1007
Washington, D.C.	517	513	510	506	502	498	495	491	487

The column highlighted orange is the baseline assumption and indicates a 20 percent overlap in open miles between Uber and Lyft in each city.

Note that decreasing the overlap increases VMT since it implies that fewer of the reported miles are double-counted. Los Angeles and San Francisco showed the greatest variation, with a difference of 100 to 200 miles per passenger per year across the percentages, while in Washington, D.C., the range was only about 50 miles per passenger per year. The highlighted column in Table 13 indicates the calculations for a baseline assumption of 20 percent overlap.

4.3.7. Net Change in VMT at Baseline Assumption (20 Percent)

The difference between the operator-driven VMT per passenger per year and the average change in VMT per passenger per year is the net change in VMT resulting from TNC use, also in units of per passenger per year (Table 14). The net change in VMT does not imply that each passenger contributed to the net change in VMT equally, but rather it represents the total net change distributed across the passenger population in each market. This allows for a more direct comparison across the markets that have different-sized passenger populations. These average changes are a function of sample data. To assess if they were statistically significant from zero, a one-tailed *t*-test was conducted, as shown in Table 14.

Table 14. Net Change in VMT From Lyft and Uber by Market.

VMT Change Due to Behavioral Change	Average Change in VMT per Passenger per Year (in Miles)	Operator VMT per Passenger per Year (in Miles)	Difference (Miles per Passenger per Year)	Change in VMT	Statistically Significance	*t*-Statistic	*p*-Value (1-Tailed)
Los Angeles	−931	1173	242	Increase	Yes (1% level)	4.881	0.000
San Francisco	−843	1077	234	Increase	Yes (1% level)	4.149	0.000
Washington, D.C.	−585	502	−83	Decrease	Yes (5% level)	−2.084	0.019

The computed net change in VMT per passenger per year found that Lyft and Uber led to an increase in VMT in the two California markets but led to a VMT reduction in Washington, D.C. The net change in all three markets was determined to be statistically significant at the 1 percent level in Los Angeles and San Francisco and at the 5 percent level in Washington, D.C.

There are many factors that may influence the results of the net change in VMT, including land use and population density. Of the three markets, Los Angeles experienced the greatest decrease in weighted VMT from passenger behavior. The only behavioral category where Los Angeles did not dominate was vehicle shedding, which was found to be the highest in San Francisco. However, these behavioral changes were not enough to offset the amount of TNC driving that facilitated these behavioral changes, leading to a net increase in VMT within the two California markets. The data indicate that although Washington, D.C. was a smaller market and had lower behavioral effects, it also had lower VMT from TNC vehicles, resulting in a net decrease in VMT within the market.

Note that the values displayed in Table 14 already account for the mileage attributed to the shared UberPOOL and Lyft Shared rides. Shared rides contribute to reduced VMT because passengers with similar routes are matched to one vehicle rather than one vehicle per passenger. However, no further discounting is required for this analysis as shared ride mileage was included in the original operator-provided mileage count. Had there been no shared rides provided by the operators, the mileage reported by the TNCs would have been higher.

4.3.8. Change in Resulting GHG Emissions from Lyft and Uber

The change in GHG emissions can be derived from the net VMT impacts through the application of fuel economy factors associated with the vehicles reported in the passenger survey and vehicles in the TNC fleets. The combined fuel economy factors associated with the personally owned vehicles or vehicles shed were determined by matching the make, model, and year with data in the EPA fuel economy database at www.fueleconomy.gov. The fuel economy for suppressed vehicles and other vehicle modes, like taxis, was determined based on assumptions because exact vehicle details are unknown. Both TNC operators reported fleet fuel economy data to inform a fleetwide average fuel economy.

The household vehicle fuel economies were aggregated as an average (harmonic mean) for each city. The harmonic mean fuel economy in Los Angeles, San Francisco, and

Washington, D.C. was 23.2 mpg, 23.0 mpg, and 22.5 mpg, respectively. The distribution of fuel economies within each market is shown in Figure 9.

