Title

Impacts of Transportation Network Companies on Vehicle Miles Traveled, Greenhouse Gas Emissions, and Travel Behavior Analysis from the Washington D.C., Los Angeles, and San Francisco Markets

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IMPACTS OF TRANSPORTATION NETWORK COMPANIES ON VEHICLE MILES TRAVELED, GREENHOUSE GAS EMISSIONS, AND TRAVEL BEHAVIOR

ANALYSIS FROM THE WASHINGTON D.C., LOS ANGELES, AND SAN FRANCISCO MARKETS

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Table of Contents

List of Tables:

List of Figures:

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About the Study

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Executive Summary

Transportation Network Companies (TNCs) like Lyft, Uber, and their global counterparts have expanded around the world over the past decade and have changed the way that people travel around cities and regions. The individual mobility benefits provided by TNCs have been clear. Passengers can summon a vehicle quickly via smartphone from almost anywhere to take them almost anywhere, with advance communication on estimated wait time, travel time, and cost. TNCs may also provide users with added mobility benefits, especially for those living in areas where public transit service is infrequent or non-existent. However, the growing popularity of TNCs has forced important questions about their impacts on the overall transportation network. While past research has focused on many different aspects of TNC impacts, including their effects on travel behavior, modal shift, congestion, and other topics, there are still many important questions.

This report advances the understanding of TNC effects on vehicle miles traveled (VMT), greenhouse gas (GHG) emissions, and personal vehicle ownership. The research also explores key questions regarding the impact of pooled TNC services, Lyft Shared rides and uberPOOL, and further investigates how TNCs alter the use of other transportation modes, including public transit. This study addresses a number of topics including offering insight into the following six research questions:

- How do TNCs impact VMT and GHG emissions?
- To what extent do TNCs affect personal vehicle ownership?
- What impact do TNCs have on the use of other transportation modes?
- How effective are pooled TNC services at increasing vehicle occupancies (i.e., Lyft Shared rides and uberPOOL)?
- Who uses TNCs, when, and for what purposes?
- How far do TNC drivers travel to reach their main passenger market and what types of vehicles do they own?

This study examines TNC impacts across three major North American markets: San Francisco, Los Angeles, and Washington, D.C. Analysis was conducted using a variety of original data sources collected during mid-2016 to early-2017 including a: 1) passenger survey (N = 8,630), 2) driver survey (N = 5,034), and 3) general population (control) survey (N = 1,650). We also received passenger and driver activity data from Lyft and Uber, obtained San Francisco driver licensing data to support the driver survey, and reviewed public vehicle registration data. It is important to note that TNC impacts vary across locations, and while certain trends emerge throughout this research, impacts due to TNCs are ultimately very location dependent and are not generalizable to other geographic markets.

Since the collection and analysis of the data applied in this study, a number of significant events have occurred. Most notably, the COVID-19 pandemic imposed an unprecedented disruption on the norms of human interaction and transportation that had otherwise persisted for the last century. Human proximity within shared spaces, long accepted as a given, had to become restricted and tightly managed. The results of these developments globally upended many forms of transportation, work life, the economy, urban living, and other longstanding conventions of societal interaction. TNCs today require in-vehicle human proximity of drivers and passengers, and their services were greatly impacted as part of this global disruption. The results of this study reflect a world and an industry operating before the pandemic. In that sense, they represent findings that are historical to the operations and behavioral responses of that pre-pandemic world. However, they can inform the relative magnitude of impacts that have occurred within the markets evaluated. The similarity of these impacts to those of the future post-pandemic world will be influenced by many factors. The results from this and other research may serve as benchmarks on performance measurements to build and improve upon. Key highlights from this work are presented below.

Impacts on VMT and GHG Emissions

We found that Lyft and Uber caused a net increase in VMT and GHG emissions in San Francisco and Los Angeles, but they enabled a slight decrease in Washington, D.C.

In San Francisco and Los Angeles, we found the VMT produced by Lyft and Uber were larger than the VMT reductions that occurred due to changes in passenger behavior and vehicle ownership. In Washington, D.C, we found that that the balance of impacts resulted in a net VMT and GHG reduction. This was possibly due to land use and built environment factors in Washington, D.C. that led to lower VMT by Lyft and Uber vehicles providing mobility services relative to the two California markets. GHG emission impacts generally follow the same pattern as VMT impacts across the three markets, we calculated GHG effects by applying fuel economy factors to the VMT calculations. VMT and GHG emission impact results are shown in Table 1 below.

Table 1. VMT and GHG Emission Impacts Summary

	VMT Impacts				***GHG Emission Impacts***			
Market	**VMT produced by Lyft and Uber***	**VMT reduced due to behavior change***	**Change in VMT***	**Statistically Significant?**	**GHG produced by Lyft and Uber****	**GHG reduced due to behavior change****	**Change in GHG****	**Statistically Significant?**
San Francisco	1,077	843	**+234 (Increase)**	Yes (1% level)	0.338	0.300	**+0.038 (Increase)**	Yes (5% level)
Los Angeles	1,173	931	**+242 (Increase)**	Yes (1% level)	0.374	0.319	**+0.055 (Increase)**	Yes (1% level)
Washington, D.C.	502	585	**–83 (Decrease)**	Yes (5% level)	0.179	0.209	**–0.030 (Decrease)**	Yes (5% level)

*Units of miles per passenger per year
**Units of metric tons (t) of carbon dioxide (CO_2) per passenger per year
Note: "Passenger" is defined here as those who used Lyft or Uber at least seven times over the study year, and at least 50 percent of these trips were within the respective market.

TNC vehicles produce VMT by driving to an area with passenger demand, deadheading while awaiting a ride request, heading to pick up a passenger, and completing the ride itself. However, there are also the less visible effects that TNCs have on VMT reduction through behavioral change. One of the key impacts is reduced vehicle ownership, as some passengers may find that they no longer need to own a car due to their TNC use. This has significant effects on the overall mileage they travel. In addition, other behavioral changes, such as the substitution of other driving with TNCs, should be taken into consideration to more accurately assess net VMT change. This study assesses four main components of Lyft and Uber VMT reduction due to behavioral change, including:

1) Change in personal vehicle use: Some passengers substitute driving their own cars with TNC use. This driving would have occurred in the absence of TNCs. Therefore, it would be

inaccurate to count TNC vehicle VMT without also counting a commensurate reduction in personal vehicle VMT. By our estimates, this effect accounts for less than a quarter of the total VMT reduced due to behavioral change in each market.

2) Change in vehicles owned or leased (personal vehicle shedding): Some passengers find that the mobility provided by TNCs, including their costs, can serve as a reasonable substitute for personal vehicle ownership. They (or their household) get rid of a vehicle as a result, and the driving that would have occurred with that vehicle no longer happens. This impact also makes up less than a quarter of the total VMT reduction in the three markets.

3) Change in vehicles that would have been acquired (personal vehicle suppression): If TNCs did not exist, then some passengers would have acquired a personal vehicle. If they had acquired a personal vehicle, they would have locked in the low marginal cost of driving (by incurring the higher fixed costs of ownership). Such vehicles are then driven thousands of miles every year. Personal vehicle suppression is when the acquisition of a personal vehicle is prevented because TNCs (or some other transportation service) provide sufficient mobility to substitute for the acquisition of a personal vehicle. For most users, TNCs do not have this effect, but when it occurs, it is relatively large in terms of reduced VMT. Personal vehicle suppression has the largest impact of the four components, accounting for more than half of the VMT reduced due to behavioral change in each of the study markets.

4) Change in use of other shared vehicle modes: Similar to the substitution of driving in personal vehicles, passengers also substitute TNCs with other modes, such as taxis, carsharing vehicles (e.g., Zipcar), and rental cars. This component has the smallest effect on VMT reduction, on average, compared to the other three components (i.e., less than 15 percent).

These impacts collectively contribute to a behavioral change that reduces the VMT and GHG emissions of the passenger population. Table 2 (below) shows the average components and total of these changes from VMT and GHG emissions. The negative numbers imply a reduction in both metrics. Table 2 shows the net change in the estimated VMT and GHG impact components, and it reveals that personal vehicle suppression is the largest TNC impact, followed by vehicle shedding or changes in personal vehicle driving (PVMT), depending on the market. In all markets, reductions due to changes in taxi, rental car, and carsharing use comprise the smallest component.

Table 2. Key Components of Average Behavioral Change in VMT and GHGs

VMT Change Due to Behavioral Change	Average Change Due to PVMT*	Average Change Due to Vehicle Shedding*	Average Change Due to Vehicle Suppression*	Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift*	Average Change in Weighted VMT per Passenger per Year
San Francisco	-163.9	-197.5	-424.5	-56.9	-842.7
Los Angeles	-194.2	-140.5	-511.1	-85.0	-930.8
Washington, D.C.	-100.2	-102.7	-303.8	-78.5	-585.2
GHG Change Due to Behavioral Change	**Average Change Due to PVMT****	**Average Change Due to Vehicle Shedding****	**Average Change Due to Vehicle Suppression****	**Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift****	**Average Change in Weighted GHG per Passenger per Year**
San Francisco	–0.066	–0.083	–0.122	–0.018	–0.300
Los Angeles	–0.072	–0.060	–0.147	–0.027	–0.319
Washington, D.C.	–0.039	–0.050	–0.087	–0.025	–0.209

*Units of miles per passenger per year
**Units of metric tons (t) of CO_2 per passenger per year

The study found that pooled TNC services (Lyft Shared rides and uberPOOL) mitigate VMT and emissions produced from TNCs. But the impact is highly sensitive to match rates and mode substitution. At the rates identified in this study, pooled TNC services were found to have a relatively modest impact and do not affect whether TNCs increase or decrease overall VMT and GHG emissions.

Using estimates from the passenger survey, we found that the miles per passenger per year produced by TNCs would have increased by 11 percent in San Francisco, 1 percent in Los Angeles, and 4 percent in Washington, D.C., if pooled TNC services did not exist. Overall VMT produced by TNCs would be slightly higher had Lyft Shared rides and uberPOOL not existed. The greater increase in San Francisco is mainly due to the relatively higher pooled TNC and matching success rates as compared with the other two markets. At the time of this study, their impact was not significant enough to substantively change whether TNCs increase or decrease overall VMT in any of the three markets. We should note that pooled TNC services within the regions studied were suspended with the COVID-19 pandemic. Evidence from this study suggests that such services were offsetting some of the VMT produced by TNCs.

It is important to note that VMT and GHG emission impacts from TNCs are not static and certain to change over time.

The mileage produced by Lyft and Uber will inevitably change over time as the services expand or contract across markets. Behavioral impacts following the recovery from the COVID-19 pandemic may exhibit different dynamics as well. For example, the magnitude of personal vehicle shedding and suppression may change. This would substantively affect the net impact of TNCs on VMT and emissions. If pooled TNC services resume, changes in matching rates will influence the degree to which they mitigate the VMT produced by Lyft and Uber. In addition, the costs of TNC services may change relative to the costs of personal vehicle ownership, which depending on the direction of change, could impact whether TNCs substitute for personal vehicle ownership in the future. These and other considerations will require future re-evaluations of how TNCs influence behavior and how efficiently they may deliver mobility services.

Impacts on Personal Vehicle Ownership

On net, we found a reduction in personal vehicles per TNC passenger of 10.4 percent in San Francisco, 10.9 percent in Los Angeles, and 7.4 percent in Washington, D.C., with a 9.6 percent average reduction across the three markets.

The availability of Lyft and Uber affects personal vehicle ownership decisions among a minority of TNC passengers. TNCs can impact passenger vehicle ownership in three ways including: 1) vehicle shedding, where a passenger decides to sell (or get rid of) a vehicle they no longer need; 2) vehicle suppression, when someone chooses not to purchase (or lease) a personal vehicle; or 3) vehicle acquisition, where a passenger decides to purchase (or lease) a vehicle. We measured these three impacts using a series of responses from the passenger survey to ensure these effects were attributable to TNCs. We also applied weighting factors derived from activity data provided by Lyft and Uber to translate sample impact estimates to population-level impact estimates. Vehicle suppression is the largest of the three impacts, where between 6.4 and 9.2 percent of passengers would have purchased a vehicle in the absence of TNCs. Table 3 summarizes the three vehicle impact metrics and the net vehicle change per passenger.

Table 3. Personal Vehicle Impacts Summary

Market	Vehicles Shed per Passenger	Vehicles Suppressed per Passenger	Vehicles Acquired per Passenger	Net Personal Vehicle Change per Passenger
San Francisco	–3.1%	–7.8%	+0.5%	–10.4%
Los Angeles	–2.6%	–9.2%	+0.9%	–10.9%
Washington, D.C.	–1.7%	–6.4%	+0.7%	–7.4%
Total (3 Markets)	–2.5%	–7.8%	+0.7%	–9.6%

Lyft and Uber enabled some passengers to reduce personal vehicle ownership, but more prominently they enabled carless households to remain carless.

We note that impacts vary across the three markets, with Los Angeles experiencing the greatest net vehicle impacts and Washington, D.C. the lowest, possibly due to differences in regional vehicle ownership and land use. We also find that suppression effects are even more pronounced among zero-car households, with this impact again being most prominent in Los Angeles. We found a suppression rate among carless households of 15 percent in San Francisco, 26 percent in Los Angeles, and 12 percent in Washington, D.C.

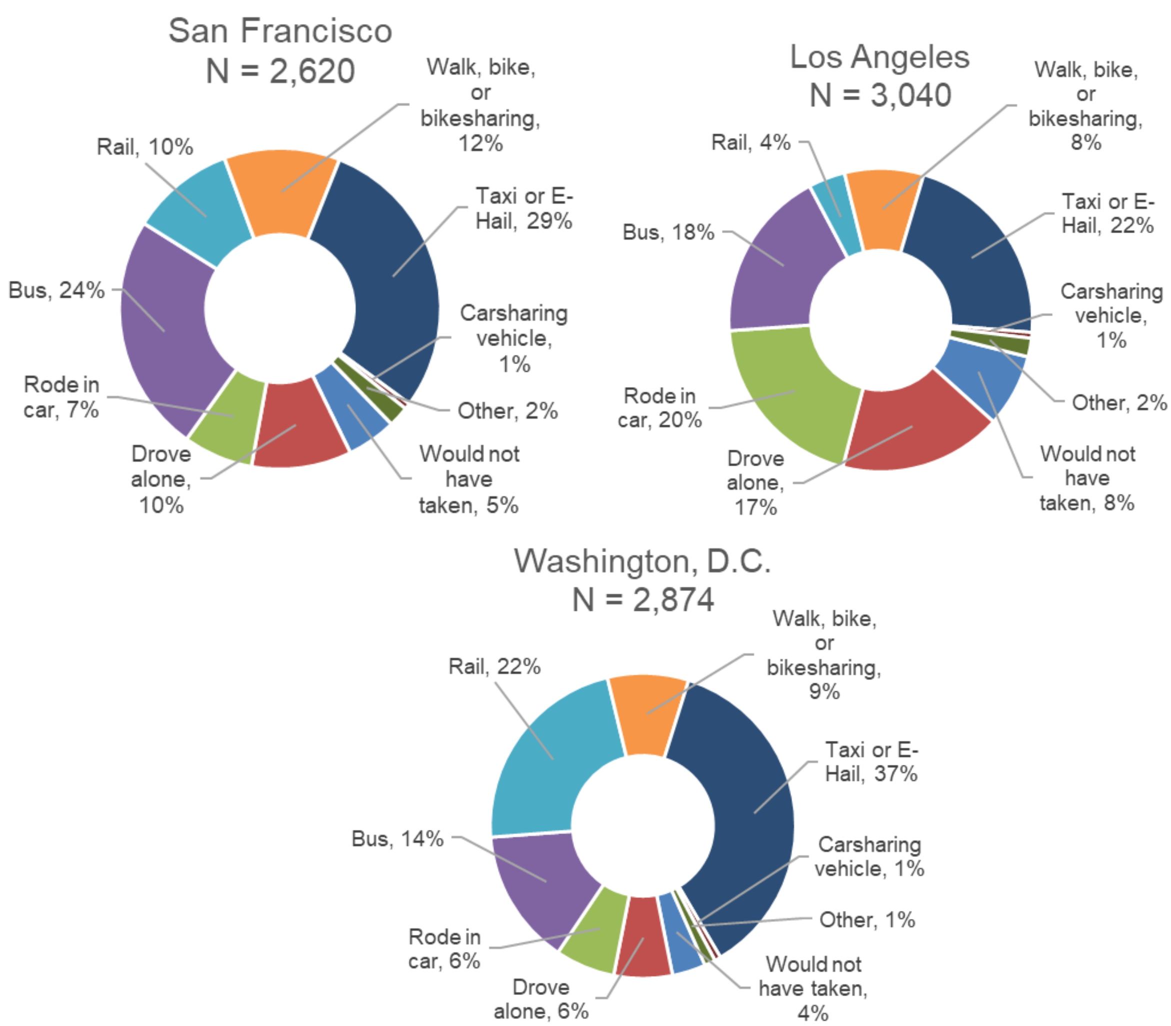
Impacts on Use of Other Transportation Modes

TNC mode substitution was found to be very location dependent, as TNCs more commonly substituted for public transit (bus and rail) in San Francisco and Washington, D.C. and more commonly substituted for driving/riding in personal vehicles in Los Angeles.

Those who use Lyft and Uber were either using these services to substitute for a different transportation mode they would have previously used (e.g., driving in a personal vehicle, public transit, etc.) or they were making an entirely new trip they would not have otherwise made in the absence of TNCs (induced demand). This study measured these modal shift impacts in several ways using data from the passenger and control surveys.

Mode substitution questions in the passenger survey measured how respondents would have traveled for their most recent trip in the absence of TNCs. Figure 1 shows that while Lyft and Uber frequently substituted for taxi or E-Hail taxi rides across all three markets, substitution patterns also differed by market. In San Francisco and Washington, D.C., a greater portion of respondents would have used public transit (bus and rail) than would have driven or rode in a personal vehicle, if TNCs were not available. The opposite was true in Los Angeles, where driving or getting a ride in a personal vehicle was more commonly replaced with TNCs than public transit.

Figure 1. Mode Substitution Among All Respondents by Market



Pooled and private TNCs were found to have different mode substitution patterns, with pooled TNC services (Lyft Shared rides and uberPOOL) drawing more heavily from public transit and private TNC services (Lyft, uberX) more likely to substitute passenger vehicle modes (using a personal vehicle, taxi/E-hail taxi, or carsharing vehicle).

Mode substitution patterns differed among those who used a pooled versus private TNC service for their most recent trip. Across the three markets, about a third to more than half of those who used pooled TNCs for their last trip would have used public transit, if TNCs were not available. This level of substitution compared to less than a third of private TNC passengers who would have used public transit, if TNCs were not available. In contrast, 56 percent to two-thirds of those who used a private TNC for their most recent trip would have used a passenger vehicle mode instead (e.g., personal vehicle, taxi/E-hail taxi, or carsharing vehicle). This compared to 40 percent or less of pooled TNC passengers who would have used a passenger vehicle instead.

We also assessed modal shift by asking respondents whether their overall use of particular modes changed due to Lyft and Uber. We found that while TNCs draw from all main travel modes (driving, bus, rail, walking, bicycling, taxi), the average change among all passenger survey respondents was less than one trip per week.

Lyft and Uber were found to draw more passengers from public transit than they were adding to it. The two services were found to enable a minority of passengers to connect to public transit—the size of which varied by market.

The study also examined first- and last-mile trips taken to link to public transit among passenger survey respondents. We found that 13 percent of trips linked with public transit in San Francisco, 7 percent did so in Los Angeles, and 8 percent in Washington, D.C. We found that while Lyft and Uber enabled some passengers to connect to public transit who would not have otherwise, this effect was limited (2 percent of respondents or less across all markets). A larger proportion of respondents would still have linked to or from the same public transit operator without TNCs (5 to 11 percent of all respondents across markets), suggesting that a significant portion of public transit use probably would have occurred anyway. An even larger proportion, who did not link with public transit during their most recent trip, would have used some form of public transit instead of TNCs (19 to 34 percent of all respondents, depending on the market).

Effectiveness of Pooled TNC Services (Lyft Shared rides and uberPOOL)

The effectiveness of pooled TNC services at increasing vehicle occupancies varied by market, where San Francisco exhibited a higher portion of pooled TNC trip requests, better matching success rates, and higher average occupancies as compared to those found in Los Angeles and Washington, D.C.

Prior to the pandemic, TNCs implemented pooled services within their higher volume markets. Such services have yet to return due to the continued risks of virus transmission. But the deployment of pooled services in the years before the pandemic yielded experiences that were instructive as to how TNC pooling could perform in terms of VMT reductions in the future.

A key benefit of pooled TNCs is that they may be able to increase vehicle occupancy rates, at least compared to private vehicles, by enabling travelers along a similar route to share rides. However, publicly available information about how effective these services are at matching passengers and increasing vehicle occupancies is limited. This study calculated some pooling metrics to provide a more detailed understanding based on available survey data.

Table 4 summarizes TNC pooling data within the passenger survey sample. A pooled TNC trip was requested for a quarter of TNC ride requests in Los Angeles and Washington, D.C., while in San Francisco, this share was 39 percent. The share of pooled TNC requests appeared to influence matching success rates, as almost three-quarters of pooled TNC trips were matched in San Francisco, but only about half were matched in Los Angeles and Washington, D.C. The matching success rates also affected the average occupancies of pooled TNC trips, with an average pooled TNC occupancy (not including the driver) of 2.31 in San Francisco, 1.90 in Los Angeles, and 2.03 in Washington, D.C. The overall trip-based occupancy of TNCs (both pooled and private services combined) was 1.93 in San Francisco, 1.79 in Los Angeles, and 1.76 in Washington, D.C. These occupancies were slightly higher than the occupancy in personal automobiles in United States, which averaged 1.67 persons per vehicle-mile in 2017 (NHTS 2017).

We note that the trip-based occupancy metrics in Table 4 do not include miles driven from vehicle deadheading (empty vehicle miles without passengers) before and after travel to the passenger markets or between passenger trips, since we were not able to collect this information. However, based on the occupancies below, we determined that if total deadheading represents more than 16 percent of total miles, then the true average occupancy of TNC vehicles within these markets is probably lower than the 1.67 persons per vehicle-mile benchmark.

Table 4. TNC Pooling Metrics Summary

Metric	Percent of TNC Trips Requested as a Pooled Service	Matching Success Rate of Pooled TNC Trips	Average Occupancy of Pooled TNC Trips	Average Occupancy Overall (Pooled and Private Combined)
San Francisco	39%	72%	2.31	1.93
Los Angeles	25%	49%	1.90	1.79
Washington, D.C.	25%	57%	2.03	1.76

As with TNC VMT and behavioral change, pooled TNC use and matching rates can be subject to considerable change over time. Should pooling return to TNCs, they may return to different levels than those found within this study. This will influence the degree to which pooling can mitigate TNC VMT or influence traveler behavior. Understanding match rates over time is critical to evaluating the performance of pooled TNC use, its ability to more efficiently use space within passenger vehicles, and its capacity to reduce VMT and GHG emissions from TNC activities in the future.

Passenger Sociodemographics and Trip-Making Behavior

Overall, the findings showed that individuals who use TNCs were generally younger, of higher income, and more educated than the general population of the corresponding region. TNC passengers also tended to have lower vehicle ownership rates, commuted using public transit at a higher rate, and were less reliant on single-occupant vehicles for commuting, as compared with the general populations in each market.

A number of TNC studies have examined who uses TNCs, when, and for what purposes. The findings in this study are mostly similar to those from related research. We found in the general population (control) survey that 39 to 43 percent of respondents across the three markets were Lyft or Uber users, similar to proportions found in previous studies. We found the majority of Lyft and Uber passengers were under the age of 40. Average per capita incomes among passenger survey respondents were 23 to 34 percent higher than those in the respective market populations, although this discrepancy was not as pronounced in the control survey. There were double the proportion of passenger survey respondents with bachelor's degrees or higher as compared to the corresponding population of each market.

While the passenger survey had higher portions of white respondents as compared with the racial distributions of the general populations, the control survey showed that racial makeups of those who have used TNCs match more closely with the respective general populations. This suggests that while TNC passengers (of any given trip) may be more likely to be white compared with the general population, the fact that someone has used TNCs is not a strong indicator of any particular racial makeup in the three study markets. We also found that those who use Lyft and Uber constitute a portion of the population that have fewer personally owned vehicles and are more likely to be zero-car households than the general population.

We explored when and for what purposes passengers take TNC trips. Fridays and Saturdays were the most popular days for TNC trips, making up 35 percent of respondents' most recent trips in San Francisco, 40 percent in Los Angeles, and 36 percent in Washington, D.C. During weekdays, the distribution of trips followed a common peak-travel profile, with the majority of trips in each market made during the morning (7 to 11 a.m.) and evening (5 to 9 p.m.) periods. We found a more evening-focused pattern on weekends.

Passengers use Lyft and Uber for a wide range of trip purposes, with similar distributions across the three markets. A significant portion of trips were to a restaurant/bar or for social/recreational purposes, ranging from 40 to 44 percent of respondents' most recent trips. Commuting to and from work or school was also a common TNC trip purpose, constituting 20 to 22 percent of trips, depending on the market. This proportion of work and school commute trips matched closely with national trip-making patterns, as about a quarter of trips are made to or from work nationally (NHTS 2017).

Driver Attributes and Travel Behavior

The average commute distance from drivers' origins to their primary passenger pickup markets was 19 miles in San Francisco and 14 miles in both Los Angeles and Washington, D.C. San Francisco's higher average is due to a higher concentration of drivers who traveled longer distances to their passenger market.

TNC drivers' choices and behavior are critical to understanding the full scope of TNC impacts. The driver survey allowed for insights into how far drivers traveled to reach their main passenger pickup market and what types of vehicles they owned.

Understanding the distance that TNC drivers commute to and from the primary location to pick up passengers is key to analyzing the total mileage produced by TNCs and understanding broader equity implications on the driver population. It is important to note that the majority of drivers in all three markets traveled 15 miles or less from their typical origin to their primary passenger market. These distances are not exceptionally long compared to average commutes in the three markets.

We asked drivers what city they lived in and found that although less than one-quarter of respondents lived in the core city, more than half of all respondents indicated the core city as their primary passenger pickup market (e.g., the city boundaries of San Francisco or Washington, D.C. and core county subdivision of Los Angeles). Most driver respondents lived within areas of immediate proximity to the core city, while a relatively small portion (i.e., less than 15%) lived in areas outside of the respective core-based statistical area (CBSA).

TNC vehicles were found to be much newer than the average car in the U.S., at 4.5 years on average compared to the average U.S. vehicle that has been reported to be more than 11 years old (IHS Markit 2016).

We asked respondents of the driver survey about the type of vehicle they drive and whether they had acquired any vehicles due to TNC activity. The majority of driver respondents used a conventional gasoline vehicle, but a notable portion used hybrid vehicles, including a quarter of driver respondents in San Francisco. Although most drivers owned their vehicle prior to driving with Lyft and/or Uber, between 34 to 43 percent across the three markets purchased their vehicle either partially or primarily due to TNC driving. These vehicles tended to be newer (3.5 years old, on average) and included an even higher share of hybrids as compared to the share among the broader driver survey respondents. The dynamics of these vehicle age differences may change with vehicle costs and technology over time.

Trends in public vehicle registration data and registrations per capita of the population over 18 years (18+) suggest that TNCs, through impacts of shedding and suppression, may have been reducing vehicle ownership in aggregate magnitudes that were starting to become visible within broader registration data before the pandemic occurred.

As part of the broader study, we analyzed trends in public vehicle registration data from the three CBSAs from 2010 to 2019. We also evaluated how estimated impact rates derived from the passenger survey would translate to vehicle registrations within the overall CBSA as well as the core jurisdiction, given estimates of the passenger survey population size. We found that since 2016, average registration growth rates were lower than the average rates observed from 2012 to 2016 in all markets. Within some jurisdictions, vehicle registrations and/or vehicle registrations per capita (18+) showed declines after 2016. There are many factors that impact aggregate vehicle registrations, including population growth. We found that the estimated order of magnitude of changes in vehicle ownership of the broader population due to TNCs would be consistent with the overall scale of registrations within their respective markets. We recognize that there are a considerable range of factors that influence aggregate vehicle registrations over time. But we note that the declines and reduction in growth trends occurred during a generally robust economy when vehicle ownership growth would be normally expected. While macroeconomic factors likely have greater impacts on population-level vehicle ownership fluctuations than the availability of TNCs alone, this study suggests that the presence of TNCs may influence aggregate vehicle ownership rates.

Conclusions and Recommendations

While TNCs have been associated with a number of consumer and societal benefits, including increased mobility for passengers and reductions in personal vehicle ownership rates among some households, they have brought challenges as well. This study showed that TNC services alter many aspects of travel choices and behavior among passengers, which in turn have broader systemwide impacts. We found that in two of the three markets analyzed, San Francisco and Los Angeles, TNCs were causing an increase in VMT and GHG emissions. In the third market, Washington, D.C., Lyft and Uber may have enabled a small reduction in VMT and GHG emissions. This research suggests that while pooled services (e.g., Lyft Shared rides and uberPOOL as deployed before the pandemic) can help mitigate some of the VMT and emissions produced by TNCs, this effect was modest at the time of the study. This research also indicates that Lyft and Uber were likely drawing more from public transit use than they were adding to it.

As TNCs and other forms of shared mobility continue to evolve and mature, policies that guide these systems toward sustainable outcomes should also develop. The impacts of the COVID-19 pandemic have forced an adaptation upon many transportation systems that is still ongoing. As the landscape of shared mobility continues to evolve, further research will be needed to understand how impacts shift within a post-pandemic world and better inform policy decisions. Based on findings from this study and others, we provide six policy recommendations that could help mitigate the negative effects of TNCs while encouraging more positive outcomes within this emerging future.

- <u>Mitigate negative externalities and encourage positive impacts through pricing</u>: Since this study and past research demonstrates that TNCs can increase VMT, emissions, and congestion, measures should be taken to mitigate these negative effects. Road charging is one possible approach that includes pricing transportation modes or infrastructure to achieve desired policy outcomes. Pricing mechanisms could include: trip-based fees, mileage-based pricing, spatiotemporal pricing, occupancy-based fees, and access to high occupancy vehicle or express lanes, among others. While pricing approaches should ideally apply to all forms of transportation, most notably single-occupancy vehicles, steps should also be taken to curb the negative impacts associated with TNCs. Prior to the pandemic, U.S. cities had begun to explore TNC pricing to achieve positive policy outcomes, but additional experimentation and understanding are needed.

- <u>When it is again safe to share space in vehicles or pool, explore how to promote pooling and increase vehicle occupancies</u>: Prior to the pandemic, TNCs presented an opportunity to increase passenger vehicle occupancies and reduce reliance on personal vehicle ownership through pooling. However, the pandemic stopped pooling services within TNCs for public safety reasons. It has since re-launched in a small number of markets. TNCs and other innovations may one day help usher in larger reductions in transportation emissions, if a variety of mobility services (including public transit) can offer sustainable and high occupancy alternatives to private vehicle ownership and use. Policies and pricing approaches that encourage pooled rides should be prioritized to facilitate these potential benefits. For example, when pooling is safe from a public health standpoint, operators and policymakers should consider establishing mechanisms for sharing passengers who request pooled rides across multiple platforms in real time, which could increase matching rates and vehicle occupancies. Also, it is important to consider how pooled TNC services may interact with other modes. This study found that pooled TNCs drew a notable portion of riders from public transit. In addition, we found that pooled TNC services had a relatively modest impact on reducing overall VMT and GHG emissions. Future post-pandemic policies that bolster the effectiveness of shared rides and public transit are needed to increase overall vehicle occupancies and for positive outcomes to be realized.

- <u>Improve data sharing</u>: Transportation agencies require timely and reasonably detailed data to understand regional travel behavior and to make informed planning and policy decisions. Outside of a few U.S. public agencies that receive data from TNC operators, there are generally limited data sharing requirements for TNCs. This is due in part to competition and passenger/driver privacy concerns of companies. Additional work is needed among private, public, and academic sector stakeholders to achieve successful data sharing agreements that help answer important public policy questions while addressing private sector concerns.

- Promote socially beneficial public-private partnerships and use cases: Some public agencies have been testing pilot projects with TNCs, spanning a number of use cases including: first- and last-mile linkages to public transit, public transit or paratransit overlay or substitution, services and subsidies for low-income and disabled populations, and late-night or special-event services. Since this study suggests that unrestricted TNCs tend to substitute more with public transit than add to it, the details of how a pilot project operates services or offers subsidies is critical to achieving positive societal outcomes. Pilots and lessons learned from public-private partnerships may advance more efficient and equitable mobility across a range of built environments.

- Extend the benefits of TNCs equitably: The findings from this study and others showed that those who used TNCs were generally younger, of higher income, and more educated than the general population. Since TNCs and other shared mobility services can provide increased access to activities and employment opportunities, measures should be taken to ensure these services are available to underserved groups. Policies or subsidies that encourage operators to serve certain populations or geographical areas could increase transportation equity.

- Incentivize TNC vehicle electrification: As TNC drivers are motivated to reduce operating costs in the hopes of increasing their take-home pay, there is some natural alignment between the economic interests of drivers and policymakers to decrease transportation emissions through the use of more fuel-efficient vehicles. TNC vehicles already tend to be much newer than the average car in the U.S., and TNC drivers own gasoline-electric hybrid vehicles at a much higher rate than the general population. Additional incentives and infrastructure should be considered to promote the expansion zero emission vehicle use within the TNC fleet. Some public entities have begun to explore related policies, including California's Senate Bill 1014, which requires TNCs to reach annual emission reductions targets starting in 2023.

In the report that follows, we present the background, methodology, and results that support the findings presented in this Executive Summary. These results build on the work of previous studies and will hopefully support ongoing research. The prevalence and persistence of TNCs across the world's metropolitan regions show a clear mobility benefit for the user. The findings of this study show that greater behavioral shifts and operational efficiencies may be needed before TNCs can more substantively contribute to achieving VMT reductions and GHG emission goals.

Introduction

One of the notable transportation innovations of the 21st century has been the growth and proliferation of shared mobility services. Although the expansion of tech-enabled shared mobility has occurred primarily within the past decade, shared mobility services are not a new phenomenon. The first carsharing service began in 1948 in Zurich (PBOT 2011), and the first bikesharing service was launched in 1965 in Amsterdam (Van der Zee 2016). Shared mobility has opened new ways for travelers to access the transportation benefits of automobiles, bicycles, and other vehicles in cities across the world without the costs or burdens of vehicle ownership. Since the late 1990s, shared mobility has evolved into different designs and business models in the United States, including carsharing, bikesharing, microtransit, and transportation network companies (TNCs), also known as ridesourcing and ridehailing.

Lyft and Uber have led the development and growth of TNCs in North America since the launch of Uber (first as a black car service) in 2010 and the introduction of Lyft and uberX (peer-to-peer on-demand TNC services) in San Francisco in the summer of 2012. By simplifying and standardizing how travelers summon rides, TNCs scaled their services globally with incredible speed. As of November 2021, Lyft is active in about 538 cities in the United States and Canada, and Uber operates in more than 1,090 cities across approximately 71 countries (Lyft 2021; Uber 2021). We note that city definitions may differ between operators as these statistics were obtained from each company's individual website. TNCs have also undergone rapid user growth in recent years within the United States (Jiang 2019).

The scaling of these services has been driven by leveraging the versatility of the smartphone, using the already abundant supply of personal vehicles and drivers who are willing to share revenues with the platforms in exchange for access to a steady supply of passengers. Furthermore, up until the start of the COVID-19 pandemic, TNCs were offering pooled services in select markets (e.g., Lyft Shared rides and uberPOOL), which matched passengers traveling along similar routes. Since their introduction in San Francisco in August 2014, both operators expanded pooled options into major U.S. and global markets.

From the customer perspective, the mobility benefits attained through TNC services are clear. People can use a smartphone to arrange for travel almost anywhere within a metropolitan area in which these services operate. Reliable service and competitive wait times allowed travelers to access a vehicle more seamlessly than was previously the case with other services in many cities. A 2014 exploratory study in San Francisco found that 90 percent of TNC passengers typically waited 10 minutes or less for a vehicle, as compared with just 35 percent of taxi passengers (Rayle et al. 2016). While the cost of TNCs can vary significantly by location and time, the ease of use has drawn many consumers to take TNC trips on a regular basis. Furthermore, the use of a driver's personal vehicle and the on-demand nature of these services have permitted this mode to spread to regions that had not previously offered shared mobility.

Transportation has traditionally been a fossil-fuel powered industry, and for this reason greenhouse gas emissions remain stubbornly difficult to reduce. At the same time, the rapid expansion of TNC services has raised important questions about their impact on travel behavior, vehicle miles traveled (VMT), vehicle ownership, and greenhouse gas (GHG) emissions. This study was conceptualized to contribute to the understanding of these dynamics. At the outset of the study, we hypothesized that TNC services would have different impacts based on passenger circumstances. Some travelers might increase their overall VMT due to making trips that they previously would not have made at all or due to shifting from public transit or active modes, such as walking or biking. Other passengers might decrease their overall VMT by driving less, selling a vehicle, or forgoing a personal vehicle purchase. In other words, there is a distribution of change among TNC passengers who both increase and decrease their VMT and GHG emissions. The broader presence of TNC services also comes with the public and private costs of additional miles driven between passenger pickups, also known as deadheading or empty miles. One of the critical questions our study set out to address was: What is the balance of these effects or the net impact that TNC services (both private and pooled) have on travel behavior, VMT, and GHG emissions? The findings presented in this study shed light on whether TNC services like Lyft and Uber are decreasing or increasing VMT and GHG emissions. Furthermore, the study sheds light on the general impact and performance conditions that facilitate the overall direction of shift in one direction or another.

Since the collection and analysis of the data applied in this study, a number of significant events have occurred. Most notably, the COVID-19 pandemic imposed an unprecedented disruption on the norms of human interaction and transportation that had otherwise persisted for the last century. Human proximity within shared spaces, long accepted as a given, had to become restricted and tightly managed. The results of these developments globally upended many forms of transportation, work life, the economy, urban living, and other longstanding conventions of societal interaction. TNCs today naturally require in-vehicle human proximity and their services were greatly impacted as part of this global disruption. They have yet to fully recover to pre-pandemic levels of activity. The results of this study reflect a world and an industry operating before the pandemic. In that sense, they represent findings that are historical to the operations and behavioral responses of that pre-pandemic world. However, they can serve to inform the relative magnitude of impacts that have occurred within the markets evaluated. The similarity of these impacts to those of the future post-pandemic world will be a function of many factors. The results from this and other research may serve as benchmarks on performance measurements to build and improve upon.

The study evaluated the net impacts in three major U.S. markets: San Francisco, Los Angeles, and Washington, D.C., using various original data sources collected from mid 2015 to early 2017. In addition, this report assessed the impacts that pooled services (operating before the pandemic) had on VMT and GHG emissions and contrasts these effects with those of private TNC services. Lyft and Uber collaborated on the development of methods for aggregating key platform data and connecting information to the original survey data. To obtain a comprehensive picture of the net impacts of TNC services, we used six main data sources:

- A passenger survey that drew 8,630 respondents across three core-based statistical areas (CBSAs) (San Francisco, Los Angeles, and Washington, D.C.) to capture self-reported changes in travel behavior and vehicle ownership since the introduction of TNC services.
- A control survey, with 1,650 respondents, to compare sociodemographic and travel behavior trends between those who use TNC services and those who do not.
- A driver survey, with 5,034 responses, to investigate driver behavior, home and primary passenger market locations, and vehicle characteristics across the three study markets.
- Operator activity data from Lyft and Uber related to aggregate mileage and trips in the three CBSAs.
- San Francisco driver registration data, which provided additional insight into the home locations of licensed drivers in the city.
- Vehicle registration data from each CBSA, which provide insight into trends in overall vehicle registrations and registrations per capita (18+), during the decade in which TNCs have arisen but prior to the pandemic.

Through our analysis, we document the behavioral impacts, estimate the net effects on VMT and GHG emissions, and generate recommendations for operators and policymakers to consider as Lyft, Uber, and similar services continue to emerge and evolve in the mobility landscape of cities.

Background: Previous Work and Literature

As Lyft and Uber have become ubiquitous in American cities, policymakers, advocates, and researchers have sought to understand how these services are changing travel behavior and affecting the environment. Several studies have investigated how TNC impacts the use of other transportation modes, as well as the sociodemographics of passengers who use these services. Less has been known about the impacts on vehicle ownership, VMT, and GHG emissions. Researchers have turned to a wide range of methodologies to measure the impacts of TNCs, including using survey results to determine behavioral trends and analyzing samples of passenger and vehicle activity data.

In this section, we discuss TNC study findings that have focused on mode substitution, vehicle ownership, and VMT. We also review findings on trip characteristics, traffic congestion, and passenger demographics. Much of the research that has been done to date, similar to this study, covers the TNCs as they operated before the pandemic.

Mode Substitution Impacts

A number of studies assessing the impact of TNC services on modal shift have found that passengers are either substituting a trip they formerly made with another transportation mode (public transit, driving, walking, biking, etc.) or making a new trip they otherwise would not have made without the availability of TNC services (i.e., induced demand). There have been conflicting conclusions regarding the extent to which TNCs competes with public transit. While some studies conclude that TNCs are largely not substituting for public transit trips (Feigon and Murphy 2016; Hampshire et al. 2017; Feigon and Murphy 2018), several others suggest that a significant portion of travelers do substitute TNCs for public transit, biking, and walking (Rayle et al. 2016; Henao 2017; Clewlow and Mishra 2017; Gehrke et al. 2018; NYCDOT 2018).[1]

Past surveys show that the degree to which TNCs substitute for other travel modes varies by city and land-use context (as shown in Table 5). Except for the study in Austin, Texas (Hampshire et al. 2017), the Table 5 shows what transportation mode respondents would have used if TNC services were not available. Denser cities like New York City, Boston, and San Francisco exhibited some of the highest proportions of passengers who would have used public transit for their last TNC trip, had TNCs been unavailable. The studies by Clewlow and Mishra (2017) and Feigon and Murphy (2016) employed different methodologies than the Rayle et al. (2016), Gehrke et al. (2018), Henao (2017), Alemi et al. (2017), and NYCDOT (2018) studies. Clewlow and Mishra (2017) asked which other transportation modes the respondents would have generally used instead of TNC services, while the Rayle et al. (2016), Gehrke et al. (2018), Henao (2017), Alemi et al. (2017), and NYCDOT (2018) studies asked what respondents would have used in place of their most recent TNC trip. The first of these methodologies asks for a generalization as opposed to an answer about a specific trip. This generalization does not allow for a representative snapshot of TNC mode replacement, and the low taxi mode replacement share in the Clewlow and Mishra (2017) study as compared with the other studies

[1] Mode replacement studies employ various methodologies, including the survey instrument used and the analysis methods chosen. Different methodologies can have a large impact on findings.

may be the result of the differences in survey question design. In addition, results in the Clewlow and Mishra (2017) and the Feigon and Murphy (2016) studies were aggregated across seven U.S. cities. Results in the Alemi et al. (2017) study were aggregated across multiple locations in California as well.

The mode replacement in the Feigon and Murphy (2016) study included a survey population of individuals who use TNCs more than any other shared mode (bus, train, carsharing, and bikesharing). This methodology represents a specific subset of frequent TNC passengers. The Alemi et al. (2017) and NYCDOT (2018) studies allowed respondents to select more than one mode to indicate how they would have made their last trip. The Hampshire et al. (2017) study was unique from the other seven as it analyzed behavioral change due to the suspension of Lyft and Uber in Austin in mid-2016. The study's survey instrument displayed historical trip data to enable respondents to view their last Lyft or Uber trip in the Austin area before asking how they would have made this "pre-suspension" trip.[2]

Table 5. TNC Mode Substitution Impacts * † ‡

Study Authors/ Location/ Year of Survey	Rayle et al.* San Francisco 2014	Henao* Denver and Boulder, CO 2016	Gehrke et al.* Boston 2017	Clewlow and Mishra† 7 U.S. Cities†† Two Phases, 2014–16	Feigon and Murphy‡ 7 U.S. Cities†† 2016	Hampshire et al.** Austin, TX 2016	Alemi et al. ‡‡ California 2015	NYCDOT ‡‡ New York City 2017
Drive (%)	7	33	18	39	34	45	66	12
Public Transit (%)	30	22	42	15	15	3	22	50
Taxi (%)	36	10	23	1	8	2	49	43
Bike or Walk (%)	9	12	12	23	18	2	20	15
Would Not Have Made Trip (%)	8	12	5	22	1	-	8	3
Carsharing/ Car Rental (%)	-	4	-	-	24	4	-	-
Other/ Other TNCs (%)	10	7	-	-	-	42 (another TNC) 2 (other)	6 (van/ shuttle)	-

* Survey question: "How would you have made *your last trip*, if TNC services were not available?"
† Survey question: "If TNCs were unavailable, *which transportation alternatives would you use for the trips* that you make using TNC services?"
‡ Survey crosstab and question, for respondents that use TNCs more often than any other shared mode: "How would you make *your most frequent (TNC) trip* if TNCs was not available?"
** Survey question: "How do you currently make trips like the last one you took with Uber or Lyft, now that these companies no longer operate in Austin?"
†† The impacts in these studies were aggregated across Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, and Washington, D.C.
‡‡ These studies allowed multiple responses to the question: "How would you have made your most recent TNC trip (if at all) if these services had not been available?" Therefore, the percentages add up to more than 100 percent, making it challenging to directly compare to the other studies.

[2] These methodological differences should be considered when comparing mode replacement results among the studies in Table 1.

The studies in San Francisco (Rayle et al. 2016), Boston (Gehrke et al. 2018, and New York City (NYCDOT 2018) all found that if TNC services were unavailable, a greater proportion of respondents would have used public transit (30 percent, 42 percent, and 50 percent, respectively) than would have driven (7 percent, 18 percent, and 12 percent, respectively). Conversely, the studies in Colorado (Henao 2017) and Austin (Hampshire et al. 2017) found personal vehicle driving to be the most common replacement mode, in TNC's absence (33 percent and 45 percent, respectively). The two seven-city studies and Alemi et al. (2017) also found personal driving to be the most common replacement mode.

In the Austin study (Hampshire et al. 2017), a large proportion (42 percent) of respondents claimed they replaced what would have been a Lyft or Uber trip with another TNC service. This study differed from the others because it did not ask respondents what mode they would have used in the absence of all TNC services, but rather focused on the suspension of two TNC companies in particular (Lyft and Uber) in Austin.