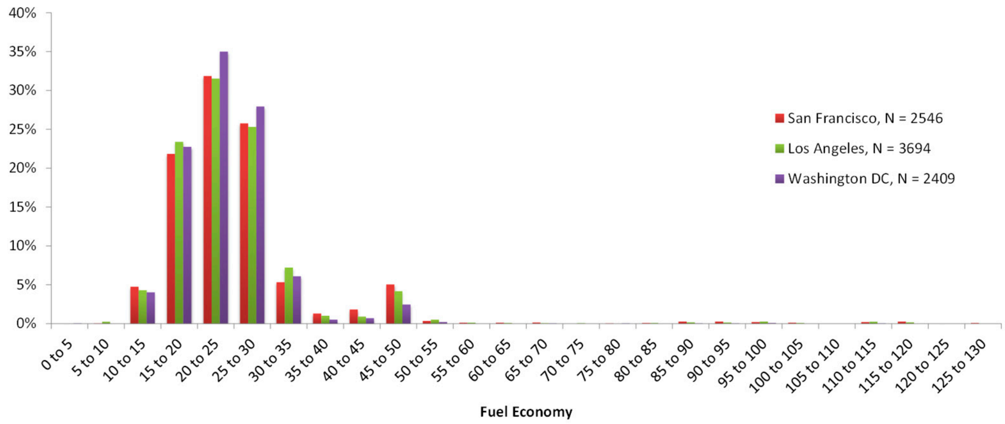

Figure 9. Distribution of household vehicle fuel economy.

As an intermediate step, total gasoline consumption was determined by multiplying VMT by the fuel economy value within each market. Finally, a mile-dependent conversion factor to determine the kg of carbon dioxide (CO_2) per gallon of gasoline consumed was applied to calculate the CO_2 emissions. A conversion factor of 8.887 kg of CO_2 per gallon of gasoline was used according to EPA methodology [23].

Similar to household vehicles, the fuel economies of shed vehicles were aggregated by harmonic mean and determined to be 23.2 mpg in Los Angeles, 23.3 mpg in San Francisco, and 22.7 mpg in Washington, D.C. The fuel economy of suppressed vehicles is unknown because these are vehicles that are yet to be acquired. These were assumed to have a fuel economy of 31 mpg. As for the TNC fleets, one of the operators provided a fuel economy distribution for all their vehicles, while the other provided the make, model, year, and percentage of total miles driven for each of the vehicles in its fleet. The TNC vehicles had a harmonic mean fuel economy of 28 mpg in Los Angeles, 28 mpg in San Francisco, and 25 mpg in Washington, D.C. Although the total number of Lyft and Uber vehicles is unknown, it was assumed that 50 to 80 percent of all the TNC vehicles operated for Uber. Following this assumption, Figure 10 displays the estimated merged fuel economy distribution of all TNC vehicles in the three target markets.

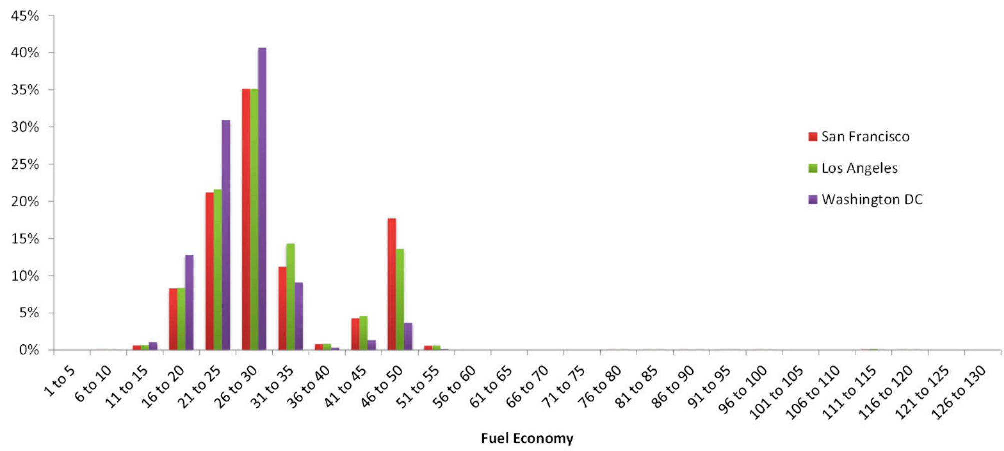

Figure 10. Approximate distribution of fuel economy (mpg) of Lyft and Uber fleet.

Table 15 shows the estimated CO_2 emissions from the behavioral contributors to VMT, based on the VMT-to-CO_2 conversions, in units of metric tons per passenger per year. The last row of Table 15 shows key parameters informing the confidence interval of the average.

Table 15. Change in GHG Emissions in Metric Tons from Behavioral Change of Passengers in Metric Tons Per Passenger per Year.