TNC impacts are still evolving, and will continue to evolve following recovery from the pandemic. One of the first exploratory studies, Rayle et al. (2016), collected responses from 380 passengers in San Francisco during the spring of 2014. This study showed that if TNCs were not available, 36 percent of respondents would have used a taxi. Among the studies, this is one of the highest proportions of respondents claiming they would have used a taxi (only Alemi et al. [2017] and NYCDOT [2018] are higher, but they allowed for multiple responses). However, this could be partially attributed to the differences in taxi markets across cities. This finding may also reflect changes in TNC mode replacement over time, as these services attract a more diverse range of passengers. Modal shift and city-specific differences are explored further in our study.

Impacts on Public Transit

Studies have also investigated the effect that TNCs have on aggregate public transit ridership in U.S. metropolitan areas. One of these studies examined the impact of Uber's entry on public transit ridership between 2004 and 2015 across the 196 U.S. Metropolitan Statistical Areas (MSAs) where Uber has had a presence. This study found that Uber is a complement for the average transit agency, increasing ridership by 5 percent after two years (Hall et al. 2018). The study used a difference-in-differences approach by comparing how public transit ridership changed in cities where Uber entered relative to cities where Uber had not yet entered. The authors use the share of Google searches for "Uber" to approximate the active drivers per resident at the MSA level, which they use as a proxy for longitudinal Uber growth rates.

A similar study, by Feigon and Murphy (2018), examined TNCs and public transit ridership trends in Chicago, Washington, D.C., Los Angeles, Nashville, Seattle, and San Francisco from 2010 to 2016. The authors concluded there was no relationship between the peak-hour TNC trip share and changes in public transit ridership in these cities. A different study using data from 2002 to 2018 found an overall effect opposite to the one found by Hall et al. (2018): that the entry and presence of TNCs cumulatively decreased heavy-rail ridership by 1.29 percent per year and bus ridership by 1.70 percent per year (Graehler et al. 2018). The authors analyzed how bikesharing and TNCs affected public transit ridership in 22 of the largest U.S. cities by using data from the National Transit Database (NTD) and controlling for various other important factors, including public transit service cuts, population and employment growth, vehicle ownership rates, and gasoline prices. This study took into account TNC's effect on public transit up to 2018. The authors used a proxy for TNC growth and made the assumption that Lyft and Uber use grows linearly starting from the date it is introduced into a new market.

Additional research are needed to further assess Lyft's and Uber's impact on public transit ridership. To investigate when public transit substitution occurs and by whom, a study by Gehrke et al. (2019) examined what passenger and trip attributes are more likely to result in the replacement of public transit trips with TNC services in the Boston metropolitan area. The authors found that passengers with lower incomes and those who possess a weekly or monthly transit pass were more likely to have substituted TNC services for public transit. In addition, relatively low TNC service cost, short TNC trip times, poor weather, and unavailability of public transit were also predictive of substitution for public transit. Another study by the Metropolitan Area Planning Council (MAPC) surveyed 599 public transit riders of Brockton Area Transit Authority (BAT) and found that while 68 percent of respondents who used TNCs did not change their use of public transit due to TNCs, 22 percent reported using BAT less, and 10 percent claimed to use BAT more, due to their TNC use (MAPC 2019). The authors conclude that TNCs are one factor among many others, including historically low gas prices, increases in telecommuting, and shifting employment locations, that are casusing year-over-year declines in BAT ridership. Both aggregate trends and individual mode choices are important to account for when assessing TNC impacts on public transit.

Vehicle Ownership Impacts

Research on TNC impacts on personal vehicle ownership —including the decision to either sell or forgo purchasing a personal vehicle—is limited, with only a few studies examining this topic to date. The study by Clewlow and Mishra (2017) found that 9 percent of respondents sold one or more household vehicles due to TNCs. In a study of passengers in Denver and Boulder, Colorado (Henao 2017), approximately 13 percent of respondents reported owning fewer cars due to the availability of TNCs.

Another study of rail transit users found that 5 percent of respondents in Atlanta, 12 percent in the San Francisco Bay Area, and 21 percent in Washington, D.C., either postponed a purchase, decided not to purchase, or sold a personal vehicle due to TNCs (Feigon and Murphy 2018). A 2017 poll of respondents who said they disposed of a personal vehicle within the last 12 months found that while most respondents purchased another vehicle, 9 percent turned to TNCs as their primary form of transportation (Henderson 2017).

The Hampshire et al. (2017) study in Austin asked respondents about the effect of the mid-2016 Lyft and Uber suspension on their personal vehicle acquisitions. This study is unique because the Austin service suspension offered an opportunity to measure vehicle suppression using revealed preference survey data. It found that 9 percent of respondents acquired a personal vehicle due to the Austin suspension and another 9 percent considered purchasing one but ultimately did not. Although Lyft and Uber were not operating in Austin from mid-2016 to mid-2017, other TNC services continued to operate in their place (e.g., Ride Austin, Fasten, Fare, and Arcade City). An even larger portion of respondents may have acquired a personal vehicle if all TNC services had exited the region.

One study analyzed the impact of TNCs on vehicle registrations in U.S. cities using a difference-in-differences methodology that exploited staggered timing of Uber and Lyft market entry (Ward et al. 2021a). The authors found that TNC entry results in a 0.7 percent increase in vehicle registrations, on average. However, the researchers note significant heterogeneity across individual cities: TNC entry is associated with a significant increase in 58 (26 percent) of U.S. cities studied, but also a significant decrease in 38 (17 percent) of cities studied.

TNCs: VMT and Trips

Studies have also assessed the impacts of TNCs on VMT and trip-making. The most comprehensive studies have employed trip-level TNC activity data in San Francisco (SFCTA 2017, SFCTA 2018) and New York City (Schaller 2017a, 2017b, 2018) to analyze mileage, trip metrics, and impacts. In addition, a study initiated by Lyft and Uber released aggregate VMT data in six metropolitan regions across the U.S. using data collected during September 2018 (Fehr & Peers 2019).

Schaller (2017a) conducted an analysis with publicly available taxi and for-hire vehicle trip and mileage data in New York City. This study found that, after accounting for mileage declines in yellow cabs and personal vehicles, TNCs and other on-demand ride services (including Uber, Lyft, Via, Gett, and Juno) contributed 600 million additional miles of vehicle travel to the city's roads between 2013 and 2016. These additional miles equated to an estimated 3.5 percent increase in citywide VMT and a 7 percent increase in VMT in Manhattan, western Queens, and western Brooklyn in 2016.

The first study by SFCTA (2017) did not attempt to predict a VMT change due to TNC services. Instead, it provided insight into the proportion of TNC trips and mileage in the city of San Francisco (not to be confused with the broader San Francisco Bay Area). This study collected TNC trip data from one month in late 2016 and found that TNC trips made up 15 percent of average weekday vehicle trips within San Francisco and 9 percent of average weekday person trips within the city. In terms of mileage, this study found that TNCs represented 20 percent of average weekday intra-San Francisco VMT (trips that originate and end within city limits only) and 6.5 percent of total VMT (including regional trips starting or ending within city limits) on an average weekday. The Fehr & Peers (2019) study also examined San Francisco and found that TNCs make up 12.8 percent of San Francisco VMT and 2.7 percent of the nine-county San Francisco Bay Area VMT (using data from September 2018). The study also analyzed five other U.S. regions, finding that TNC percentages of total VMT ranged from 1.9 to 7.7 percent in core counties and 1.1 to 2.1 percent in the associated broader regions. The authors suggest these findings show that while TNCs are likely contributing to traffic congestion, the scale is overshadowed by private car and commercial vehicle travel.

Another study, conducted later in the same year by Schaller (2017b), found that utilization rates among taxis and TNC vehicles declined in New York City between 2013 and 2017, while the number of unoccupied taxi and TNC vehicles increased by 81 percent over this time period, correlating with the increased TNC popularity. This study also found that total taxi and TNC weekday mileage in the central business district increased by 36 percent from 2013 to 2017 (Schaller 2017b).[3] A third nationwide study, also by Schaller (2018), estimated that TNC services have added 5.7 billion VMT annually in nine large U.S. metropolitan areas (Boston, Chicago, Los Angeles, Miami, New York, Philadelphia, San Francisco, Seattle, and Washington, D.C.). This study also reported that private TNC services added 2.8 VMT for each personally driven mile taken off the road; when pooled TNC services are included, the number falls slightly, to 2.6 VMT for each personal vehicle mile taken off the road. A fourth study by Schaller (2021) further examined the impact of pooled services on VMT across five U.S. markets. The study found that at pre-pandemic pooling rates, there was at least a doubling of VMT when comparing ridesourcing trips (including both private and pooled) with the modes that would have been used if TNCs were not available. Using survey data and trip characteristics that the author collected as a driver, Henao (2017) estimated that TNCs lead to 83.5 percent more VMT than

[3] This study considered only taxi and TNC vehicles and did not assess potential personal vehicle driving changes during this period.

would have been driven had TNCs not existed. Estimates of deadheading and mode substitution were taken into account in the Schaller (2018), Schaller (2021), and Henao (2017) change-in-VMT calculations. Impacts on personal vehicle ownership due to TNCs were not considered within these calculations.

All of the studies referenced in this section accounted for both in-service and out-of-service miles in their VMT calculations. Out-of-service (deadheading) miles are miles driven by TNC drivers while awaiting a passenger request and driving to the passenger pickup point. Henao (2017) estimates that about 1.6 VMT were expended for every passenger mile traveled in Denver and Boulder, Colorado. The Schaller study in late 2017 found that approximately 45 percent of overall TNC miles driven were deadheading miles, based on trip data from the New York City Taxi and Limousine Commission (Schaller 2017b). The California Public Utilities Commission (CPUC) found that deadheading miles made up roughly 40 percent of total TNC VMT in California in October 2017, based on data provided to the CPUC by Lyft and Uber (George and Zafar 2018). Using data from September 2018 across six U.S. regions, Fehr & Peers (2019) found that approximately 43 percent of total TNC VMT constituted deadheading miles, on average across the study regions. In addition, Cramer and Krueger (2016) found that 35.8 percent of all TNC miles in Los Angeles and 44.8 percent in Seattle were deadheading miles in 2015. These studies show that deadheading makes up a notable portion of TNC miles driven and is an important factor to consider when measuring VMT impacts.

The studies outlined in this section highlight the fact that TNC services rapidly gained adoption since their inception in the summer of 2012, and they constituted a notable share of total trips and miles in U.S. cities such as San Francisco, New York City, and others. Despite the many advances of these and other studies, it is still challenging to estimate the net VMT change due to the introduction of TNCs in cities.

Environmental Impacts

Research on the environmental and GHG emissions impacts of TNCs is limited. However, a few studies have examined environmental impact metrics associated with TNC activity. Ward et al. (2021b) examined the external costs and benefits of changes to air pollution, GHGs, congestion, crashes, and noise associated with trips shifting from other modes to TNCs. Using publicly available TNC trip data from Austin, New York, Chicago, and California, the researchers found that if all TNC trips were trips that shifted from private vehicle trips, then those TNCs trips would have caused a reduction in air pollutant emission externalities of 50 to 60 percent (due to avoided “cold starts” by the private vehicles). But they report that the same substitution of TNC trips for private vehicle trips caused an increase in GHG emission externalities of about 20 percent. This results in a combined air emission externality reduction of 3 to 12 percent. However, the authors found that this shift from private vehicles to TNCs would also increase externalities from congestion, crashes, and noise by about 60 percent. Altogether, they found the total change in external costs would be an increase of 30 to 40 percent, or about $0.35 per trip. The researchers also modeled a case where TNCs displace transit, walking, and biking, rather than personal vehicles, and found the increase in overall externalities would be about three times larger ($1.20 per trip).

Another study by the Union of Concerned Scientists (Anair et al. 2020) analyzed the GHG emissions impacts of an average TNC trip compared to other modes of transportation that TNC trips displace. The study found that emissions from a typical ride-hailing trip are about 69 percent higher than the average emissions of the trip it replaces. The authors calculated average emissions of a typical displaced trip as the emissions for each mode of transportation using unique mode shift distributions for pooled and non-pooled trips, weighted by the estimated frequency of pooled trips (15 percent) and non-pooled trips (85 percent). The authors estimated that 24 percent of non-pooled trips would have been taken using lower-carbon modes like transit, walking, or biking, or the rides would not have occurred at all. For pooled rides, the share of lower-carbon modes displaced is even higher at 36 percent.

Both of these studies generally found an increase in emissions or externalities as a result of TNCs. The insights of these studies are valuable. However, we note that both studies focus on impacts as a result of mode substitution on a per-trip basis. More broadly, there are additional considerations regarding the impacts from longer-term vehicle ownership and travel behavior changes that may affect travel patterns and resulting emissions that require further exploration.

Trip Characteristics and Congestion

Multiple studies have examined TNC trip characteristics, such as trip purpose, time of day, day of week, trip mileage, and occupancy. While TNCs are used for almost every conceivable trip type, many studies have found social and recreational trips to be the most common type (Rayle et al. 2016; Feigon and Murphy 2016; Clewlow and Mishra 2017; Hampshire et al. 2017; Henao 2017). Work-related and commuting trips also make up a notable portion of total trips. In one study, 21 percent of respondents claimed to have used TNCs to commute within the prior three months (Feigon and Murphy 2016). Rayle et al. (2016) and Hampshire et al. (2017) found that 16 percent and 14 percent of respondents' most recent trips were for work or commuting purposes, respectively. Airport rides also make up a notable share of TNC trips.

Studies that looked at when TNC services are used most frequently have found that trip volumes are highest on Fridays and Saturdays (SFCTA 2017; Feigon and Murphy 2018). A number of studies have shown that TNC trips are distributed throughout the day and evening, with increases during the morning and afternoon commute periods, as well as during later evening hours. In the Boston area, Gehrke et al. (2018) found that while the evening hours of 7 p.m. to midnight experience the greatest frequency of TNC trips, about 40 percent of weekday trips occur during the morning or afternoon commute periods. The SFCTA (2017) found that on weekdays, the peak number of TNC vehicles are in operation in San Francisco between 6:30 and 7 p.m. and on Fridays between 7:30 and 8 p.m. Conversely, a study of five U.S. cities (Chicago, Washington, D.C., Los Angeles, Nashville, and Seattle) using trip data from a major TNC company found that TNC use peaks on weekends and evenings but not during rush hours (Feigon and Murphy 2018). This study found that weekday TNC use during peak hours (7 to 10 a.m. and 4 to 7 p.m.) range from 20 percent to 27 percent of total TNC trip volume over the week, depending on the city. Similarly, a study of Lyft found that 23 percent of all Lyft trips in Los Angeles were taken during weekday commute hours (6 to 9 a.m. and 4 to 7 p.m.) (Brown 2018).

Many studies have examined time-of-day distributions of TNC trips. A study that directly assessed the impact of TNCs on traffic congestion measured the change in vehicle hours of delay due to Lyft and Uber (Erhardt et al. 2019). The study examined TNC vehicle effects on congestion in San Francisco between 2010 and 2016 and found that weekday vehicle hours of delay increased by 62% compared to 22% in a counterfactual 2016 scenario without TNCs. The study also reported that TNCs most heavily impacted traffic congestion in the downtown areas of the city and during evening peak hours. Similarly, a study of TNC trips in Chicago found that the downtown area experienced the highest density of TNC trips between March 2018 and February 2019, with 49 percent of all trips starting and/or ending in downtown (City of Chicago 2019).

Trip Distance

A few studies have employed trip-level activity data to measure the average distance of a TNC trip. The SFCTA (2017) study found the average weekday intra-San Francisco trip was 3.3 miles. The Schaller (2017a) study in early 2017 found that the average TNC trip in New York City was 5.4 miles. Schaller's late-2017 study found that during June 2017, the average TNC trip covered more mileage than the average taxi trip in New York City (Schaller 2017b). In Los Angeles, the average Lyft trip (based on data from late 2016) was 7.4 miles, with private Lyft trips averaging 7.7 miles and Lyft Line trips (now Lyft Shared rides) averaging 6.7 miles (Brown 2018). Feigon and Murphy (2018) found across five study cities that the median TNC trip length ranged from 2.2 to 3.1 miles per trip, depending on the city. However, this study employed ZIP Code Tabulation Area (ZCTA) origin-destination pairs, which offer somewhat less precise estimates of trip start and end locations than in the other four studies. These trip distance findings across studies highlight city-specific differences in TNC trip making that are likely due to variations in land-use context.

Occupancy

Rayle et al. (2016) found that half of TNC trips in the San Francisco Bay Area had more than one passenger (not including the driver), with an average occupancy of 2.1 passengers per trip across all respondent trips. However, the survey was conducted before the introduction of pooled services, such as Lyft Shared rides and uberPOOL. Henao and Marshall (2018) found an average trip-based vehicle occupancy of 1.4 passengers in the Denver and Boulder, Colorado area; the distance-weighted occupancy was 1.3 passengers without accounting for deadheading and 0.8 when accounting for deadheading. In Boston, Gehrke et al. (2019) found that trips made with pooled TNC services made up about one-fifth of total TNC trips in the surveyed population. The study also found the average occupancy for a trip was 1.52 passengers. A study of Lyft activity data in Los Angeles found that 29.2 percent of trips were made using Lyft Line, based on three months of trip data in late 2016 (Brown 2018). Similarly, data collected by the CPUC show that during the third quarter of 2017, 30 percent of TNC trips across the state of California were requested using pooled services, up from only 10 percent less than three years earlier (George and Zafar 2018). One study using data from three months of Lyft rides in late-2016 in the Los Angeles area found that while about one-third of Lyft trips were taken using Lyft Shared rides, these pooled trips were made by a small portion of riders (Brown 2020). Just ten percent of all Lyft riders were found to have made 94 percent of the pooled trips during this time period. The study also found that pooled rides more commonly occurred in denser and lower-income neighborhoods and in neighborhoods where clear racial or ethnic majorities exist. Another study using TNC trip data in Chicago found that those requesting trips to and from lower-income census tracts were more likely to use pooled services, while those taking trips to and from the airport were less likely to use pooled services (Hou et al. 2020). TNCs suspended pooling services due to the pandemic, but it is beginning to re-emerge in a few markets. Thus, understanding the degree to which users opt for pooled services, as these studies have done, is an important metric for understanding the potential for pooling. However, not all rides taken using pooled TNC services like Lyft Shared rides and uberPOOL are successfully matched. Depending on the dataset, some may still be nominally considered as a shared ride. An important consideration in the study of pooling is the matching rate and the occupancy levels associated with the matched rides. In the long run, the matching rate, which can move over time, is important to consider when evaluating the overall effectiveness of pooled services within a given market.

Passenger Demographics

Many studies have documented the demographic distributions of TNC passengers. Multiple studies have found that they tend to be younger and more highly educated than the general population (Dawes 2016; Dias et al. 2017; Rayle et al. 2016; Smith 2016; Henao 2017; Clewlow and Mishra 2017; Gehrke et al. 2018; Circella et al. 2018; Schaller 2018). For example, in the study conducted by Rayle et al. (2016), 84 percent of TNC respondents in San Francisco had a bachelor's degree or higher, compared to 53 percent among the general San Francisco population. The national-level study by Schaller (2018) found that frequency of TNC use is highest among 25- to 34-year-olds (followed by those aged 18 to 24) and by those with college degrees.

Some studies have also documented that TNC passengers have higher incomes than the general population (Dawes 2016; Dias et al. 2017; Clewlow and Mishra 2017), although other studies have found income distributions that align more closely with that of the study city's population (Rayle et al. 2016; Feigon and Murphy 2018; Gehrke et al. 2018; Brown 2018). Many studies have also found that TNC passengers tend to live in denser urban areas than the general population of the city or region (Dawes 2016; Smith 2016; Clewlow and Mishra 2017; Circella et al. 2018; Schaller 2018) and that there is a fairly even split between male and female users (Henao 2017; Hampshire et al. 2017; Gehrke et al. 2018).

Other studies have assessed the racial/ethnic distribution of TNC passengers. Some studies have found that TNC services tend to have slightly higher proportions of white passengers relative to the general population (Henao 2017; Hampshire et al. 2017), while others have found overall distributions that align closely with the regional population distribution (Gehrke et al. 2018; Brown 2018). And one study revealed discriminatory practices of drivers toward certain demographic factors among passengers. Ge et al. (2016) presented a study on the effect of a passenger's name on key performance metrics, such as wait time and cancellation rate. The results showed that those with first names more commonly associated with African Americans experienced longer-than-average wait times in Seattle and more frequent cancellations in Boston. Overall, the cancellation rate for such names was more than twice that of passengers with names more commonly associated with whites. Similarly, a study in Los Angeles County found that black passengers waited between 11 seconds and one minute 43 seconds longer for a Lyft or Uber to arrive than white passengers. However, taxi wait times for black passengers were found to be far worse. The study found that black passengers wait 52 percent longer than white passengers for a taxi ride in Los Angeles, which equates to about 6 to 15 minutes longer (Brown 2018).

Conclusion

The existing literature on TNCs and travel behavior has revealed impacts that are broad-reaching and significant. This study aims to build and contribute to this understanding of travel behavior and environmental impacts of TNCs and pooled services. It further aims to address some gaps in the literature by assessing the VMT and GHG emission impacts of private and pooled TNC services in the three study CBSAs (San Francisco, Los Angeles, and Washington, D.C.). The analysis is informed by TNC activity data provided by Lyft and Uber as well as data from surveys of three distinct populations, including passengers, a control group, and drivers. To better understand the behavioral impacts of TNCs, our study probes deeper into under-studied aspects of TNCs, including personal vehicle selling (or shedding) and suppression due to TNCs and their effects on VMT and emissions, pooled TNC matching and occupancy rates, the effect of pooled services on VMT, mode substitution, and first- and last-mile to public transit behavior (using TNCs to get to or from public transit stations), among other important metrics.

Methodological Overview

To evaluate the complete impact of shared mobility services such as Lyft and Uber, a variety of data sources are needed. These consist primarily of different forms of operator activity data and survey data.

Because users have the most awareness of their own travel and the ways in which TNC systems influence it, surveys are a key instrument employed in evaluation. Survey respondents report on travel behavior changes as a result of their Lyft and Uber use. They also estimate what they would have done if TNCs had not been available (even though this behavior is not directly observed). For instance, some Lyft and Uber passengers report that they would likely have acquired a personal vehicle if these services were not available. In this case, the need for a personal vehicle is suppressed due to the availability of TNC services. Personally owned vehicles are driven some distance every year, so the impact of vehicle suppression is the reduced use of a personal vehicle that was never acquired (i.e., reduced VMT). While survey data are used to measure changes in personal travel behavior, activity data from the operators are also necessary to estimate the VMT generated by TNCs in each target market. The various forms of data used in our analysis are discussed in further detail below.

In addition to analyzing the broader effects of Lyft and Uber on travel behavior, this study evaluates the impacts of pooled services: Lyft Shared rides (formerly Lyft Line) and uberPOOL. Before the pandemic, Lyft Shared rides and uberPOOL allowed passengers to request a ride with the option that one or more passengers may join the trip or may already be in the vehicle at pickup. As an incentive, passengers who would request a pooled service could travel at a reduced cost. Lyft Shared rides and uberPOOL were most effective when there were a sizable number of passengers simultaneously requesting pooled rides throughout the day. An unmatched Lyft Shared rides/uberPOOL ride is effectively the same as a private Lyft or Uber ride. From a VMT and emissions standpoint, Lyft Shared rides and uberPOOL could mitigate the impact of Lyft and Uber more broadly, if those using the pooled services would have otherwise driven alone or taken a solo ride. That is, some pooled TNC trips would have been private Lyft or Uber rides, while others would have been taken by public transit, taxi, a personal vehicle, or another transportation mode. The estimated impacts of Lyft Shared rides and uberPOOL, when they operated, are explored through our analysis of the most recent respondent trip (most recent to the time of survey taking) and how the respondent would have traveled in the absence of Lyft Shared rides or uberPOOL.

In the sections that follow, we discuss: 1) the target markets for the analysis; 2) passenger, driver, and general population surveys; 3) San Francisco driver licensing data; and 4) Lyft and Uber operator data (consisting of passenger, driver, and fleet attributes).

Target Markets

This study focused on three target markets for analysis: San Francisco, Los Angeles, and Washington, D.C. These markets were chosen because of their relative size, market maturity, and pre-pandemic availability of Lyft Line (called Lyft Shared rides) and uberPOOL services.

The boundaries of the target markets were defined by the U.S. Census Core Based Statistical Area (CBSA). The CBSA was used because it is a universally accepted unit that covers most if not the entire metropolitan region of interest, and because it comprises whole, indivisible counties or municipalities with U.S. Census data (2016), making population comparisons easier. The CBSA for each target market is defined in Table 6 below.

Table 6. Counties Included in Target Market CBSAs

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

Passenger, Driver, and General Population Surveys

We developed, deployed, and analyzed several survey instruments to evaluate key research questions. These survey instruments included: 1) a Lyft and Uber Passenger Survey, 2) a General Population (Control) Survey, 3) and a Lyft and Uber Driver Survey.

<u>Lyft and Uber Passenger Survey</u>

With assistance from Lyft and Uber, we surveyed passengers of both operators in the three target markets. Survey development was done in partnership with NRDC, creating opportunities for Lyft and Uber to review and provide input. Both operators disseminated the survey via email to their passengers over the course of five business days. The first launch was in July 2016 and the second in August 2016. The population was randomly distributed over five business days to more equally and accurately distribute responses pertaining to the most recent trip taken by day of the week (i.e., Monday, Tuesday, Wednesday, Thursday, Friday). On average, the survey took approximately 14 minutes to complete. The final sample sizes per market are shown in Table 7. The overall completion rate (the percentage of respondents starting the survey who finished it) was 62 percent. Respondents were entered into a drawing to potentially win one of 80 Amazon gift cards, each with a value of $50.

Table 7. Passenger Survey Sample Sizes

Market	San Francisco	Los Angeles	Washington, D.C.
Final Passenger Survey Sample Size	2,651	3,075	2,904

Lyft and Uber had limited information on where passengers live. While both operators have information such as billing zip code, it was agreed by researchers and operators that this field by itself could skew the survey population away from younger people (e.g., college students) who may have their billing zip code registered to an address far from their actual residence. Consequently, we agreed to an activity-based definition of what constituted a "passenger" in the target market.

A passenger used Lyft or Uber at least seven times between June 1, 2015 and May 31, 2016, and at least 50 percent of these trips were within the CBSA of the target city.

This definition ensured that people in the survey population were at least minimally active passengers and that at least half of their activity was in the targeted CBSA region. We balanced a desire to include active passengers with a desire to not set the threshold of activity too high. A too-high threshold would limit the measurement of impacts on passengers on the lower end of the use spectrum, which is important for understanding population impacts. While there was no precedent for defining passengers within a target market population prior to the execution of this survey, this definition worked fairly well and captured a spectrum of passenger respondents ranging from very active to minimally active users within the target CBSAs. Nevertheless, some respondents sampled were residents of regions outside of the defined target markets. While these individuals were eligible to enter the drawing and win the $50 gift card, their survey responses were not included in the final analysis.

The passenger survey focused exclusively on Lyft and Uber users and how they changed their travel behavior. We designed the questions to give respondents the opportunity to attribute impacts to Lyft and Uber. Respondents also had the option to indicate that Lyft and Uber had no influence on a particular behavior or decision, if changes occurred for other reasons. We asked questions about modal shift, changes in vehicle holdings, and annual VMT. Respondents were asked questions assessing whether they got rid of a vehicle due to the presence of Lyft and Uber, as well as whether they would acquire a vehicle if Lyft and Uber specifically disappeared. Responses to these questions were tabulated within the sample to generate an estimate of vehicles sold (or shed) and suppressed. The passenger survey was the primary instrument used to assess the impacts of Lyft and Uber on the sample population within the selected target markets. We weighted the impacts by frequency of TNC use by employing activity data provided by the operators, which we discuss further below.

In addition to collecting information on passenger behavior, we generated de-identified IDs (de-IDs) for all passengers. These de-IDs were used to match survey respondents with a subset of operator data (called passenger activity attributes) that were applied to support the analysis. These included anonymous attributes such as: passenger tenure with the service, the total number of trips, and the total miles traveled during the year of evaluation (in quintiles). By linking these de-IDs with operator data, we were able to assign observed TNC activity to each passenger respondent instead of relying on estimates of TNC frequency through the survey responses alone. Since passengers are known to use Lyft and Uber somewhat interchangeably, we were aware that a survey respondent through Lyft could also be a passenger (and potentially a more frequent user) with Uber and vice versa. Thus, we developed a tool to consistently match de-IDs across operators. This tool ensured that we would not compromise the identity of a respondent and that an operator would not be able to identify a passenger who was using both services. We developed a procedure of hashing and encryption that produced consistent identifiers across the operators that did not contain personal information. The encryption between our team and separately with Lyft and Uber added a layer of protection, making the presence of a particular de-ID on the other platform indeterminable. This involved the operators hashing emails with a shared key. Hashing is like one-way encryption. A string that is hashed cannot be decrypted back to the original string, even if the user knows the key that was applied to the hash algorithm. Using the key shared among Uber and Lyft ensured that a single email would hash to the same scrambled output. When researchers decrypted the de-IDs, the common hashes could be used to match passenger attributes across respondents.

General Population (Control) Survey

Our team also conducted a general population (control) survey in the three target markets. We collected a total of 550 respondents for each market; respondents each received a guaranteed incentive of $4. We deployed this survey from December 2016 to March 2017. It took respondents approximately 12 minutes to complete this survey.

The control survey provided us with a separate approach for evaluating how Lyft and Uber impact the behavior of the general population. This survey was unlike the passenger survey, which focused exclusively on Lyft and Uber customers, and it produced a general population sample to compare Lyft and Uber users with nonusers along the same questions. For example, we included questions in the general population survey about public transit use, vehicle ownership, and other travel behavior, so we could better compare the travel behavior of TNC users with nonusers and identify overall population trends. The control survey also allowed us to compare sociodemographic differences between TNC users and nonusers. The control survey helped us more accurately isolate and quantify the effects of Lyft and Uber by examining the travel behavior profiles of those who did and did not use TNC services.

A survey software company deployed the general population survey. We provided the survey company with the distribution of five demographic attributes for each target market CBSA using the American Community Survey five-year estimates of 2014 (U.S Census ACS, 2014). These attributes were gender, age, race/ethnicity, income, and education. We generally drew the panel to match the sociodemographic distributions of the general population within each target market (the CBSA) as closely as possible. We analyzed the general population survey to evaluate how travel and sociodemographic patterns differed more broadly between Lyft and Uber users and nonusers.

Driver Survey

We also conducted a short survey of Lyft and Uber drivers in the three target markets. We designed this survey with input from both operators, who sent the survey to drivers in the target markets in late October and early November 2016. The survey was deployed and response data were collected at UC Berkeley. Respondents took, on average, about eight minutes to complete the survey, and the completion rate was 96 percent. Drivers could opt into a drawing to win one of 60 $50 Amazon gift cards. The final sample sizes for the three markets are shown in Table 8, below.

Table 8. Driver Survey Sample Sizes

Market	San Francisco	Los Angeles	Washington, D.C.
Final Driver Survey Sample Size	1,300	2,568	1,166

Previous work, including media reports, suggests that some TNC drivers travel significant distances to reach major Lyft and Uber passenger markets. We designed our survey instrument to provide insight into the scope and scale of this behavior. We asked driver survey respondents to answer several questions about their travel and location, including their home zip code and typical passenger market, so that we could assess how far drivers typically travel to reach their primary passenger market. The survey also asked questions about driver behavior with respect to engaging the app (e.g., miles typically driven before logging in to the Lyft and/or Uber apps) and total distances driven as a result of Lyft and Uber activity. We used this information as well as other questions to estimate additional distances that drivers traveled to drive for Lyft and Uber. These data provide insights on the unseen magnitude of driving that is not registered by the Lyft and Uber apps.

Driver Business Registration Data

To support the driver survey, we obtained a public data set for the city of San Francisco, which contained the business registration locations of transportation network company (TNC) drivers and the registration date. The data set provided indicators as to whether the registered businesses were drivers with Lyft or Uber. This data set allowed an analysis of the spatial distribution of individual drivers who registered their business from 2014 to early 2017. Unlike the driver survey, where driver frequency was collected with location pairs, these data could not provide insight into the frequency of service as correlated with locations. But as a nearly comprehensive population, it provided context as to the distribution of home locations for drivers registered as businesses providing services with Lyft and Uber. This analysis is presented in the results section with the driver survey for the San Francisco CBSA and serves as an additional data source for examining where TNC drivers reside.

Activity and Emission Data

To support the survey analysis, Lyft and Uber provided passenger and driver activity data to our research team. These data were necessary to make several assessments. First, we requested specific distributions of activity among passengers and drivers to understand how well the responses to the surveys represented the broader population of passengers and drivers. We linked passenger activity attribute data to the passenger survey to evaluate whether adjustments (or weights) were necessary to better match the sample with the passenger population. This provided a more precise measurement of activity (for miles and trips) than can be provided by survey responses alone. For example, if a respondent was a more frequent user than the average Lyft and Uber passenger, we adjusted our analysis of their impacts accordingly. For this study, we measured the change in the raw sample. Then we scaled the impacts to match the frequency of use to the broader population by applying weights. This was done because surveys about shared mobility services, such as carsharing or bikesharing, can be skewed in favor of respondents who are more frequent users (i.e., respondents who use a service more frequently are more likely to take a survey about it). Related to this, respondents who use a service more frequently are also more likely to be substantively impacted by it. This can lead to a bias in the impact results (generally an overestimation), if the point of the survey is to make population-level conclusions. Weighting by activity data (e.g., frequency of use, distance of travel, etc.) can adjust these impacts to more accurately reflect the likely balance of impacts at the population level.

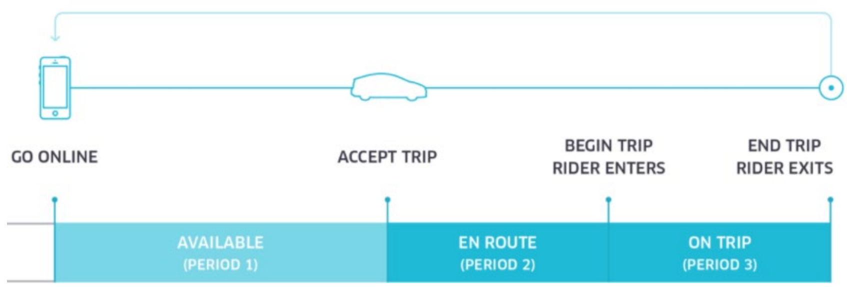
Below we discuss five types of data: 1) vehicle activity data, 2) combined average miles per passenger, 3) intersection of Lyft and Uber passenger populations and driver open miles, 4) pooled service impacts of Lyft Shared rides/uberPOOL on VMT, and 5) GHG emissions and fuel economy.

Vehicle Activity Data
We collected operator data to determine the miles driven by Lyft and Uber drivers. Passengers can estimate the distance that they travel using TNC services (albeit imperfectly), but they cannot estimate the other distances logged by drivers. With data made available by Lyft and Uber, driving was assessed in three phases. For this report, we defined these phases as follows:

> 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.
>
> 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 was not being shared as a Lyft Shared rides or uberPOOL trip.
>
> Fare Phase (Period 3): Drivers have an assigned passenger in the vehicle and are transporting this person to his or her destination.

Lyft and Uber have their own terminology for these phases, as displayed in Figure 2.

Figure 2. TNC Trip Phases



Source: Uber Blog 2015

Due to competitive (and proprietary) concerns, the operators were very sensitive to providing total VMT during the time frame of the passenger survey. The study team, with input from Lyft and Uber, agreed to instead report miles per passenger, defined as followed:

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

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.

This measure defines the average miles driven per member of the passenger population. The net VMT and emission impacts were calculated by re-weighting the sample by the frequency-of-use distribution of the passenger population in each market. Thus, if it was found that the overall passenger population used these services less frequently than respondents in the survey sample, the impact results of the passenger survey sample were adjusted accordingly. This re-weighted sample was used to calculate VMT and emission impacts from the behavioral change of the population. The population-level driving per passenger and behavioral change of the population were evaluated together to assess the net impacts of Lyft and Uber in the target markets. These calculations are further discussed in the results section.

Combined Average Miles Per Passenger

While the total miles driven per passenger per operator is a useful metric, it has a few problems. First, as noted earlier, it is common knowledge that many people use both apps. In other words, many of the same passengers are in both operator populations. But on the Lyft and Uber platforms, each user is unique. Operators cannot compare or share information to determine how many of their passengers also use the other platform. This means that the miles per passenger metric defined above may be double-counting passengers. As mentioned earlier, the operators provided us with passenger activity attributes, such as frequency of use and miles traveled. We used the survey and these attributes to determine the share of passengers that are members of both Lyft and Uber and adjusted the ratios to account for double-counting in the passenger population.

The same overlap occurs with miles driven. It is well known that many drivers actively use both apps, sometimes simultaneously. Lyft and Uber agreed that during the Open Phase of driving, miles registered on one platform may be simultaneously registered by the other platform. If a driver is open to passengers on both platforms, then for every mile driven during this phase, two miles are measured (one by each operator). The operators also agreed that during the Fetch and Fare phases of driving, the measurement of miles was likely to be mutually exclusive (i.e., there was no double counting). Drivers were likely to log out of the platform that they were not using; otherwise, they might have to decline a passenger and damage their rating. Therefore, we agreed that some discounting of miles driven in the Open Phase was needed to prevent double-counting and an overestimate of miles driven on both systems. For these reasons, we developed a methodology for combining the miles-per-passenger ratio from Lyft and Uber into one single ratio, which we use in our calculation of VMT and greenhouse gas (GHG) impacts. We needed to estimate the intersection of two specific metrics to calculate the combined average miles per passenger, as described below:

Intersection of Lyft and Uber Passenger Populations and Driver Open Miles

We first estimated the overlap in the passenger populations of Lyft and Uber to weight the ratios we received from the operators to better reflect the total passenger populations within the three study markets. To estimate this overlap, we calculated the proportion of survey respondents who were passengers of both Lyft and Uber as a share of the total sample population. We assumed that these proportions (or percentages) found in the sample were a best estimate of the proportions in the overall populations in each target market. Using this assumption, we calculated the weighting factors needed to adjust the miles-per-passenger data we received from each operator and account for double-counting of open miles. This adjustment is based on an imperfect assumption, but we considered it preferable to making no adjustment.

We then estimated the overlap of driver open miles that were double-counted on the Lyft and Uber platforms. Both operators disclosed the percentage of open miles driven in each of the three markets. This allowed us to calculate the ratio of open miles driven on Uber to open miles driven on Lyft. To determine the percentage of overlapping open miles between operators, we performed a sensitivity analysis (from 0 percent to 30 percent of open miles overlap, in increments of 5 percentage points). For the final calculations, we used the assumption of a 5 percent overlap of open miles between operators, an estimate that was informed by discussions with other researchers focused on the same topic. The open miles overlap calculation and sensitivity analysis are outlined further in the VMT and GHG impacts section of this report.

App Off Driving

A final adjustment was made in consideration of driving conducted for Lyft or Uber but is not recorded by the app. This was "app-off" driving to or from the passenger market, sometimes referred to as "Period 0." This driving is due to Lyft and Uber, but it is not measured by the operators. It also only applies to certain drivers and is most consequential for those drivers that travel long distances to serve specific passenger markets in high demand. To estimate this driving, drivers were asked, for an average month, "Approximately how many miles have you driven specifically due to driving with Uber and Lyft?" They were then asked: "If you can, please estimate what percent of these miles is driven with both apps off (going to and from markets or not looking for passengers)." We applied the response to these questions to generate a relative percentage of app-off driving due to Lyft and Uber for the driver population within each market. This was then applied to scale up the operator miles per rider in each market.

Pooled Service Impacts of Lyft Shared Rides/uberPOOL on VMT and GHGs

In addition to calculating VMT and GHG impacts using population-level miles-per-passenger data, we also explored the implications of pooled services (Lyft Shared rides and uberPOOL) for VMT and GHG emission impacts of TNC services. Pooled TNC services had to be suspended due to the pandemic. The results discussed in this report cover the experience pooling as it operated prior to the pandemic. Pooled services are starting to re-emerge within a few cities. As pooled services return to more regions, they have the potential to mitigate a portion of the overall TNC miles driven by pooling passengers with similar origins and destinations. While we can say intuitively that these services produce fewer miles per passenger than a private Lyft or Uber ride, they may also be introducing additional competition with public transit and active transportation modes due to their lower cost relative to private TNC services. In other words, while a pooled TNC passenger who would have otherwise taken a private Lyft or Uber or driven alone decreases his or her VMT, a passenger who would have otherwise used public transit or an active mode instead increases VMT when using pooled TNC services. Due to competitive (and proprietary) concerns of the operators, we did not receive disaggregated trip-level data specifying whether a trip was made using Lyft Shared rides or uberPOOL. However, the trip mileage generated by these pooled services is reflected in the aggregate miles-per-passenger data we received from the operators, as described above.

To estimate the specific VMT and GHG implications of pooled services, we used our passenger survey to analyze metrics from respondents' most recent trips, including data on match rates. We calculated the average percentage change in VMT and GHG emissions per passenger across each study city by using stated mileage, trip occupancy (with other Lyft Shared rides and uberPOOL passengers), and mode replacement responses. By comparing the VMT per passenger from a respondent's most recent pooled TNC trip and in a hypothetical scenario without Lyft Shared rides or uberPOOL, we calculated the change and percentage change in VMT and GHG per passenger of the pooled services. The results and methodology for these calculations are outlined in further detail in the analysis of the most recent TNC trip and VMT and GHG impact sections.

GHG Emissions and Fuel Economies

The TNC impact on GHG emissions is a key metric of interest for the public, policymakers, and operators. We translated the VMT impacts to GHG impacts by using fuel economy factors derived from the U.S. Environmental Protection Agency's (EPA) fuel economy database. The passenger survey collected the make, model, and year of vehicles personally owned by respondents, as well as those sold due to the availability of TNCs. For Lyft and Uber vehicles, the operators provided data that allowed us to calculate the distribution of fleet fuel economy and produce averages to apply to VMT generated by TNC activity. Using these data, we computed the average (harmonic mean) Lyft or Uber vehicle to have a fuel economy of 28 miles per gallon (mpg) in San Francisco, 28 mpg in Los Angeles, and 25 mpg in Washington, D.C. For suppressed vehicles, those that would have been acquired an automobile in the absence of TNC services, we assumed a fuel economy of 31 mpg, since this is similar to the generally newer vehicles in the Lyft and Uber fleet. In the sections that follow, we present the results of this research across all survey and operator data types collected.

Passenger Survey—Results and Discussion

The following sections present results from the passenger survey and discuss key findings. The passenger survey sections include: 1) sociodemographics, 2) mode use and modal shift impacts, 3) impacts of Lyft and Uber on vehicle ownership, 4) impacts on VMT and GHG emissions, and 5) analysis of the respondent's most recent TNC trip and associated impacts.

Sociodemographics—Passenger Survey

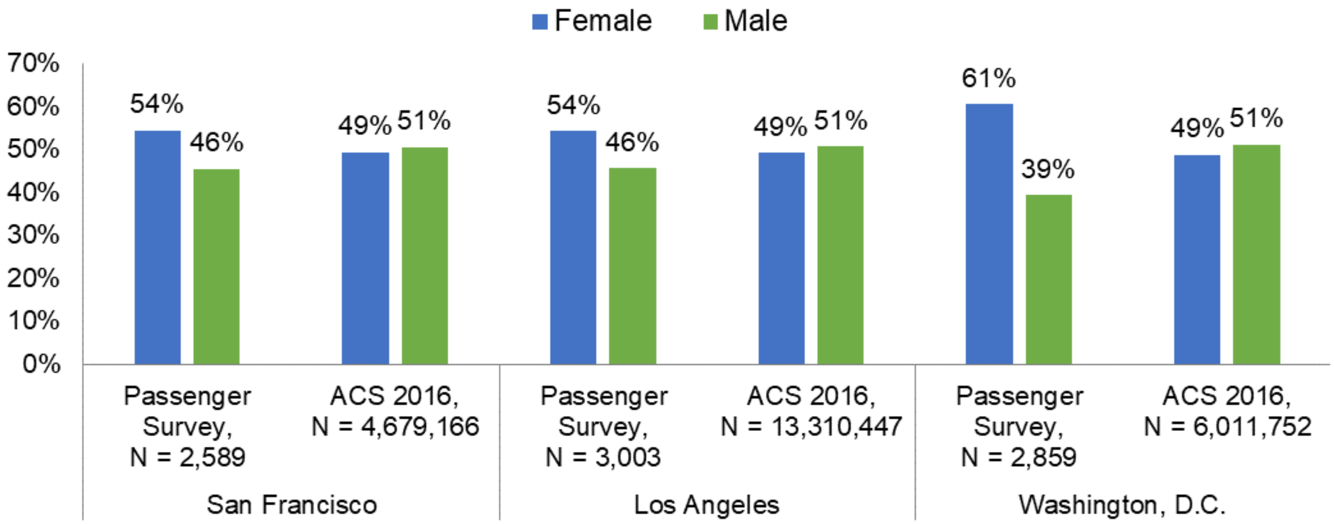
To better understand the demographic makeup of TNC passengers, we focused on seven sociodemographic factors in the passenger survey: gender, age, race/ethnicity, income, education, household size, and households with children. To compare the sociodemographic distributions of TNC passenger respondents with the general population in each corresponding area, we used the 2016 five-year estimates from the American Community Survey (ACS) for each target market core based statistical area (CBSA). TNC passengers are typically 18 years and older, and the ACS 2016 data similarly reflect this age range.[4]

Gender

Across all markets, the majority of passenger survey respondents were female (Figure 3). In comparison, the gender split in the general population (U.S. Census ACS 2016) is fairly even, suggesting that the passenger survey population is disproportionately female in each of the target markets. Washington, D.C., shows the largest gap, with females outnumbering males by 22 percentage points. This disproportionately female gender makeup may also suggest that women were slightly more likely to respond to the passenger survey.

[4] The ACS 2016 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.