GHG Change Due to Behavioral Change	Los Angeles	San Francisco	Washington D.C.
Average Change Due to PVMT	−0.072	−0.066	−0.039
Average Change Due to Vehicle Shedding	−0.060	−0.083	−0.050
Average Change Due to Vehicle Suppression	−0.147	−0.122	−0.087
Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift	−0.024	−0.016	−0.022
Average Change in Weighted GHG per Passenger per Year	−0.303	−0.287	−0.199
N	3075	2651	2904
Standard Deviation	0.9	1.0	0.8
Sample Mean Margin of Error	0.041	0.049	0.036
Average Change in Weighted GHG per Passenger per Year and 99% Confidence Interval About the Sample Mean	−0.303 (−0.344, −0.261)	−0.287 (−0.336, −0.237)	−0.199 (−0.234, −0.163)

The GHG emissions from TNC VMT were similarly calculated in terms of tons of CO_2 per passenger per year. Table 16 shows the net change resulting from the difference between the CO_2 reductions from travel behavior and the CO_2 additions from TNC activity. Table 16 also shows the results of the 1-tailed t-test, p-value, and the degree of statistical significance from zero. All three markets had statistically significant changes in net GHG emissions, with San Francisco and Los Angeles showing an increase at the 5 and 1 percent level, respectively, and Washington, D.C. showing a decrease at the 5 percent level.

Table 16. Net Change in GHG From Lyft and Uber by Market.

GHG Change Due to Behavioral Change	Behavioral Change per Passenger per Year	Operator GHG Emissions per Passenger per Year	Difference (*t* per Passenger per Year)	Change in GHG	Statistically Significant?	*t*-Statistic	*p*-Value (1-Tailed)
Los Angeles	−0.303	0.374	0.071	Increase	Yes (1% level)	3.259	0.001
San Francisco	−0.287	0.338	0.051	Increase	Yes (5% level)	1.930	0.027
Washington, D.C.	−0.199	0.179	−0.020	Decrease	Yes (5% level)	−2.097	0.018

The results show that despite the GHG reductions from behavioral changes, the miles driven by Lyft and Uber exceeded those reductions in Los Angeles and San Francisco. In Washington, D.C., the reductions from behavioral changes were large enough to produce a net reduction in GHG emissions. The vehicle suppression impacts were found to be the largest behavioral contributor to the reduction in VMT, comprising 50 to 55 percent of reductions in all three markets. If the suppression impact or the operator-produced VMT were different, then broader conclusions on how TNCs impact VMT and emissions could also change.

As noted previously, a precise determination of vehicle suppression is challenging due to the hypothetical nature of the question. The number of suppressed vehicles was determined by a series of questions in the passenger survey (see Appendix A for question design and structure). Vehicle suppression rates are subject to change over time according to the cost of TNC trips, the cost of owning a vehicle, and many other factors.

The sensitivity of the vehicle suppression rates and annual operator miles per passenger can show how conclusions regarding net VMT vary with different magnitudes of these effects. Table 17 shows how variations in vehicle suppression from 0 to 15 percent and annual operator mileage from 20 to 200 percent of the baseline value would impact the net change in VMT for each city. The vehicle suppression rate that was computed for this analysis is highlighted in green and the calculated or baseline operator VMT per passenger per year is highlighted in gray. The computed net-positive VMT values indicate a net increase in VMT while negative values indicate a net decrease in VMT. All calculations that are a departure from the baseline values are made under the assumption that all other factors remain equal (i.e., ceteris paribus).

Table 17. Sensitivity of Personal Vehicle Suppression and Operator Miles per Passenger per Year in San Francisco, Los Angeles, and Washington, D.C.

San Francisco										
Percent of Operator Miles per Passenger	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
Suppression Rate / Operator Miles per Passenger	**215**	**431**	**646**	**862**	**1077**	**1293**	**1508**	**1723**	**1939**	**2154**
0.0%	-203	13	228	443	659	874	1090	1305	1521	1736
1.0%	-257	-42	174	389	605	820	1035	1251	1466	1682
2.0%	-311	-96	120	335	550	766	981	1197	1412	1627
3.0%	-366	-150	65	281	496	712	927	1142	1358	1573
4.0%	-420	-204	11	226	442	657	873	1088	1304	1519
5.0%	-474	-259	-43	172	388	603	819	1034	1249	1465
6.0%	-528	-313	-97	118	333	549	764	980	1195	1411
7.0%	-582	-367	-152	64	279	495	710	925	1141	1356
7.8%	-627	-412	-196	19	234	450	665	881	1096	1311
9.0%	-691	-476	-260	-45	171	386	602	817	1032	1248
10.0%	-745	-530	-314	-99	116	332	547	763	978	1194
11.0%	-799	-584	-369	-153	62	278	493	709	924	1139
12.00%	-854	-638	-423	-207	8	223	439	654	870	1085
13.0%	-908	-692	-477	-262	-46	169	385	600	815	1031
14.0%	-962	-747	-531	-316	-100	115	330	546	761	977
15.0%	-1016	-801	-586	-370	-155	61	276	492	707	922