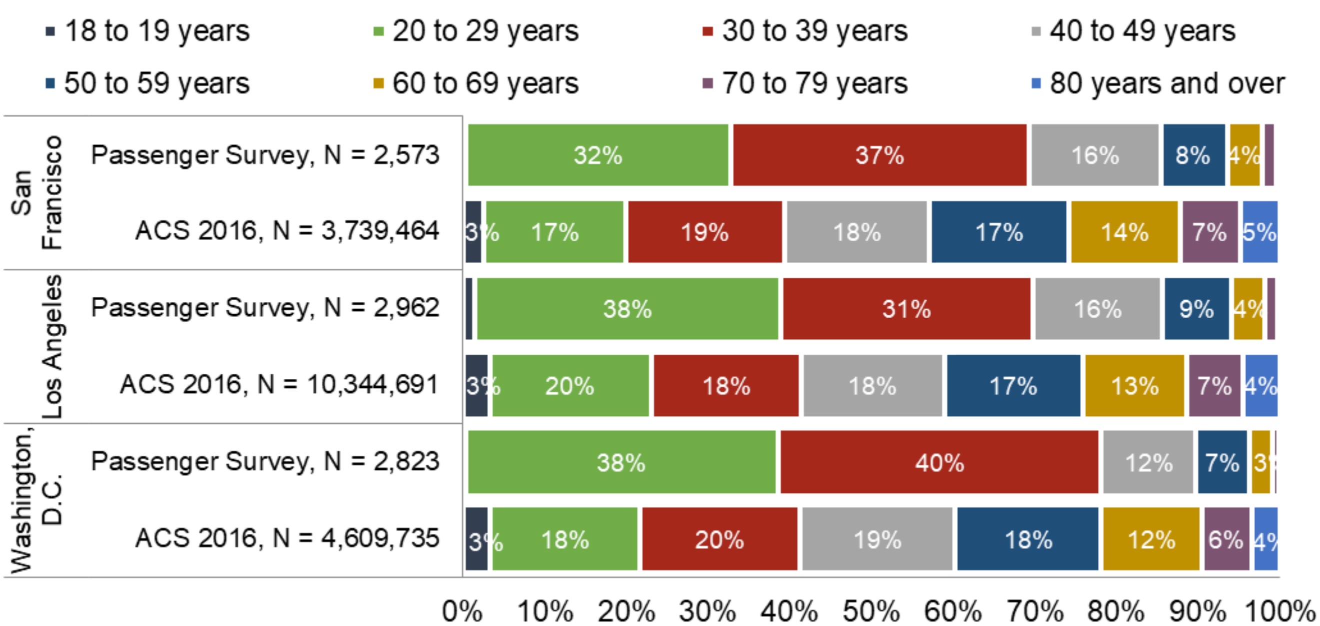
Figure 3. Passenger Survey Gender Distribution



Age

Across all markets, the passenger survey sample population was proportionally younger than the CBSA population, with the majority of respondents under the age of 40 (Figure 4). In all markets, about one-third of the passenger survey respondents were 20 to 29 years old, nearly double the percentage in the general populations. Another one-third of respondents were between the ages of 30 and 39. In contrast, only about 20 percent of the overall market populations fell into this age group. Only 10 percent to 15 percent of passenger survey respondents in each market were 50 years or older, whereas this age cohort comprised over one-third of the population in each of the target CBSAs.

Figure 4. Passenger Survey Age Distribution



Race/Ethnicity

Table 9 shows the passenger survey race/ethnicity distribution along with the ACS 2016 distribution. Across all three markets, the proportion of white respondents in the passenger survey was larger than in the CBSA populations, ranging from 17 to 19 percentage points higher depending on the market. The proportions of those identifying as Asian matched up closely between the passenger survey and ACS 2016 in each of the three markets, while Hispanic or Latino and African American survey respondents were generally underrepresented. The proportions of Hispanics and Latinos in the passenger survey were less than half the proportions that existed in the corresponding CBSA populations. Washington, D.C., had the largest discrepancy in African American respondents; where 25 percent of the overall population was African American, in contrast to 13 percent of the passenger survey population.

Table 9. Passenger Survey Race/Ethnicity Distribution

	San Francisco		Los Angeles		Washington, D.C.	
	Passenger Survey, N = 2,454	ACS 2016, N = 4,577,530	Passenger Survey, N = 2,826	ACS 2016, N = 13,189,366	Passenger Survey, N = 2,689	ACS 2016, N = 6,011,752
White	59%	41%	49%	30%	64%	47%
Black or African American	3%	7%	5%	6%	13%	25%
American Indian or Alaska Native	0.4%	0.2%	0.4%	0.2%	0.2%	0.2%
Asian	21%	24%	16%	15%	10%	10%
Native Hawaiian or Pacific Islander	1%	1%	1%	0.3%	0%	0.1%
Hispanic or Latino	8%	22%	22%	45%	6%	15%
Two or more races	8%	4%	7%	2%	6%	3%
Other	0%	0.4%	0%	0.3%	0%	0.3%

Income

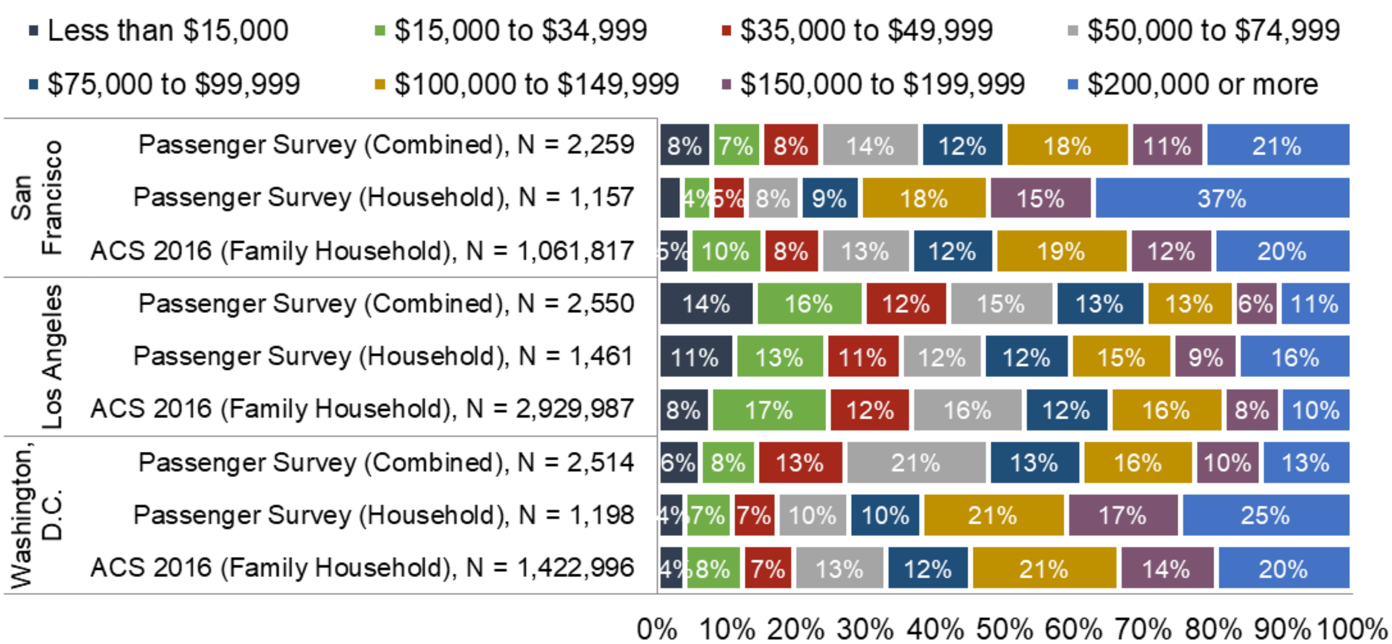
Across all three markets, respondent household incomes skewed toward higher incomes relative to the respective general populations.[5] In San Francisco, 71 percent of passenger survey households had incomes of $100,000 or more, compared with 52 percent in the overall CBSA. This difference is less pronounced in Los Angeles and Washington, D.C., although even in those cities, the survey households earning $100,000 or more exceeded the CBSA populations by 6 to 7 percentage points. Note that the percentages or numbers discussed in this report are sometimes slightly different than those displayed in corresponding figures or tables due to rounding.

In each market, around half of the passenger respondents lived in family households: 51 percent in San Francisco, 57 percent in Los Angeles, and 48 percent in Washington, D.C. To account for the variety of housing- and income-sharing situations in the target markets, the passenger survey distinguished between those living in family households (living with children, a partner, relatives, or parents) and

[5] Respondents were asked to indicate their gross 2015 pre-tax income (the most recently completed year before the survey).

individuals in nonfamily households (living alone or with housemates/roommates).[6] This distinction is directly relevant for assessing the impacts of TNCs and other shared mobility modes; many people who use these services were in nonfamily households because they were younger and lived in urban environments. To balance the comparison of the sample incomes with those of the population, Figure 5 below presents the comparative distributions of combined household and individual income, and household income separately, alongside the income distribution of family households from the ACS 2016. Table 10 presents the broader measure of the per capita income in each CBSA against the average income per person of all passenger survey respondents (both households and individuals).

Figure 5. Passenger Survey Combined and Household Income Distribution



For Table 10, average income was approximated by summing the midpoint values of each income range and dividing by the aggregate number of household members (total people) in our passenger survey for each market. The average income per person in the passenger survey ranged from 23 percent to 34 percent higher than the CBSA income per capita, depending on the market. These findings indicate that passenger survey respondents had higher incomes than those found in their respective CBSAs, on average.

[6] The ACS classifies family households and nonfamily households uniquely. People who are related and living together make up a family household. The Census also classifies roommates who are not related as nonfamily households. Within such households, the income of two or more roommates is summed to produce a nonfamily household income, and the Census reports this distribution separately. In this study, we classify households as "individuals with whom you live and with whom you share income." Respondents identified as households (living with children, a partner, relatives, or parents) were asked to report their total household income, while those classified as individuals (living alone or with housemates/roommates) were asked to report their individual income. However, the Census does not report income information of individuals in nonfamily households, only their collective income. This aggregation may underreport the purchasing power of individuals, since most such households do not pool income for big decisions or share in the purchase of major assets (such as vehicles).

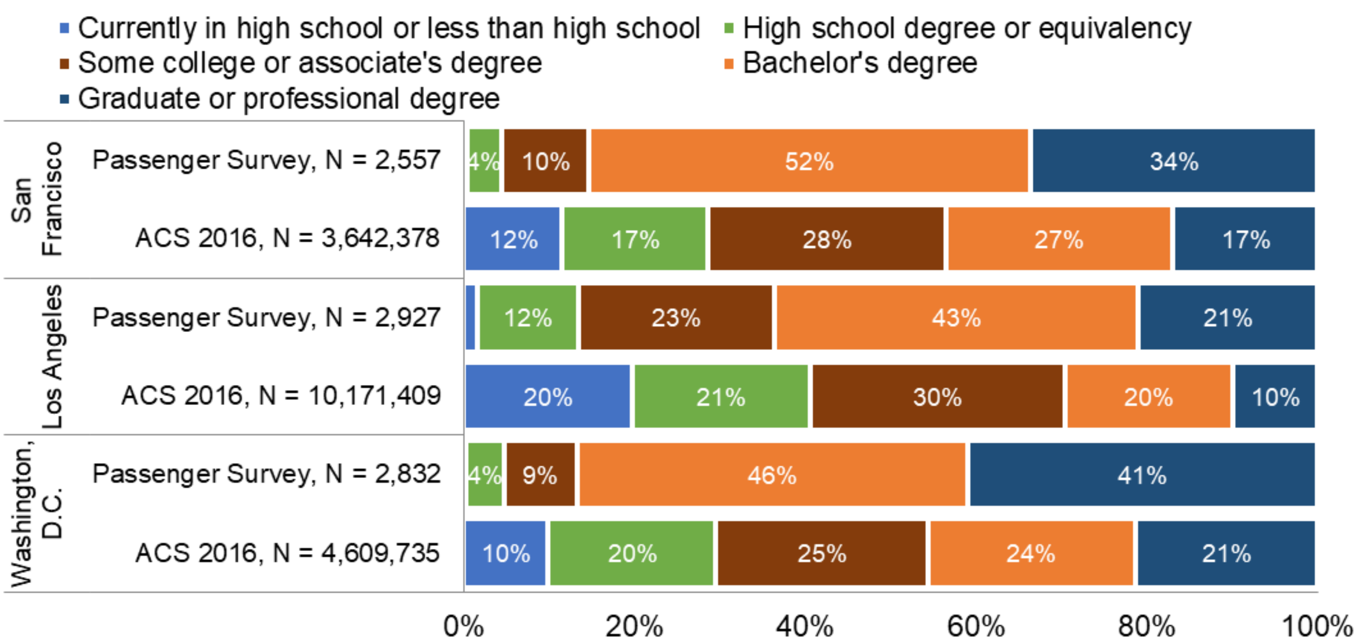
Table 10. Passenger Survey Income per Person and CBSA Income per Capita

	San Francisco		Los Angeles		Washington, D.C.	
	Passenger Survey, N = 2,259	ACS 2016, N = 3,789,906	Passenger Survey, N = 2,550	ACS 2016, N = 10,716,690	Passenger Survey, N = 2,514	ACS 2016, N = 4,838,219
Income per Person/ per Capita	$61,429	$45,955	$37,941	$30,874	$55,961	$44,958

Education

Across all three markets, the passenger survey respondents were more educated than the general population of those 18 years and older (Figure 6). The percentages of passenger survey respondents with bachelor's degrees or higher were about double those in the respective populations, with 85 percent in San Francisco, 64 percent in Los Angeles, and 87 percent in Washington, D.C. holding at least a bachelor's degree. Generally, the distributions reiterate findings from previous shared mobility studies.

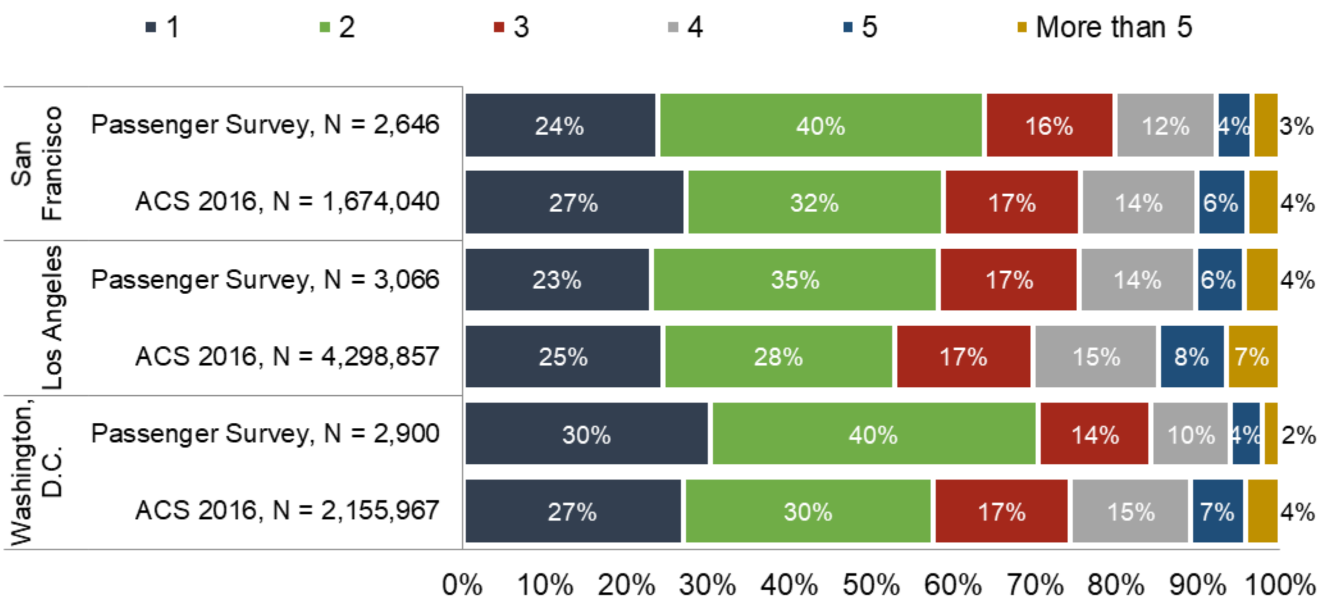
Figure 6. Passenger Survey Education Level



Household Size

The passenger survey asked for the household size of those classified as individuals (living alone or in nonfamily households) as well as households within our survey instrument (Figure 7). The distributions for the passenger survey respondents and for the ACS are fairly similar across all three markets. However, there was a slightly greater proportion of two-person households among survey respondents compared with the general populations across all the markets.

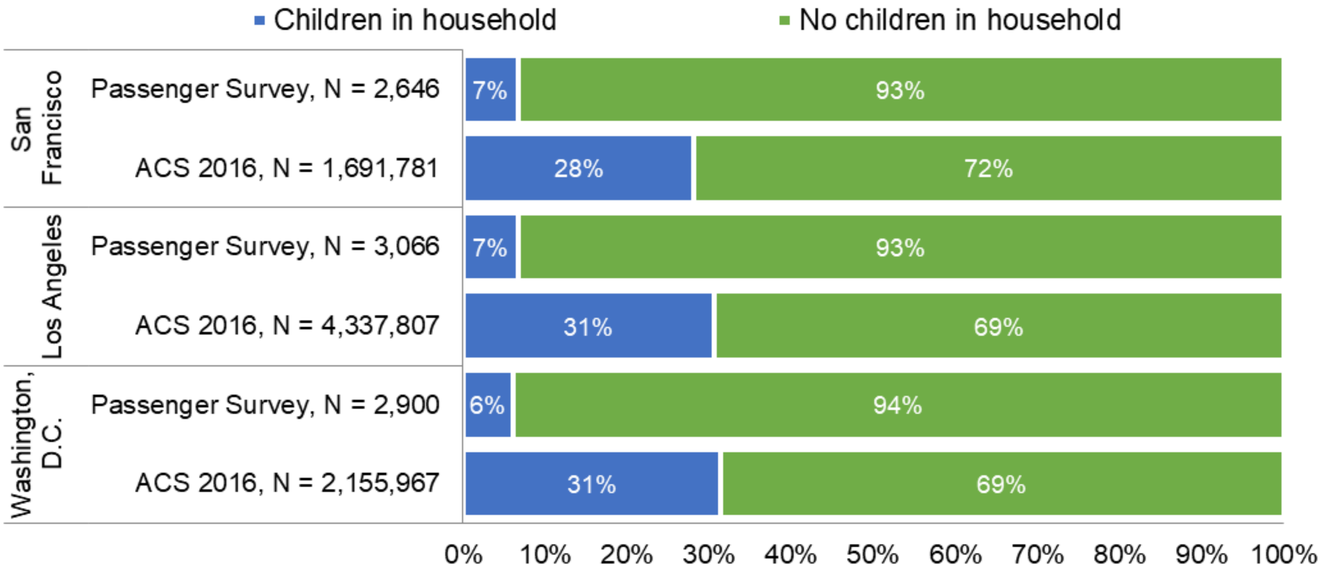
Figure 7. Passenger Survey Household Size Distribution



<u>Households With Children</u>

In each of the three markets, the passenger surveys contained very low proportions of households with children compared with the proportions found in the overall CBSA populations. There is at least a 20 percentage point difference between households with children in the ACS and households with children in the passenger survey, across all three markets. (Figure 8). The very low proportion of households with children exhibited in the passenger survey reflected the generally younger makeup of the respondents, as well as the more urban focus of this population. Other factors include the technical limitations that can discourage families from using TNCs. For example, there are car seat requirements, which vary from state to state. In California, children under age eight and under 57 inches require the use of a child restraint system (booster seat), and children under two must be in a rear-facing car seat. Rear-facing seats, in particular, require considerable effort to install and remove from vehicles.

Figure 8. Passenger Survey Presence of Children (Under 18) in Household



<u>Summary of Passenger Survey Sociodemographic Results</u>

Passenger survey respondents across the three markets have sociodemographic makeups that were different from those found in the corresponding general populations. Overall, passenger survey respondents were more likely to be female and white compared with the gender and racial distributions among the general population. However, our control survey, discussed further in a subsequent section, shows that the gender and racial makeups of those who have used TNCs matches up more closely with the respective general populations.

The passenger survey also shows that TNC passengers tended to be younger, had higher incomes, and had higher levels of educational attainment than the corresponding general populations. Across the three markets, the majority of passenger survey respondents were under the age of 40, and about a third were under the age of 30. Average per capita incomes among passenger survey respondents were 23 percent to 34 percent higher than those among the respective CBSAs, although this discrepancy is less pronounced among control survey respondents, which we discuss further in the control survey section. The percentages of passenger survey respondents with bachelor's degrees or higher were around double those in the respective CBSA populations. Last, passenger survey respondents had very low proportions of households with children compared with the proportions found in the overall CBSA populations.

In general, the sociodemographic results found in the passenger survey match closely with findings from previous shared mobility studies. We investigate Lyft and Uber passenger sociodemographics further in the control survey section, where we compare the demographic makeup of those who use TNC services with those who do not.

Mode Use and Modal Shift Impacts—Passenger Survey

Respondents to the passenger survey were asked a series of questions to measure their use of different transportation modes as well as the effect that Lyft and Uber had (if any) on their use of these modes. This section provides an overview of mode use among passenger respondents and quantifies the nature and magnitude of the impact of TNCs on their use of other transportation modes. Overall, this section presents the work commute mode of respondents, the current modal use and frequency of use, the modal shift impacts of TNCs, and the frequency-of-use impacts and average change in trips among passenger survey respondents, followed by a summary of modal shift results.

Work Commute Mode

If respondents reported being employed or in school, they were asked to indicate their main transportation mode used for their commute. The passenger survey results are displayed in Table 11 alongside the ACS 2016 five-year estimates for journey to work (commute) mode in each CBSA. We note that these data on commute mode were collected well before the COVID-19 pandemic. The share of commuters telecommuting reported in this study was very likely lower than it is now.

Overall, the passenger survey populations in the three market areas used public transit at a higher rate and were less reliant on single-occupant vehicles for commuting, as compared with the general population in each CBSA. Between 8 percent and 12 percent of passenger survey respondents reported that they commuted with Lyft or Uber, depending on the market. How this compares with the population is unknown since the ACS did not track TNC commuting.

A significantly lower proportion of passenger survey respondents drive alone to work than do people in the general population. In addition, respondents were more likely than the general population to be public transit commuters across all three markets. The percentages of respondents using public transit for commuting were about three times higher than the corresponding percentages among the general populations of Los Angeles and Washington, D.C. and more than two times higher in San Francisco. The relatively low proportion of respondents who drive alone to work may be due to low rates of vehicle ownership among the respondents, as well as land-use context factors that we explore further in subsequent sections of this report.

There were also higher proportions of commuters who used active modes (such as bicycling, bikesharing, or walking) in the passenger survey than in the general population. Active-mode commuters made up 15 percent of survey respondents in San Francisco, 7 percent in Los Angeles, and 16 percent in Washington, D.C. Telecommuting (working from home) was one mode that the survey sample used less commonly relative to the general CBSA population. Only 1 percent to 2 percent of passenger survey respondents telecommute, depending on the market, whereas 5 percent to 6 percent of workers telecommute within the general population. Again, the pandemic has likely altered these numbers substantively.

Table 11. Main Passenger Survey Commute Mode to Work

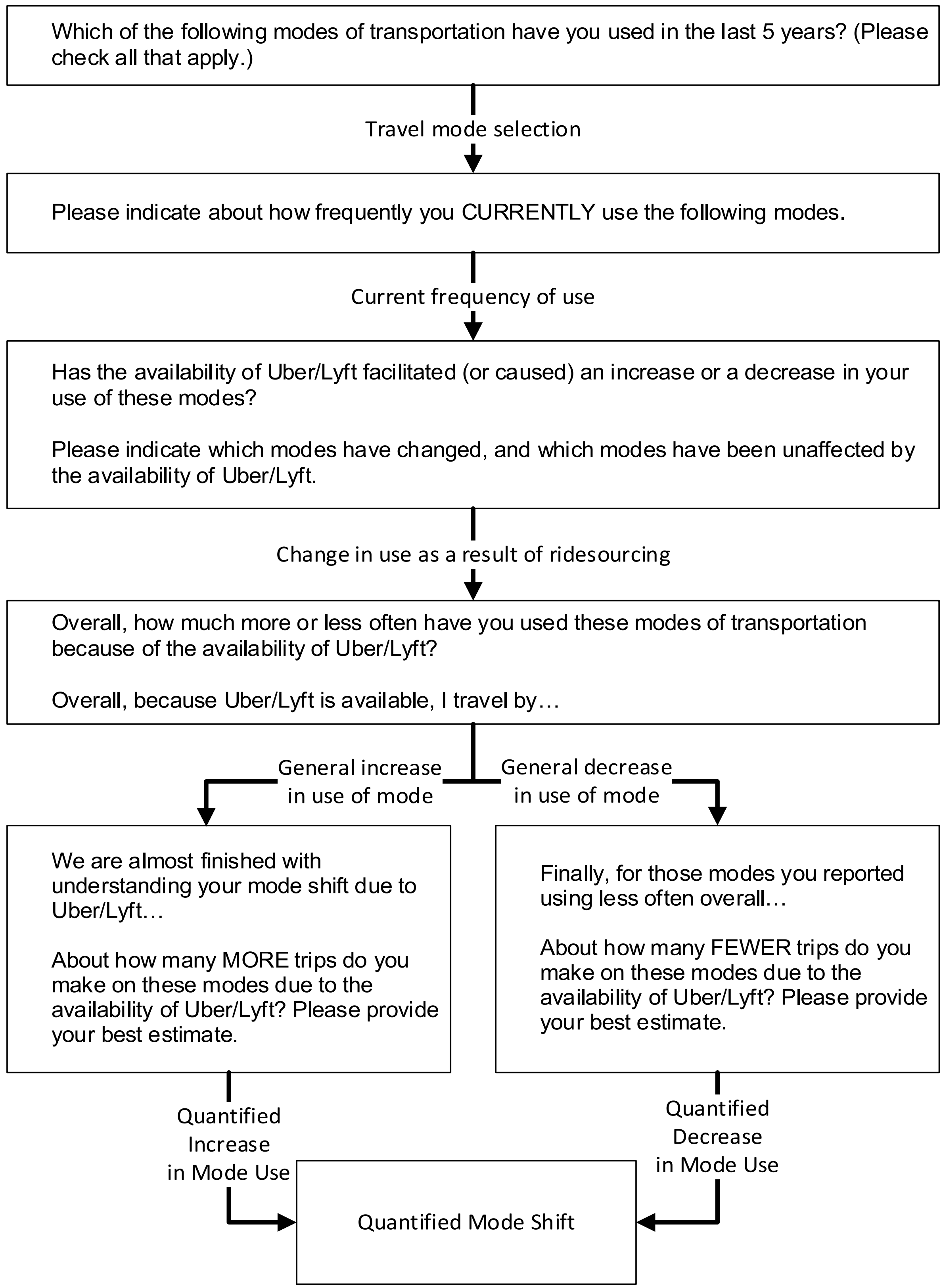
	San Francisco Passenger Survey, N = 2,398	San Francisco ACS 2016, N = 2,237,382	Los Angeles Passenger Survey, N = 2,754	Los Angeles ACS 2016, N = 6,093,213	Washington, D.C. Passenger Survey, N = 2,745	Washington, D.C. ACS 2016, N = 3,164,716
Drive Alone	26%	59%	55%	75%	26%	66%
Carpool or Vanpool	5%	10%	8%	10%	4%	10%
Public Transit	40%	17%	15%	5%	45%	14%
Bus	18%	n/a	11%	n/a	13%	n/a
Rail	23%	n/a	4%	n/a	32%	n/a
Bicycling or Bikesharing	5%	2%	3%	1%	5%	1%
Walking	10%	4%	4%	3%	11%	3%
Lyft/Uber	9%	n/a	12%	n/a	8%	n/a
Telecommute	2%	6%	1%	5%	1%	5%
Other	3%	2%	1%	1%	1%	1%

<u>Mode Shift Analysis</u>
Our mode shift analysis was supported by a series of survey questions, as outlined in Figure 9. This series of questions sought to narrow the number of modes a respondent would have to address, on the basis of previous responses. To begin, we asked passenger survey respondents a set of questions about their use of all transportation modes within the past five years. This first question defined the set of modes that were relevant to the respondent's travel patterns. Subsequent questions focused only on these modes, although some core travel modes remained even if not previously selected.

Respondents were next asked whether using Lyft or Uber had caused any change in the use of each selected mode during the past five years. They could indicate that they used certain modes but that Lyft and Uber had no effect on their use.

For those modes for which Lyft or Uber did cause a modal shift, respondents were then asked to indicate the general direction of this change. With this question, they had an opportunity to report "no change" in use, or they could indicate on an ordinal scale (from "much more" to "much less") that their use had changed in direction. Finally, if respondents indicated that a change had occurred in one direction or another, then they were asked to quantify approximately how large that change was in terms of frequency (i.e., the change in number of trips per week or month).

Figure 9. Schematic of Mode Shift Questions

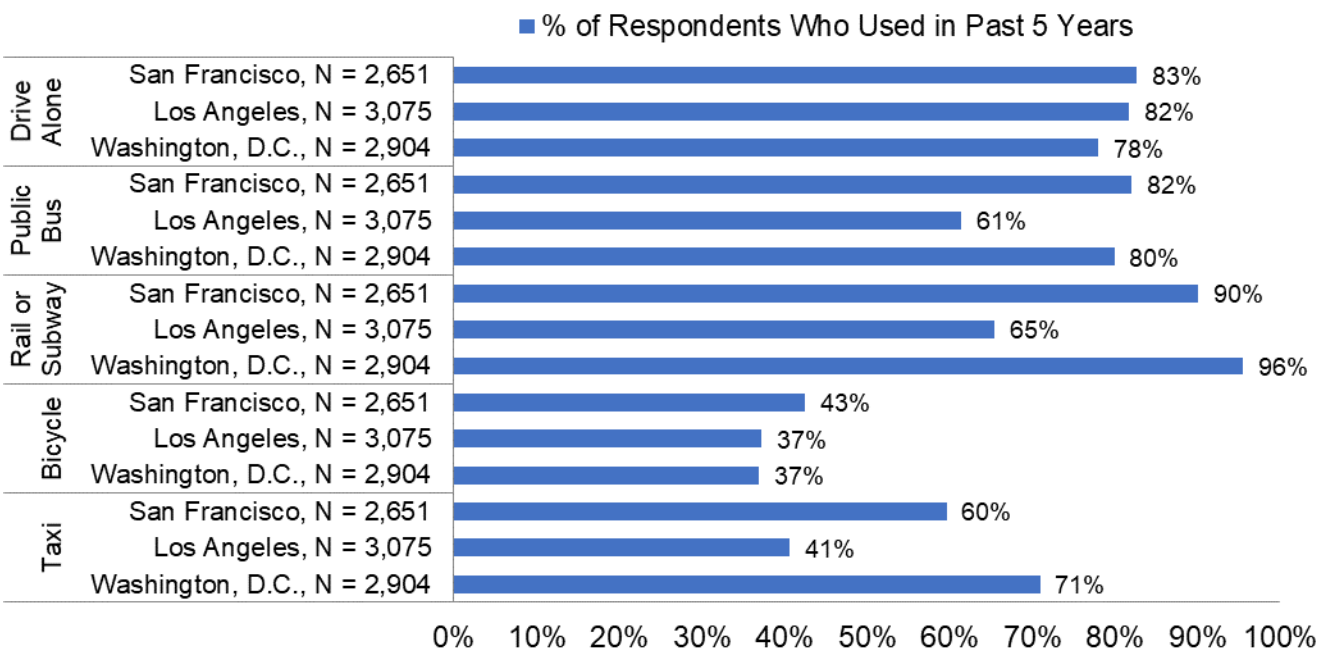


Current Mode Use and Frequency of Use

We wanted to capture the mode use profile of our survey respondents in order to understand modal shift due to Lyft and Uber (Figure 10). We chose a five-year time frame because it covered the time before and during the emergence of TNC services. This method also allowed for subsequent questions to be displayed only to respondents who indicated that they were users of each respective mode.

The majority of respondents in each market had driven alone, taken a public bus, or used rail/subway in the past five years (from the time of the survey). However, the proportion of public transit users (bus and rail) was lower in Los Angeles than in the other two markets. In addition, 60 percent of passenger survey respondents had used a taxi within the last five years in San Francisco, 41 percent had in Los Angeles, and 71 percent had in Washington, D.C.

Figure 10. Distribution of Passenger Survey Mode Use in the Past Five Years



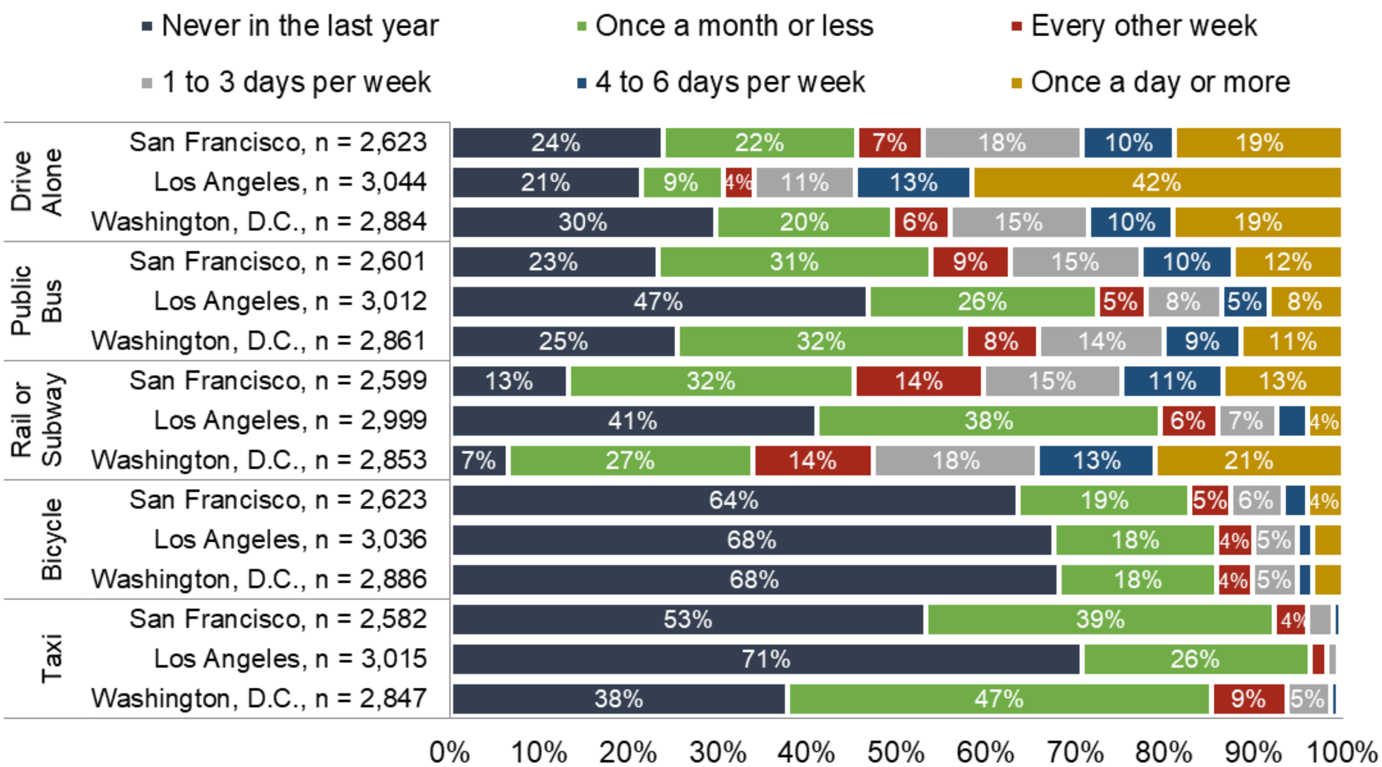
In the passenger survey, we also asked respondents how frequently they currently (at the time of the survey) used each mode to better understand their travel profiles. Respondents were asked only about the modes that they had reported using in the past five years. Figure 11 (below) shows the frequency-of-use distribution for those modes within each market. Note that this distribution includes all respondents, including those who indicated that they did not use the mode in the past five years. "Nonusers" of the mode were aggregated into the "Never in the last year" category.

The distributions show some significant distinctions in how respondents within the various markets travel. As expected, driving alone is most frequently done in Los Angeles, where about 66 percent of respondents drove alone one day a week or more often. Some 47 percent of respondents in the San Francisco CBSA drove alone at least once a week, and 44 percent of respondents did so in the Washington, D.C., CBSA.

Bus and rail use followed a similar pattern but in the inverse order. In Los Angeles, 22 percent of respondents used the bus once a week or more, while in San Francisco and Washington, D.C., usage was modestly higher at 37 percent and 34 percent, respectively. For rail use, the differences were larger. Only 14 percent of respondents reported using rail or subway at least once a week in Los Angeles. In the San Francisco CBSA, the proportion was 40 percent, and in Washington, D.C., 53 percent. Note that these aggregations are slightly off using the rounded numbers in Figure 11.

Compared with other modes, the frequency of cycling and taxi use in all three markets was far lower. For bicycle use, the distributions across CBSAs were surprisingly similar, where 10 percent to 13 percent of respondents used a bicycle once a week or more. For taxis, 2 percent to 6 percent reported using taxis at least once a week, with the most frequent usage reported in Washington, D.C.

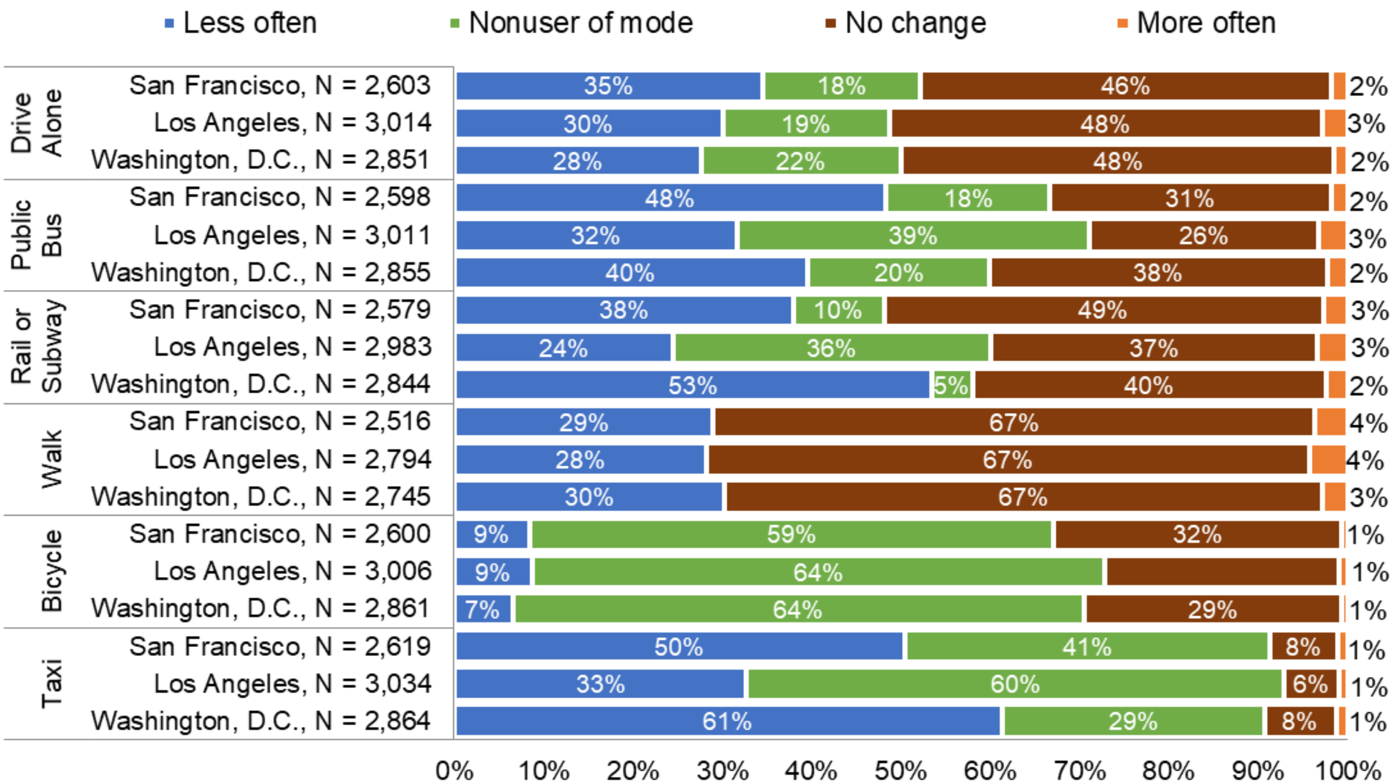
Figure 11. Distribution of Passenger Survey Mode Use



<u>Modal Shift Impacts</u>

Respondents were asked to indicate whether or not the availability of Lyft and Uber facilitated either an increase or a decrease in their mode use. Respondents who indicated that their use of a particular mode had changed due to the availability of Lyft and Uber were then asked to indicate the relative magnitude of change for each mode. Figure 12 (below) summarizes the directional shifts in the use of driving alone, public bus, rail or subway, walking, bicycling, and taxi. The mode shift results displayed denote the responses to the directional modal shift questions among all respondents. Those who experienced no change in their use of a particular mode are included in the "no change" category of Figure 12. Those who had not used the mode in the past five years are included in the "nonuser of mode" category. It should be noted that all respondents were asked to indicate whether TNCs had or had not caused a change in walking. Walking was not considered in preceding mode-use sections because we assumed all respondents had walked to a destination in the past five years. Across all six modes, a greater proportion of respondents broadly reported a negative shift (a reduction) in mode use than reported a positive shift.

Figure 12. Passenger Survey Distribution of Modal Shifts



The majority of respondents in each of the three markets across the six modes was either nonusers of the mode or reported no change in use due to Lyft and Uber. There were four exceptions: rail/subway use in Washington, D.C., public bus use in San Francisco, as well as taxi use in San Francisco and Washington, D.C., which had slight majorities of respondents indicating that they used these modes less often due to TNCs. While some respondents reported using modes more often due to Lyft or Uber, this portion did not exceed 4 percent of passenger survey respondents for any mode in any market.

Between 32 percent and 48 percent of respondents indicated that they used public buses less often due to the availability of Lyft and Uber, with the highest portion of respondents reporting this effect in San Francisco. The majority of respondents in San Francisco and Washington, D.C., used taxis less often due to TNCs, while this percentage was 33 percent in Los Angeles. However, it is important to note that respondents in all three markets were not very frequent taxi users, with the vast majority using taxis once a month or less, as indicated previously in Figure 11.

The majority of respondents either did not drive alone or reported no change in how often they drove alone due to the availability of Lyft and Uber. However, a significant portion of respondents also shifted away from driving alone: About one-quarter to one-third of respondents in each market reported driving alone less often due to TNCs.

Rail use also saw reductions, as 38 percent, 24 percent, and 53 percent of respondents in San Francisco, Los Angeles, and Washington, D.C., respectively, reported using rail or subway less often due to Lyft and Uber. Only 2 percent to 3 percent reported using rail and subway more often, depending on the market. Slightly more than one-quarter of respondents in each of the three markets walked less often due to TNCs, while 3 percent to 4 percent of respondents indicated that they walk more often due to Lyft and Uber. Only 7 percent to 9 percent of respondents, depending on the market, claimed to bike less often due to the availability of Lyft and Uber. However, biking had only a small group of users: Less than half of the respondents in each market had biked within the past five years.

Overall, these results suggest that TNC passengers, on net, were using these six common modes less often due to Lyft and Uber, with varying magnitudes depending on the mode and market. Overall, the results suggest that Lyft and Uber were broadly acting as a new mode within the set of choices for travelers, drawing from each of the main travel options. While the results above yield insight into the general directions of change, the magnitude is not revealed. Questions asked of these respondents in follow up delved into the relative size of the behavioral modal shift in the following section.

Frequency-of-Use Impacts

Respondents who indicated either a positive or negative direction of change due to Lyft and Uber for each mode were asked in a follow-up question to estimate the resulting change in the number of trips they take with each mode. This estimate is a rough one, but it still provides some quantification of the relative magnitude of behavioral change that has occurred with respondent activities.

Respondents whose mode use was impacted by the availability of Lyft and Uber reported how many fewer or how many more times per week or month they used each mode due to TNCs. Respondents could opt to indicate that they were unsure of the change. For those using a mode less often, respondents could also indicate that they no longer used a mode at all due to TNCs.

We used responses to these questions to estimate an average change in trips per week for each mode. These metrics were calculated by estimating a midpoint of change in trips per week, based on the range of change indicated in each answer option (e.g., the answer option "2 to 4 times fewer every week" was estimated as 3 fewer trips per week). We calculated an average change in trips per week for two respondent populations: all respondents (considering nonusers of each mode to have no change in frequency of use) and users of the mode (presenting the average among only those who had used the mode in the past five years). There are limits to the precision of these numbers, as the values are estimated from word-based rather than numerical responses. But the measure provides some context as to a rough center point of behavioral change to better define whether it is large or small within a given mode.

For those who stopped using a particular mode due to TNCs, we assumed these respondents decreased their mode use by the average usage frequency of that mode among all respondents in the CBSA who had previously used that mode within the past five years. The share of such respondents is small for each mode. This may be an upper estimate of that impact, since those ceasing use of a mode may be more likely to be infrequent users (though we expect a mix of cases). But the numerical impact of this assumption does not, by itself, significantly change the average. Additionally, we note that modal shifts are relative to how frequently each respondent used a particular mode prior to the introduction of TNCs. While it is difficult to summarize these relative shifts across the entire respondent population, the mode use and modal shift results displayed in this section give context to how often TNC passengers used other transportation modes and the overall modal shift effects due to TNCs.

Table 12 (below) shows how this mapping was done from the ordinal responses to a numerical value. It acts as a frame of reference for the average changes in trips per week displayed in Figure 13 to Figure 18 below. Note that the categories in the figures that follow are aggregations of these response categories.