Los Angeles										
Percent of Operator Miles per Passenger	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
Suppression Rate / Operator Miles per Passenger	**235**	**469**	**704**	**938**	**1173**	**1408**	**1642**	**1877**	**2112**	**2346**
0.0%	-185	50	284	519	753	988	1223	1457	1692	1926
1.0%	-240	-6	229	463	698	933	1167	1402	1637	1871
2.0%	-296	-61	174	408	643	877	1112	1347	1581	1816
3.0%	-351	-116	118	353	587	822	1057	1291	1526	1761
4.0%	-406	-172	63	298	532	767	1001	1236	1471	1705
5.0%	-462	-227	8	242	477	712	946	1181	1415	1650
6.0%	-517	-282	-48	187	422	656	891	1125	1360	1595
7.0%	-572	-338	-103	132	366	601	836	1070	1305	1539
8.0%	-627	-393	-158	76	311	546	780	1015	1249	1484
9.2%	-696	-462	-227	8	242	477	712	946	1181	1415
10.0%	-738	-503	-269	-34	200	435	670	904	1139	1373
11.0%	-793	-559	-324	-89	145	380	614	849	1084	1318
12.0%	-849	-614	-379	-145	90	324	559	794	1028	1263
13.0%	-904	-669	-435	-200	35	269	504	738	973	1208
14.0%	-959	-725	-490	-255	-21	214	448	683	918	1152
15.0%	-1015	-780	-545	-311	-76	159	393	628	862	1097

Washington DC										
Percent of Operator Miles per Passenger	20%	40%	60%	80%	100%	120%	140%	160%	180%	200%
Suppression Rate / Operator Miles per Passenger	**100**	**201**	**301**	**402**	**502**	**603**	**703**	**803**	**904**	**1004**
0.0%	-181	-81	20	120	221	321	422	522	622	723
1.0%	-228	-128	-28	73	173	274	374	475	575	675
2.0%	-276	-175	-75	26	126	226	327	427	528	628
3.0%	-323	-223	-122	-22	79	179	279	380	480	581
4.0%	-371	-270	-170	-69	31	132	232	332	433	533
5.0%	-418	-317	-217	-117	-16	84	185	285	385	486
6.4%	-485	-384	-284	-184	-83	17	118	218	319	419
7.0%	-513	-412	-312	-211	-111	-11	90	190	291	391
8.0%	-560	-460	-359	-259	-158	-58	42	143	243	344
9.0%	-607	-507	-407	-306	-206	-105	-5	95	196	296
10.0%	-655	-554	-454	-354	-253	-153	-52	48	149	249
11.0%	-702	-602	-501	-401	-301	-200	-100	1	101	202
12.0%	-750	-649	-549	-448	-348	-248	-147	-47	54	154
13.0%	-797	-697	-596	-496	-395	-295	-194	-94	6	107
14.0%	-844	-744	-644	-543	-443	-342	-242	-141	-41	59
15.0%	-892	-791	-691	-591	-490	-390	-289	-189	-88	12

The column header highlighted gray indicates the baseline operator mileage per passenger per year. The row header highlighted green indicates the baseline vehicle suppression rate. The table values are highlighted on a spectrum from green to red with green values indicating a greater decrease in VMT and red values indicating a greater increase in the VMT.

Table 17 indicates that at the baseline annual mileage, the vehicle suppression rate in San Francisco would need to increase to about 13 percent for there to be a net decrease in

VMT. If the vehicle suppression rates were to remain the same, then the annual operator miles per passenger would need to be less than 80% of the baseline value for there to be a net decrease in VMT. In Los Angeles, at the baseline 9.2% suppression rate determined by the passenger survey, VMT reductions are shown once operator miles are at 60% of 1173, the baseline measure of operator miles per passenger per year. Alternatively, if the miles per passenger per year remain the same, then the suppression rate would need to increase to 14 percent to yield VMT reductions.

The sensitivity analysis for Washington, D.C. revealed that the net VMT reductions observed would not have occurred had the operator miles been 20% higher or had the suppression rate been 2.5% lower. The city had the lowest suppression rate of the three markets evaluated, and these results show how relatively minor movements in either the operator-driven miles or the vehicle suppression rates could result in different conclusions.

5. Conclusions

While TNCs first emerged over a decade ago, their sustained role in regional mobility in cities throughout the world strongly suggests that TNCs and similar services will continue to operate in ways that influence travel behavior and vehicle ownership. As such, it is important to understand the vectors of impacts that can occur and insights that are drawn from their measurement. This research presents findings to better understand how TNCs impact travel behavior, net VMT, and net GHG emissions within three major metropolitan regions. The study used a survey of passengers, a survey of drivers, as well as activity and fleet data provided by the major TNC operators Uber and Lyft.

The passenger survey explored the impacts of TNCs on personal vehicle ownership as well as the use of other automotive travel modes. The components of these impacts included changes in personal vehicle driving, changes in the use of rental cars, taxis, and carsharing, changes in vehicles owned (shedding and acquisition), and reductions in vehicles that would have been acquired (suppressed). The results from this survey supported the calculation of VMT and vehicle ownership changes on a per passenger per year basis, where the sample was weighted to account for frequencies of use in the population.

The survey found that the net change in personal vehicles ranged from a reduction of 7.4% to 10.9% across the markets and was 9.6% across all three markets. These vehicle ownership impacts were mostly driven by the suppression effect, where roughly three quarters of the vehicle reductions were from vehicles that were not acquired as a result of TNCs. These vehicle ownership impacts translate directly to VMT impacts as a personal vehicle not acquired or held is a vehicle that is not driven. Reductions in VMT combined from vehicle shedding and suppression ranged from 69% to 74% of the VMT reductions and from 68% to 71% of GHG reductions from travel behavior change.

The study also used several sources to determine the VMT and GHG emissions that result from TNC operations. First, Uber and Lyft provided measurements of activity from TNC vehicle driving that could be measured by the app. These measurements were adjusted to account for double counting that occurred with drivers that had both apps on at the same time while waiting to receive a passenger. Additional TNC driving, including traveling to and from the passenger market, was also measured through a driver survey. Taken together, these inputs enabled an estimation of TNC miles per passenger per year.

The net VMT and GHG emissions from TNC operations accounted for the vectors of travel behavior change and TNC vehicle driving. The results showed that TNCs increased VMT and emissions in the two California markets but decreased them in the Washington, D.C. market. The reduction found in the latter market was a function of lower miles driven per passenger alongside relatively robust travel behavior impacts. These behavioral impacts within San Francisco and Los Angeles were larger, but not large enough to compensate for substantively higher driving by TNC vehicles.

The results of this study demonstrate the need to evaluate several components of behavioral change to understand the net impact of TNC and similar operations. Additionally, the sensitivity analysis shows that changes in key factors can tilt the net results from positive to negative, in some cases with very small shifts in influential factors. The findings make clear that a consideration of personal vehicle suppression and the commensurate VMT and GHG impacts is important for a complete impact assessment. TNC operations shift travel behavior through mode shift and sometimes substitute for other trips that would have been taken in a personal vehicle. However, TNCs can more significantly influence the holding and acquisition of personal vehicles, the reduction or prevention of which yields more powerful emission reduction impacts. As such, VMT and GHG impacts from TNCs can vary by geographical location based on vehicle dependence and the availability of other competing transportation modes. For example, the VMT and GHG impacts of TNCs may be different in more rural and car-dependent areas where more trips rely on a personal vehicle, which could influence overall vehicle shedding and suppression impacts. Furthermore, data from this study show that weighting results by frequency of use makes an important adjustment to these powerful impacts. Such impacts would be overstated in a raw sample, where more frequent users are more likely to have such impacts and more likely to respond to a survey about those effects. However, equally important is the fact that such impacts do not need to occur in a large portion of the population to counteract much of the mileage driven by TNCs. In our sensitivity analysis, suppression impacts on at least 14% of the user population would yield negative net emissions in all three markets.