Table 12. Mapping of Change in Use to Trip Frequency

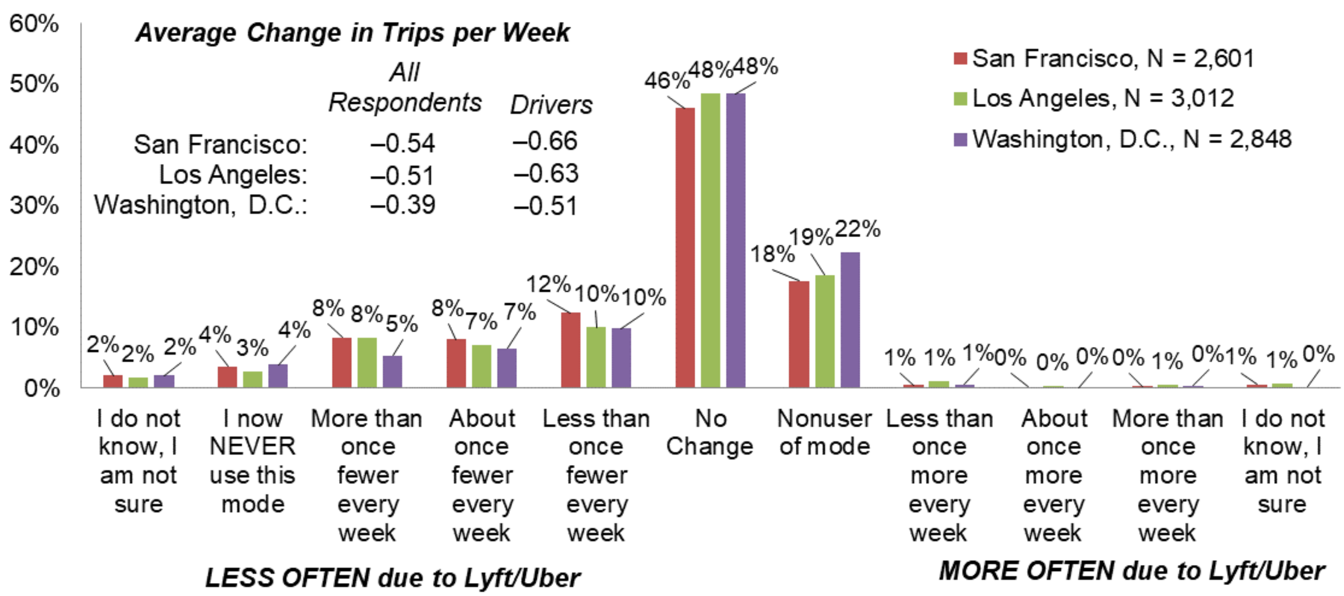
No Change in Mode Use or Nonuser of Mode	**Trips/week**
No change	0
Decrease in Mode Use	**Trips/week**
I do not know, I am not sure	N/A
A negligible difference	–0.05
Less than once fewer every month	–0.125
About once fewer every month	–0.25
About once fewer every week	–1
2 to 4 times fewer every week	–3
More than 4 times fewer every week	–6
I now NEVER use this mode	*Response average*
Increase in Mode Use	**Trips/week**
I do not know, I am not sure	N/A
A negligible difference	0.05
Less than once more every month	0.125
About once more every month	0.25
About once more every week	1
2 to 4 times more every week	3
Greater than 4 times more every week	6

The distributions shown in Figure 13 through Figure 18 consider all passenger survey respondents. They present the frequency change of those who used the mode less often due to Lyft and Uber on the left side, those who experienced no change or who were nonusers of the mode near the center, and those who used the mode more often due to TNCs on the right side.

Driving Alone

Across the three markets, passenger respondents experienced a reduction in solo driving trips per week, on average (Figure 13). Of the respondents who drove alone less often due to TNCs (on the left side of the figure), the majority in each market reported relatively limited reductions in driving due to TNCs, amounting to about one time less (or fewer) every week. However, some respondents reported more significant reductions in driving, with 8 percent of all respondents in San Francisco and Los Angeles and 5 percent in Washington, D.C., reporting driving alone more than once less every week. At the extreme end, the availability of Lyft and Uber led 3 to 4 percent of respondents to stop driving alone, depending on the market. On average across all respondents, the reduction in drive-alone trips per week was 0.54 in San Francisco, 0.51 in Los Angeles, and 0.39 in Washington, D.C. Considering only those who had driven alone in the past five years, the average reductions were estimated to be of slightly higher magnitudes. In terms of trips per week, they were 0.66 in San Francisco, 0.63 in Los Angeles, and 0.51 in Washington, D.C.

Figure 13. Frequency-of-Use Change Due to Lyft and Uber: Drive Alone

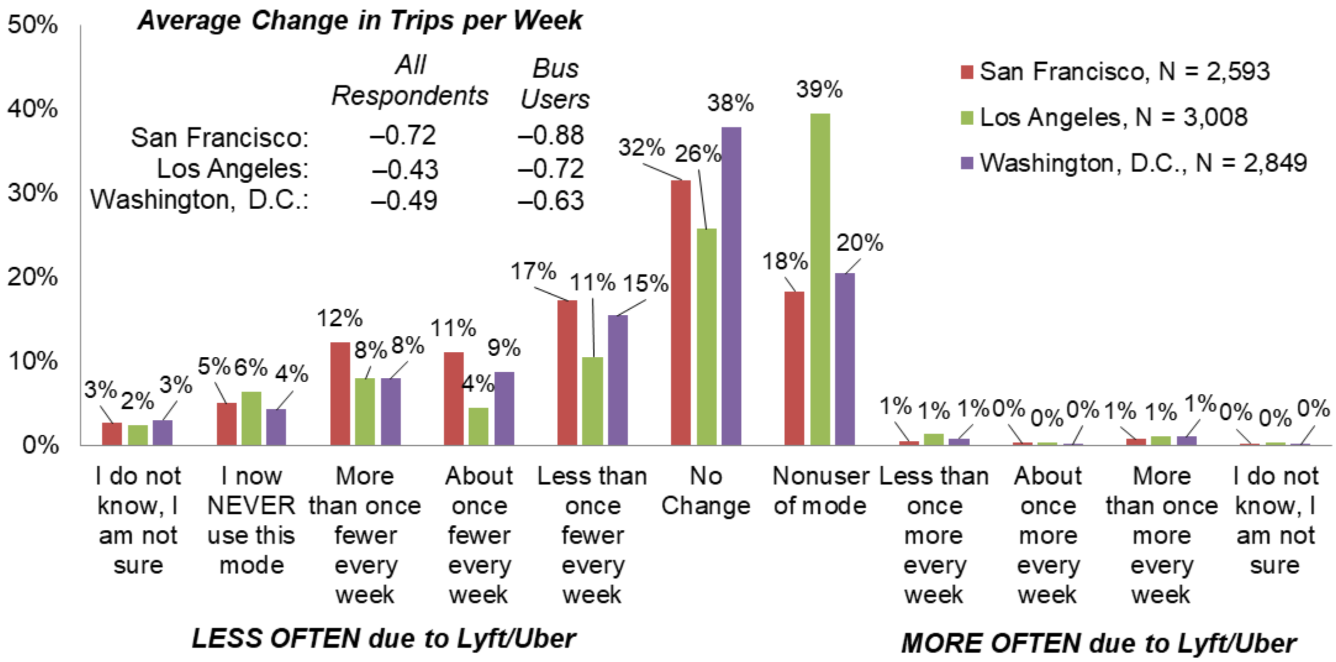


Public Bus

Across all three markets, respondents reported an overall reduction in public bus use (Figure 14). The reductions in bus use due to TNCs were greater than the reported changes in driving alone. Out of the three markets, the highest proportion using buses less was in San Francisco; almost half (48 percent) of respondents indicated they reduced their bus use due to Lyft and Uber. This portion was slightly lower in Los Angeles and Washington, D.C., at 32 percent and 40 percent, respectively. Almost half of those using buses less often in San Francisco reported a reduction in use of at least once fewer every week.

In Los Angeles, 6 percent of respondents reported stopping their use use of buses as a result of Lyft and Uber, versus 5 percent in San Francisco and 4 percent in Washington, D.C. Los Angeles also had the highest portion of non bus-user respondents, with 39 percent claiming not to have used the bus in the past five years. The estimated average decrease in bus trips per week among all respondents due to TNCs was greatest in San Francisco, at 0.72 trips less per week, on average. Among only those who had used the bus within the past five years (again from the time of the survey), the average reduction in trips per week ranged from 0.63 in Washington, D.C., to 0.72 in Los Angeles, to 0.88 in San Francisco.

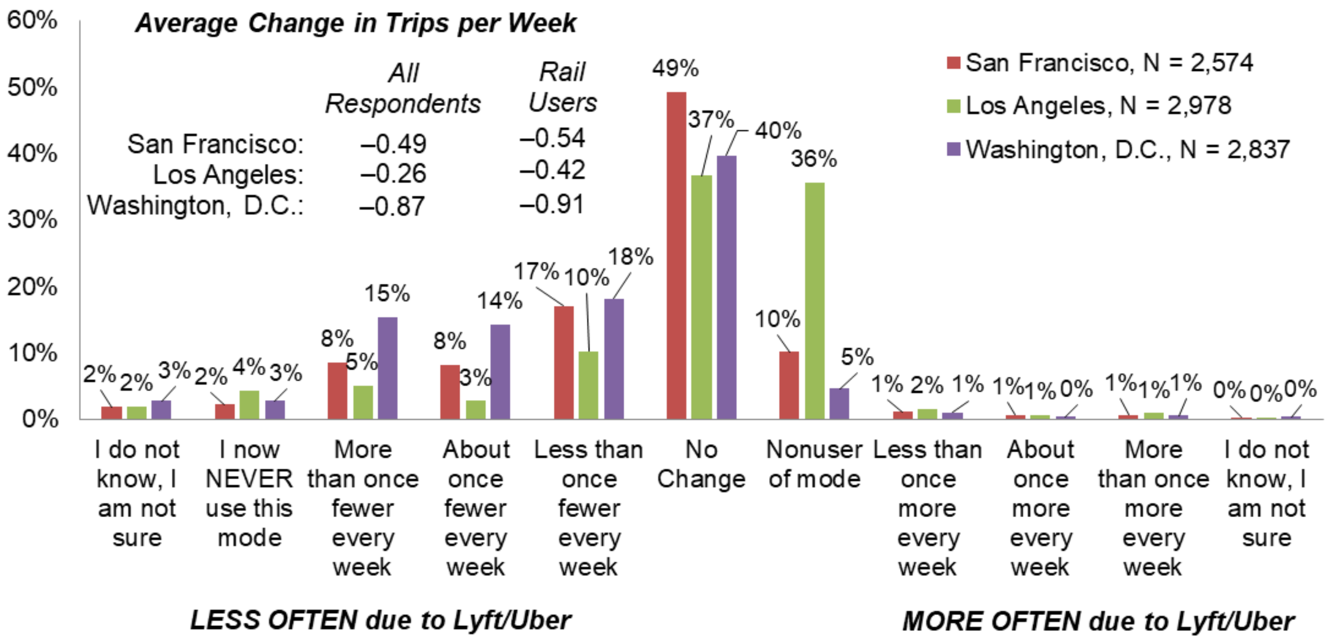
Figure 14. Frequency-of-Use Change Due to Lyft and Uber: Public Bus



<u>Rail or subway</u>
Across all three markets, passenger survey respondents reported a net reduction in rail and subway use due to TNCs (Figure 15). The greatest portion of respondents who decreased their rail use due to TNCs was in Washington, D.C., with 30 percent of all respondents reporting that they decreased their rail use by at least one fewer trip every week. In comparison, only 17 percent of all respondents in San Francisco and 8 percent in Los Angeles decreased their rail use by equivalent frequencies. Two to four percent of all respondents reported that they stopped using rail due to Lyft and Uber, depending on the market. In Los Angeles, 18 percent of respondents who used rail less often by some amount due to Lyft and Uber reported ceasing rail use altogether, whereas only 6 percent and 5 percent of such respondents did the same in San Francisco and Washington, D.C., respectively.

The average change in rail or subway trips per week due to TNCs among all respondents varied from a 0.26 trip per week decrease in Los Angeles, to a 0.49 decrease in San Francisco, to a 0.87 decrease in Washington, D.C. The average change in rail trips per week among only rail users ranged from a 0.42 reduction in Los Angeles to a 0.91 trip per week reduction in Washington, D.C. Thus, in terms of public transit impacts, the largest impacts on buses were experienced in the San Francisco CBSA, while the largest impacts on rail were observed in the Washington, D.C. CBSA. The elevated changes in rail use in Washington, D.C., may also have been caused by the very active SafeTrack maintenance activity underway at the time, which involved heavily reduced service for consecutive weeks.

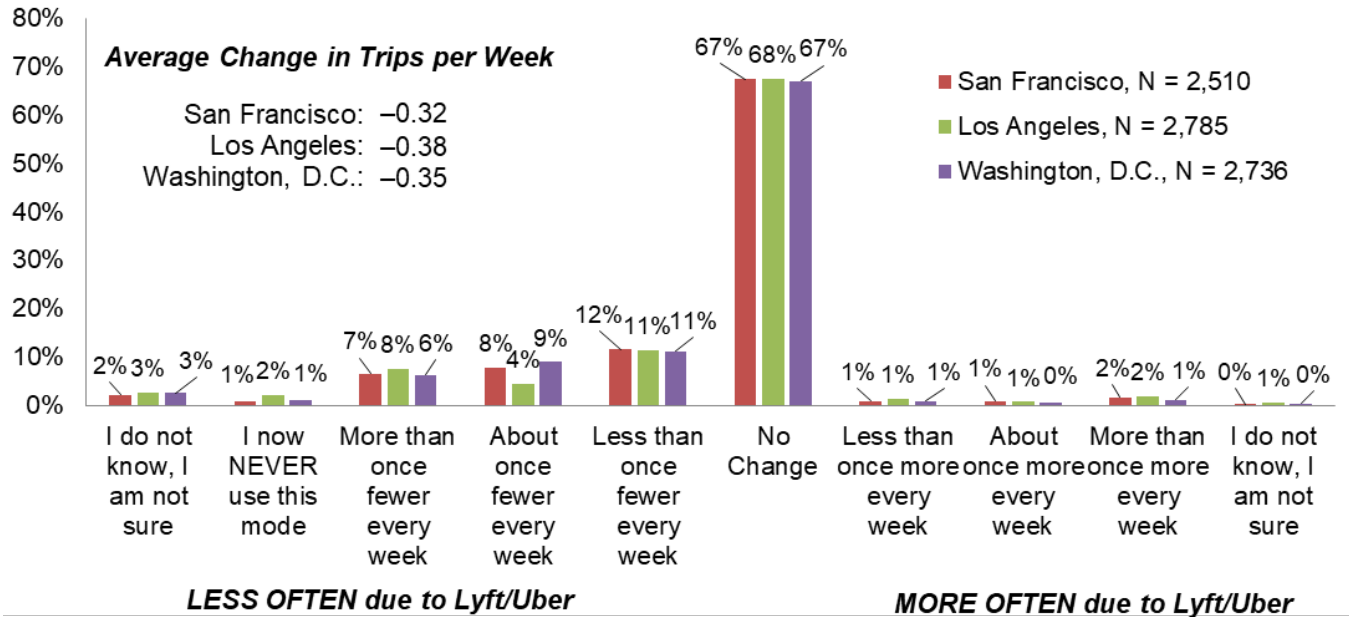
Figure 15. Frequency-of-Use Change Due to Lyft and Uber: Rail or Subway



Walking

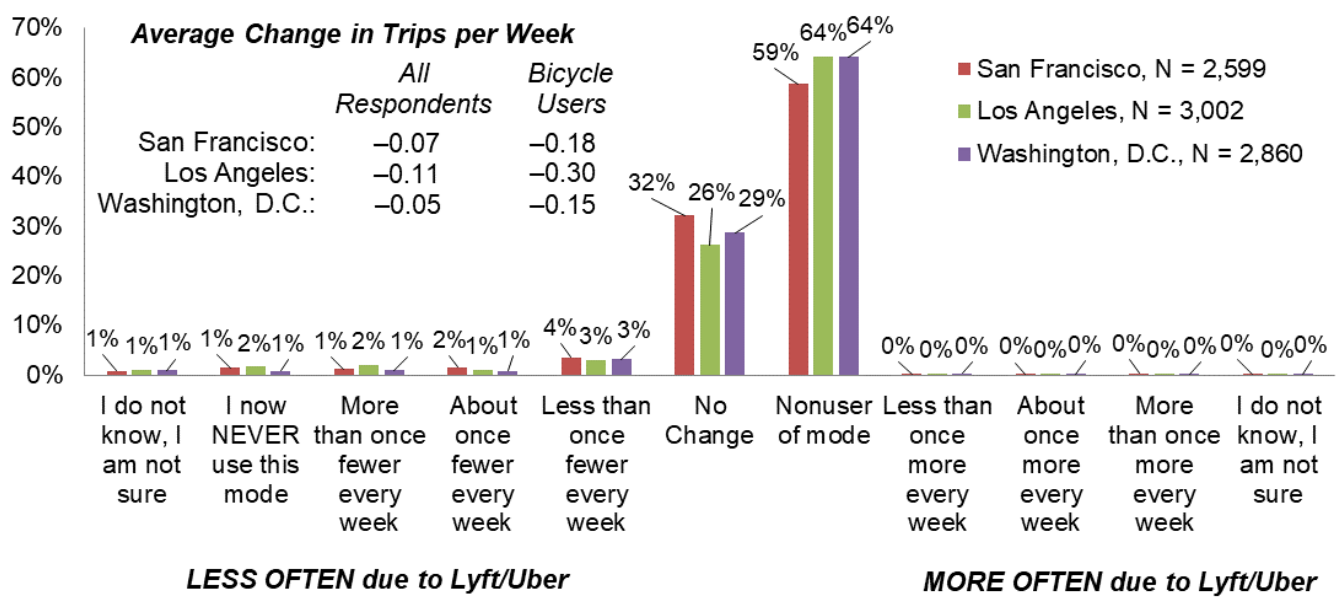
Across all three markets, survey respondents walked less due to TNCs, on average (Figure 16). The results were fairly uniform across all three markets, with 11 percent to 12 percent of all respondents walking less than one fewer time per week due to TNCs. Between 12 percent and 15 percent of respondents reduced their walking by greater amounts, depending on the market. The average decrease in walking trips per week due to Lyft and Uber among passenger survey respondents was estimated to be 0.32 in San Francisco, 0.38 in Los Angeles, and 0.35 in Washington, D.C. We note that the passenger survey was deployed before the introduction of services such as Lyft Shared Saver and Uber Express POOL, which encouraged passengers to walk a short distance to a pick-up location to better streamline pooled TNC rides. While walking mode shift magnitudes may have been influenced by these options, we expect that directions likely remained a net negative shift due to TNC services.

Figure 16. Frequency-of-Use Change Due to Lyft and Uber: Walking



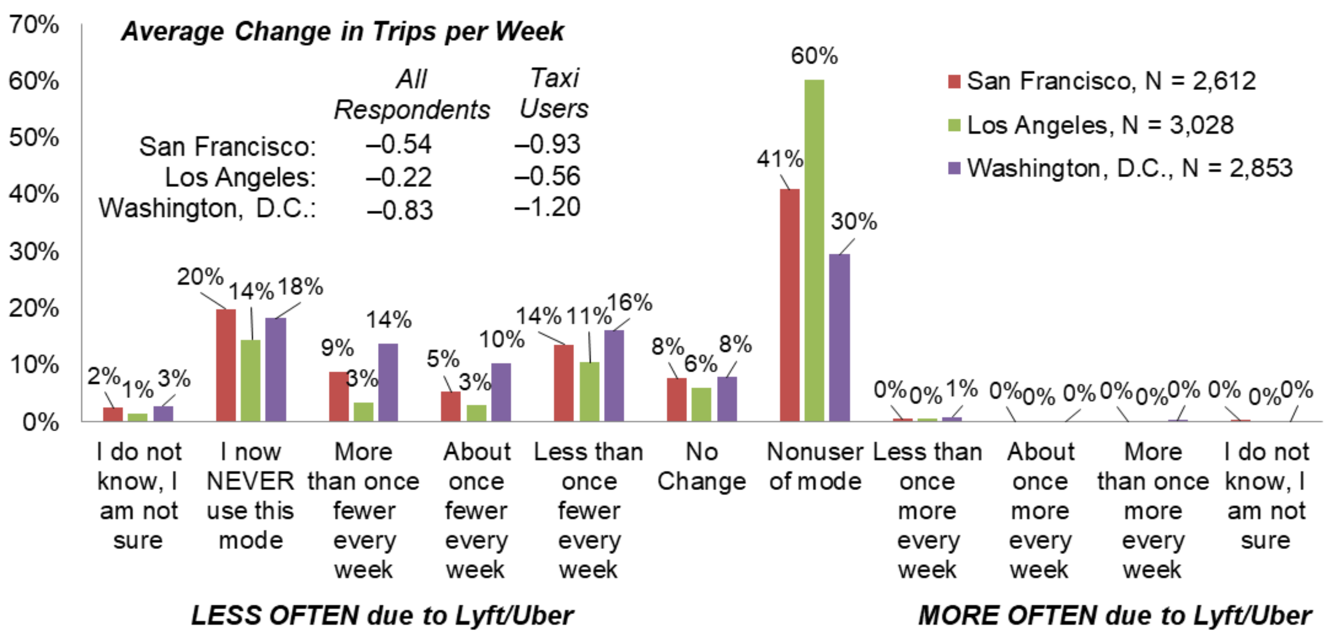
<u>Bicycling</u>
In all three markets, at least 90 percent of the respondents either had not used a bicycle in the past five years or experienced no change in their bicycle use due to Lyft and Uber (Figure 17). Less than half of the passenger survey respondents had used a bicycle in the last five years (from the time of the survey). Very few respondents in each market reported reductions in their frequency of bicycling due to Lyft and Uber availability. The results suggest Lyft and Uber have a limited impact on bicycling.

Figure 17. Frequency-of-Use Change Due to Lyft and Uber: Bicycling



Taxis
While the largest portion of respondents in each of the three markets had not used a taxi in the past five years, the next-largest portion of respondents reported stopping use of taxis as a result of Lyft and Uber availability (Figure 18). Across the respondent sample, the proportion stopping use was 20 percent in San Francisco, 14 percent in Los Angeles, and 18 percent in Washington, D.C. Among only those who reduced their taxi use, the proportion was higher. Within the subset of respondents reducing their taxi use, 30 percent to 44 percent reported stopping taxi use across markets. The estimated average decrease in taxi trips among all respondents due to Lyft and Uber was highest in Washington, D.C., at 0.83 fewer trips per week, then San Francisco at 0.54 fewer trips per week and Los Angeles at 0.22. Among those who had used a taxi in the past five years, the average reduction in trips per week was naturally higher, at 0.93 in San Francisco, 0.56 in Los Angeles, and 1.20 in Washington, D.C. It is interesting to note that although there were large reductions in taxi use, a significant portion of respondents did not use taxis in the first place. Forty-one percent of respondents had not used a taxi in the past five years in San Francisco, while 60 percent had not in Los Angeles, and 30 percent had not in Washington, D.C.

Figure 18. Frequency-of-Use Change Due to Lyft and Uber: Taxi



Summary of Modal Shift Results
The results of this analysis suggest that on average, Lyft and Uber draw from all the main travel modes. The result is consistent with the expectations of a discrete mode choice model, where the introduction of a new mode draws share from all the other modes available. However, the magnitude of modal shift resulting from Lyft and Uber differed depending on the mode, location, and respondent group.

The average change in trips per week (for all respondents and users of the mode) are rough estimates of the center points of the distribution in magnitude of mode shift impacts as quantified in terms of frequency. It is derived from the change in mode use that respondents reported as being due to Lyft and Uber. Such a measure is inherently an approximate one, as the respondents were estimating their behavioral change that is specifically attributable to Lyft and Uber.

While there was an average decrease in trips per week due to Lyft and Uber for each of the six common modes across all respondents and users of the mode only, the average change was less than one trip per week across the three study markets in all cases except one (among taxi users in Washington, D.C.). This suggests that while TNC services were having notable impacts on mode use for most of the surveyed population, the frequency effects were not more than about one trip per week, on average.