Finally, key factors in this analysis are far from static over time. The data were collected before the pandemic and though TNC operations have generally returned to pre-pandemic services, the net impacts found in this study are the result of a balance of factors that continually change due to technology and economic circumstances. The efficiency of TNC operations in miles driven per passenger are subject to change along with the travel behavior impacts. The capacity of TNC operations to substitute for personal vehicle holdings may shift with changes in cost of both TNC trips and of vehicle acquisition. The emissions of TNC operations will also be heavily influenced by increasing electrification, where GHG emissions will be increasingly decoupled from VMT and more associated with grid mix and the time of vehicle charging. These and other factors point to the need for the continued re-assessment of TNC impacts in terms of both vehicle activity and travel behavior impacts across diverse markets within and outside the United States. Additional research could further our understanding of these impacts in several areas. Future research should explore TNC electrification and implications for system impacts and performance. This may involve modeling predictions of VMT and GHG emissions as more TNC drivers adopt lower- and zero-emission vehicles. It may explore how existing infrastructure could be expanded or improved to ensure that the electrification of TNCs is able to deliver the same mobility as conventional vehicles. Additional research could also provide further insights as to how VMT and GHG impacts might vary across different built environments and different cities. The results presented in this study explore three distinct metropolitan regions, but there are other urban environments and regions within and beyond the United States that may yield distinct patterns of impact when all factors are taken into consideration. These and other supporting research efforts can help guide public understanding and policy design to better maximize TNC mobility benefits while limiting environmental costs.

Author Contributions: Conceptualization, E.M. and S.S.; methodology, E.M. and S.S.; validation, E.M.; formal analysis, E.M.; investigation, E.M. and B.W.; resources, S.S.; data curation, E.M.; writing—original draft preparation, E.M., S.S. and B.W.; writing—review and editing, E.M., S.S. and B.W.; visualization, E.M. and B.W.; supervision, E.M. and S.S.; project administration, S.S.; funding acquisition, S.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The following figures describe the survey question structures for personal vehicle suppression (Figure A1), vehicle acquisition (Figure A2), and vehicle holdings and driving change (Figure A3).

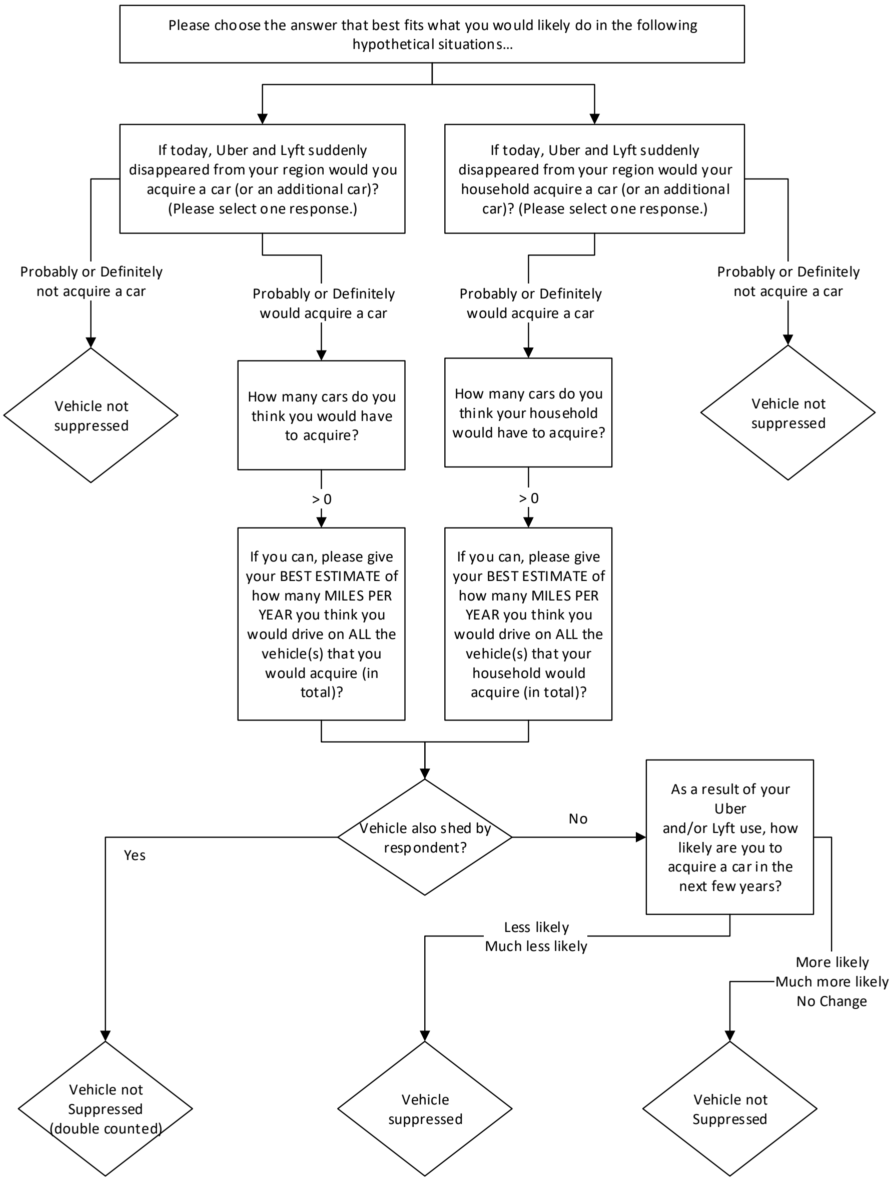

Figure A1. Personal vehicle suppression question structure.

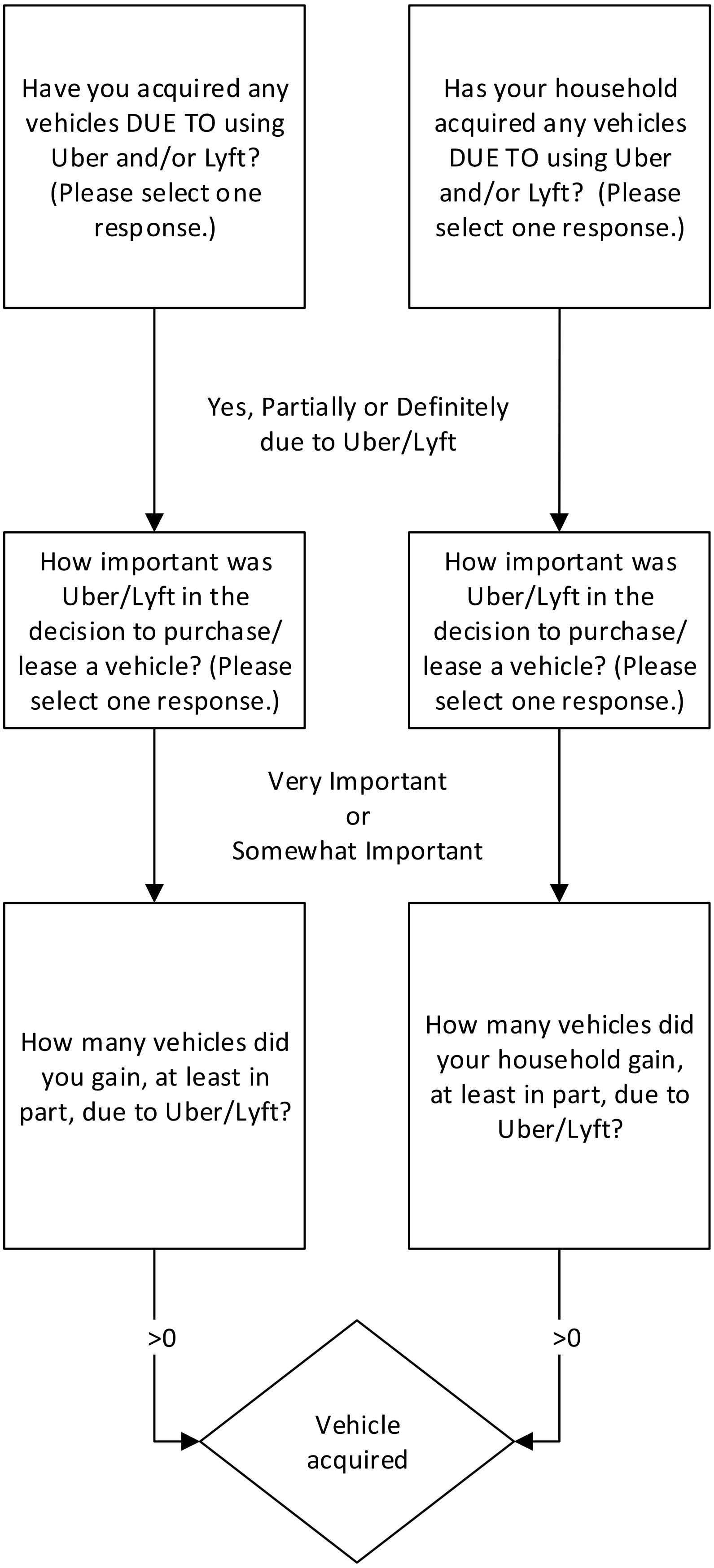

Figure A2. Vehicle acquisition question structure.

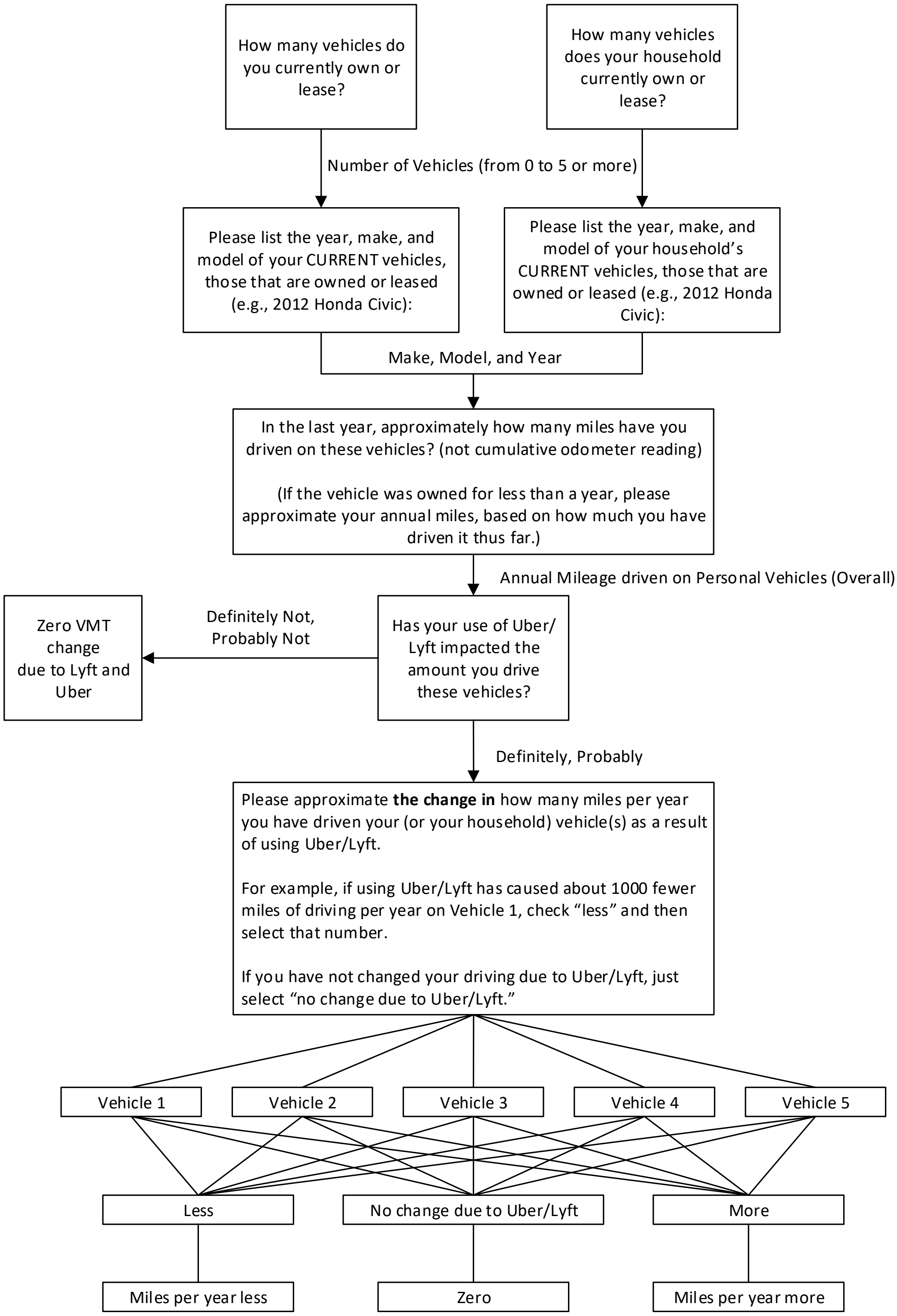

Figure A3. Vehicle holdings and driving change question structure.

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