It is important to consider city- and region-specific impacts when assessing the modal shift effects of TNCs. They can vary significantly, as summarized in Table 13 and Table 14. As noted previously, in San Francisco, the largest frequency-of-use reductions among all respondents due to TNCs was for buses (average decrease of 0.72 trips per week); in Los Angeles, driving alone (average decrease of 0.51 trips per week); and in Washington, D.C., rail/subway (average decrease of 0.87 trips per week). However, Washington, D.C.'s data may have been influenced by major rail maintenance work that happened concurrently with this study—therefore the permanence of this mode shift may be confounded. In addition, the measured magnitude of frequency-of-use reduction depends on whether all respondents or only those who have used each given mode in the past five years are considered.

Among users of the mode, the largest frequency-of-use reduction in San Francisco and Washington, D.C. were for taxis (at 0.93 and 1.20 fewer trips per week, respectively); in Los Angeles it was for buses (at an average decrease of 0.72 trips per week). These differences in average trip reductions per week are correlated with the relatively low portion of respondents who used these modes in the markets within the past five years.

Table 13. Summary of Selected Mode Use and Modal Shift Results Due to TNCs, by Mode (displayed by lowest and highest proportions and values)

Mode	Percentage of Respondents Who Used Mode in Past Five Years			Modal Shift Range (Percentage of Respondents Using Mode Less Often, the Same/Nonuser, or More Often)			Average Change in Trips Per Week Range (All Respondents)	Average Change in Trips Per Week Range (Users of Mode)
	SF	***LA***	***DC***	***Less***	***Same or Nonuser***	***More***		
Drive Alone	83%	82%	78%	28–35%	64–71%	2–3%	0.39–0.54 *less*	0.51– 0.66 *less*
Public Bus	82%	61%	80%	32–48%	50–65%	2–3%	0.43–0.72 *less*	0.63–0.88 *less*
Rail or Subway	90%	65%	96%	24–53%	44–72%	2–3%	0.26–0.87 *less*	0.42– 0.91 *less*
Walking	n/a	n/a	n/a	28–30%	67% (all 3)	3–4%	0.32–0.38 *less*	n/a
Bicycling	43%	37%	37%	7–9%	90–93%	1% (all 3)	0.05– 0.11 *less*	0.15– 0.30 *less*
Taxi	60%	41%	71%	33–61%	37–66%	1% (all 3)	0.22– 0.83 *less*	0.56–1.20 *less*

It is also important to understand the differences in proportions (Table 14). Even though the proportion of those using taxis less often in Washington, D.C., was higher than the "less often" percentages for any other mode and CBSA pair, the average decrease in taxi trips per week among all respondents was not the greatest out of the six modes in any of the three CBSAs. This is because there are large portions of respondents who do not use taxis (30 percent to 60 percent, depending on the market) relative to the percentages of nonusers of other modes, like driving and public transit. However, when we consider the average change in trips per week due to TNCs of only users of each particular mode, the average change in taxi trips per week becomes the highest of any mode and CBSA pair in two of the three markets. These findings suggest that there is a concentrated decline in taxi use among users of the mode. But the change in use of other modes like driving and public transit may have been larger overall, since greater portions of respondents (and the general CBSA populations) use these modes.

Table 14. Summary of Selected Mode Use and Modal Shift Results Due to TNCs, by CBSA

CBSA	Metric	Drive Alone	Public Bus	Rail or Subway	Walking	Bicycling	Taxi
San Francisco	% used in past 5 years	83%	82%	90%	n/a	43%	60%
	Modal shift						
	Less often	35%	48%	38%	29%	9%	50%
	No change	46%	31%	49%	67%	32%	8%
	More often	2%	2%	3%	4%	1%	1%
	Nonuser of mode	18%	18%	10%	n/a	59%	41%
	Average change in trips/week						
	All respondents	–0.54	–0.72	–0.49	–0.32	–0.07	–0.54
	Users of mode	–0.66	–0.88	–0.54	n/a	–0.18	–0.93
Los Angeles	% used in past 5 years	82%	61%	65%	n/a	37%	41%
	Modal shift						
	Less often	30%	32%	24%	28%	9%	33%
	No change	48%	26%	37%	67%	26%	6%
	More often	3%	3%	3%	4%	1%	1%
	Nonuser of mode	19%	39%	36%	n/a	64%	60%
	Average change in trips/week						
	All respondents	–0.51	–0.43	–0.26	–0.38	–0.11	–0.22
	Users of mode	–0.63	–0.72	–0.42	n/a	–0.30	–0.56
Washington, D.C.	% used in past 5 years	78%	80%	96%	n/a	37%	71%
	Modal shift						
	Less often	28%	40%	53%	30%	7%	61%
	No change	48%	38%	40%	67%	29%	8%
	More often	2%	2%	2%	3%	1%	1%
	Nonuser of mode	22%	20%	5%	n/a	64%	29%
	Average change in trips/week						
	All respondents	–0.39	–0.49	–0.87	–0.35	–0.05	–0.83
	Users of mode	–0.51	–0.63	–0.91	n/a	–0.15	–1.20

Impacts of Lyft and Uber on Vehicle Ownership

The availability of services like Lyft and Uber can impact the personal vehicle ownership of passengers. Since vehicles can also be leased rather than owned, we also refer to this as "vehicle holdings", like a portfolio of vehicles held in some way. TNC services can reduce vehicle holdings in two primary ways. First, TNC passengers can decide to shed personal vehicles that they no longer need to own or lease. Second, TNCs can enable personal vehicle suppression, which occurs when someone chooses not to purchase a personal vehicle at all. The premise behind suppression is that in an environment without TNC services, some travelers would eventually acquire a personal vehicle, which comes with notable fixed and variable ownership costs. Because Lyft and Uber provide automotive mobility without the costs of auto ownership, some passengers would opt not to purchase a personal vehicle, thus saving or deferring considerable up-front vehicle expenses.

Vehicle shedding and suppression both reduce vehicles on the road, but their effects on vehicle holdings and use are manifested in different ways, which requires distinct approaches for evaluation. Shedding removes a vehicle from a household and eliminates the associated cost of retaining it (leasing/financing, insurance, parking costs, and so on). People may shed a vehicle via sale, donation, or disposal. The shedding effect is linked to a discrete and measurable event, and it is relatively easy for respondents to recall if and why they got rid of a personal vehicle. Getting rid of a personal vehicle also takes time and energy, which presents a barrier if the vehicle retains some utility or emotional attachment.

In contrast, personal vehicle suppression is the avoidance of an action. It describes something that did *not* happen, as opposed to something that happened. Just as shedding a vehicle takes initiative, so does acquiring a vehicle. It is arguably easier not to acquire a vehicle than it is to get rid of one. Vehicle suppression does exist in the hypothetical and does not typically have a specific vehicle associated with its impact. Despite the more latent nature of the impact, vehicle suppression plays an important role in reducing overall private vehicle use: the fewer cars people own, the fewer vehicles miles they drive. On the flip side, our survey also explored whether the presence of Lyft and Uber caused any passengers to acquire a vehicle; among other reasons, this could occur if they needed a new vehicle to become a Lyft or Uber driver.

After discussing the impacts of Lyft and Uber on vehicle ownership in this section, we detail in the following sections the characteristics of vehicles held by the respondents, vehicle shedding, vehicle suppression, and vehicle acquisition. For these impacts, rebalancing impacts to reflect likely population impacts are important. As described in the methodology, we apply weighting to the survey data to reflect the fact that certain respondents may be more likely to take a survey about their Lyft or Uber use, and these respondents may also be more likely to have experienced certain measured impacts. Weighting adjusts for these effects to better estimate the likely impacts present within the overall passenger population.

<u>Total Vehicle Holdings</u>

Passenger survey respondents were asked to indicate the number of vehicles they owned. If they were classified as a household, they were asked to indicate household vehicle holdings. Otherwise, they were asked about their vehicle ownership as an individual (not considering the ownership of other household members, like roommates). After reporting the number of vehicles held, respondents were asked to report the make, model, and year of the vehicle(s) they owned. Questions were then asked about the total annual driving conducted using those vehicles, as well as the changes in personal driving using these vehicles as a result of Lyft and Uber availability.

We compared the number of vehicles held by respondents in the sample with the vehicle holdings estimated for the general populations in each CBSA. We estimated the vehicle holdings of the general populations using the ACS five-year 2016 estimates for vehicles by household size. The data from the sample were rendered to match the household size categories as presented by the ACS. The ACS measures are estimates from samples taken over five years and do not represent an exact vehicle count. However, the ACS estimates provide sufficient information to draw insights about how the distribution of vehicle ownership among the general population compares to the survey sample.

San Francisco Vehicle Holdings

Table 15 shows the distribution of the household vehicle holding metrics for the San Francisco market.

Table 15. Household Vehicle Holdings of Population and San Francisco Sample

General Population (U.S. Census ACS 2016)—San Francisco CBSA

Household Size	Census Estimated Distribution of Vehicles in Household of Given Size	Households With Zero Vehicles	Estimated Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	395,858	125,647	456,210	0.87	28%
2	888,802	50,239	527,692	1.68	10%
3	568,660	16,681	280,694	2.03	6%
4 or More	967,773	15,061	409,444	2.36	4%
Total or Average	2,821,093	207,628	1,674,040	1.69	12%

Passenger Survey Sample—San Francisco

Household Size	Distribution of Vehicles in Household of Given Size	Households With 0 Vehicles	Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	672	605	1,217	0.55	50%
2	991	202	861	1.15	23%
3	360	37	241	1.49	15%
4 or More	640	26	332	1.93	8%
Total or Average	2,663	870	2,651	1.00	33%

The key measures for comparison are the vehicles per household and the percentage of households with zero vehicles. In general, the CBSA population exhibited a higher level of vehicle ownership than the sample, and this difference widens as the households become larger. In the general population, the vehicles per household measure is 0.87 for one-person households; this increases to 2.36 for households with four or more people. By contrast, the vehicles per household measure in the sample ranges from 0.55 to only 1.93 across the same categories.

The distribution of households with zero vehicles exhibited similar distinctions between the sample and general population. The ACS estimates that about 28 percent of one-person households in the San Francisco CBSA do not own any vehicles. Within the sample, about 50 percent of one-person households had zero vehicles. As household size increased within both the population and the sample, the likelihood of zero vehicles declined considerably. Within the San Francisco general population, only 10 percent of two-person households had zero cars, while in the sample, this share was 23 percent. Overall, only 12 percent of households within the San Francisco CBSA were car-free, whereas in the sample this figure was 33 percent.

Los Angeles Vehicle Holdings

The vehicle holdings patterns found in the Los Angeles market (Table 16) are similar to those found in San Francisco. The main difference is that automobile ownership rates were generally higher in Los Angeles.

Table 16. Household Vehicle Holdings of Population and Los Angeles Sample

General Population (U.S. Census ACS 2016)—Los Angeles CBSA

Household Size	Census Estimated Distribution of Vehicles in Household of Given Size	Households With Zero Vehicles	Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	1,019,856	192,487	1,054,906	0.97	18%
2	2,122,087	78,728	1,218,745	1.74	6%
3	1,495,403	35,285	723,957	2.07	5%
4 or More	3,077,150	51,202	1,301,249	2.36	4%
Total or Overall	7,714,496	357,702	4298857	1.79	8%

Passenger Survey Sample—Los Angeles

Household Size	Total Vehicles in Household of Given Size	Households With Zero Vehicles	Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	930	420	1,258	0.74	33%
2	1,244	94	842	1.48	11%
3	595	50	367	1.62	14%
4 or More	1,244	57	608	2.05	9%
Total or Average	4,013	621	3,075	1.31	20%

In the Los Angeles general population, there were 0.97 vehicles per household among one-person households; as in San Francisco, this number rose to 2.36 for households with four or more people. For the sample, a similar pattern holds, with vehicles per household reaching 2.05 for the largest of households. The percentage of households with zero vehicles also followed a pattern resembling San Francisco's, albeit with lower absolute values. In the population, 18 percent of one-person households did not have a vehicle. This percentage dropped by two-thirds to 6 percent for two-person households and reached 4 percent for households with four or more people. The sample exhibited a similar decline in the percentage of zero-vehicle households, but it was not as fast or as large as the decline found in the population. Thirty-three percent of one-person households in the sample had no vehicle, this drops by two-thirds, to 11 percent, for two-person households. The percentage fell to 9 percent for households with four or more people. Across the entire population, 8 percent of households in the Los Angeles CBSA were carless, whereas 20 percent of passenger survey respondents were similarly carless.

Washington, D.C., Vehicle Holdings

Washington, D.C., had the same general pattern of vehicle ownership across household size (Table 17) as did San Francisco and Los Angeles. Interestingly, the distribution of the population's vehicle ownership appeared more like that of Los Angeles, whereas the sample appeared more like San Francisco's distribution.

Table 17. Household Vehicle Holdings of Population and Washington, D.C., Sample

General Population (U.S. Census ACS 2016)—Washington, D.C., CBSA

Household Size	Census Estimated Distribution of Vehicles in Household of Given Size	Households With 0 Vehicles	Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	548,664	123,940	580,435	0.95	21%
2	1,173,155	46,938	655,746	1.79	7%
3	748,289	21,271	361,170	2.07	6%
4 or more	1,277,044	23,191	553,315	2.31	4%
Total	3,747,152	215,340	2,150,666	1.74	10%

Passenger Survey Sample - Washington, D.C.

Household Size	Total Number of Vehicles in Household of Given Size	Households with 0 Vehicles	Total Households of Given Household Size	Vehicles per Household	Percentage of Households With Zero Vehicles
1	716	772	1,454	0.49	53%
2	975	217	901	1.08	24%
3	332	56	255	1.30	22%
4 or more	507	43	294	1.72	15%
Total	2,530	1,088	2,904	0.87	37%

The total vehicles per household in the Washington, D.C., CBSA population was 0.95 for one-person households and rose to 2.31 for households with four or more people. However, within the sample, the total vehicles per household was 0.49 for one-person households and increased to only 1.72 for households with four or more people. In the general population, 21 percent of one-person households were without cars. Similar to Los Angeles, this measure fell by two-thirds, to 7 percent, among two-person households and declined to 4 percent for the largest households. On the other hand, the Washington, D.C., sample showed similarities to San Francisco: More than half (53 percent) of all one-person households had zero cars. As household size increases, the share of zero-car households declined but not nearly as precipitously as observed in the population. About one-seventh (15 percent) of households in the sample with four or more people had no personal vehicles. Overall, merely 10 percent of the Washington, D.C., CBSA population was carless, whereas across the sample this share was 37 percent.

Summary of Household Vehicle Holdings

Broadly, Table 15, Table 16, and Table 17 show that the general population within each of the target markets exhibited higher vehicle ownership than the sample population, although both the sample and population generally showed the same downward trends in the percentage of carless households as household size increased. However, we cannot conclude from these data alone that Lyft and Uber were causing reductions in vehicle ownership among the sample population. Rather, this section showed that carless or car-light households (those with fewer cars than average) were more likely to be passengers of Lyft and Uber to meet their automobile mobility needs.

Another general observation, from Table 17, is that the household vehicle ownership characteristics of the Washington, D.C. CBSA population were similar to those of the Los Angeles population, while the Washington, D.C. sample had more in common with the San Francisco sample. This is possibly due to the fact that relative to San Francisco and Los Angeles, the Washington, D.C., CBSA has a far more diverse collection of land uses, including outlying areas of considerably lower density. While the passenger survey sample drew largely from Lyft and Uber passengers in the core downtown areas of Washington, D.C., a considerable proportion of the general population is located in the broader Washington, D.C. CBSA, which is far more auto-oriented and even rural—and thus, like Los Angeles, has higher rates of auto ownership.

Finally, recall that our survey framed questions to respondents based on whether they were classified as an individual or a household (as noted in the passenger sociodemographics section). For example, respondents living only with roommates (where cost is shared, but not income) were asked questions as an individual and not as a household. The Census, on the other hand, considers such arrangements to be households (nonfamily households specifically), and it aggregates collected data accordingly. In our survey, people living with one or two roommates are considered individuals because this best characterizes how they make vehicle purchase and travel decisions. Therefore, our survey sample yields a larger proportion of one-person households than exist in the general population. But, it represents personal vehicle holdings of individuals perhaps more accurately than the Census. Those using Lyft and Uber come from a cohort of the population that has fewer vehicles overall than the general population and a greater share of households with zero cars. Still, the population using Lyft and Uber have plenty of cars to shed and may be using the services to substitute for acquiring a personal vehicle. We explore these impacts in the subsections that follow.

Frequency of TNC Use

During our study planning, we anticipated that respondents could exhibit a bias in terms of their frequency of TNC use. Specifically, those who use Lyft and Uber frequently may be more likely to take a survey about it, and frequent users are also more likely to exhibit substantial impacts from the service (such as shedding or suppressing a vehicle). This bias, if present in the sample, is important to consider. To compensate for this possible bias in the survey sample, we weighted shedding and suppression results based on the respondent's frequency of Lyft and Uber use.

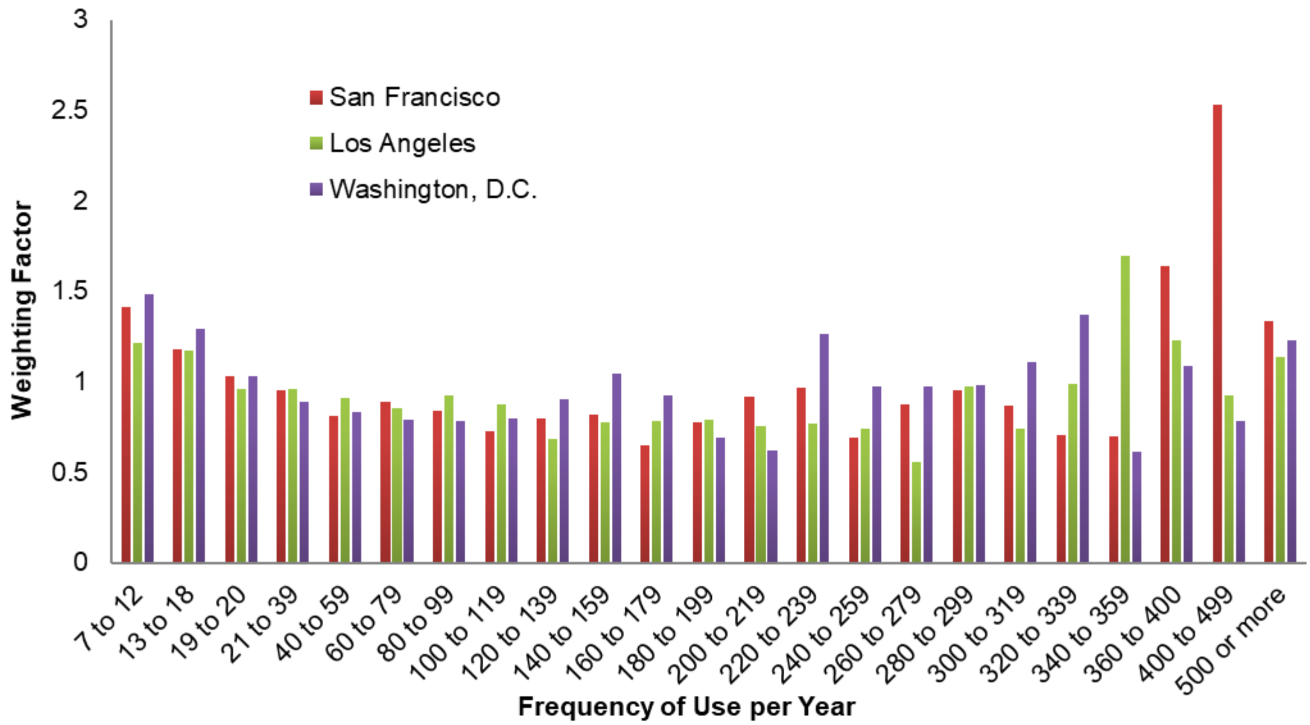
We combined frequency of use for both services from activity data provided by the operators and the survey. Lyft and Uber collaborated to produce a common de-identified ID (De-ID) that would match across passengers, using a uniquely encrypted common ID for each operator. This process permitted a common ID to exist across respondents, regardless of whether they took the survey with Lyft or Uber, yet prevented either operator from inadvertently learning the identities of passengers using the other service. Through the provision of activity data, we matched frequency of use across respondents, yielding a match rate of 97 percent across the entire sample. That is, we were able to match 97 percent of the encrypted De-IDs collected during the survey with activity data provided by Lyft and Uber. This matching permitted us to combine activity data from both operators for a respondent and provided a more complete picture of the respondent's overall usage and mileage with the two operators. When we were unable to match a De-IDs to activity data, but a survey response about frequency was given, we used this stated (combined) frequency in its place.[7]

The distribution of frequency of use within each target market shows the degree to which the sample in each market was systematically skewed toward higher frequency of use relative to the general population (Figure 19). The populations each contain relatively high shares of infrequent users (those who used Lyft or Uber fewer than 13 times per year). As explained in the methodology, the minimum criterion for inclusion within the sample and population was using Lyft and Uber at least seven times annually, with 50 percent of trips occurring within the target market. This condition was required because the operators did not have better methods at the time to identify whether individuals lived within a particular target market. Any passenger at these frequency levels (using Lyft and Uber less than 13 times per year) would have had their vehicle impacts automatically counted as zero, on account of being relatively inactive TNC passengers. However, we still considered the miles driven to accommodate this travel in aggregate mileage measurements, which will be explored in the subsequent VMT analysis.

We computed the weights derived from these frequency distributions as the population percentage divided by the sample percentage within the same category. We used the individual frequency-of-use covariates across users of both operators and the population frequencies separately. These produced weights for Uber and weights for Lyft within each of the frequency categories. We then averaged these weights to produce the final weights. This was done because the sample population frequency of use was unknown relative to the general population. For example, the sample, through covariates and survey responses, could tell us the combined frequency of use of each individual. But the operator population frequencies would tell us only the within-operator frequency-of-use distribution. There is no way to know the combined distribution with these data. To compensate, we considered the within-operator weight computation to be a close estimate, and in general the weights aligned across the two operators. Figure 19 shows a distribution of these weights by frequency category. Weights above the value of 1 indicate that the frequency-of-use category was underrepresented in the sample, whereas values below 1 indicate that the category was overrepresented in the sample.

[7] Annualized trips per year were measured during the defined study period of June 1, 2015 to May 31, 2016.

Figure 19. Distribution of Weights by Frequency of Use



As mentioned above, the analysis considered only those respondents who were active users of the services over the study year. This was defined as those who used Lyft and Uber more frequently than about 1.5 times a month, on average. That is, vehicle impacts of any respondents, such as shedding or suppression, were counted only if a respondent used Lyft and Uber (combined) more than 20 times a year. This restriction creates a more conservative criterion for vehicle impact metrics that are derived from survey responses. A respondent who uses Lyft or Uber less than this amount may report that TNCs enabled her or him to shed or suppress a vehicle. For such respondents, the effect of Lyft and Uber may be very real. Lyft and Uber may be providing mobility insurance (the ability to travel by car if absolutely needed) or facilitating mobility needs that were infrequent but for which a vehicle had been absolutely necessary and retained. These two scenarios, along with others, could lead to a personal vehicle being shed or suppressed. But at such infrequent usage rates, there is greater doubt that this effect is meaningful in displacing a personal vehicle. In the interest of being conservative, we opted not to count vehicle ownership impacts of respondents who reported using Lyft and Uber less than this frequency.

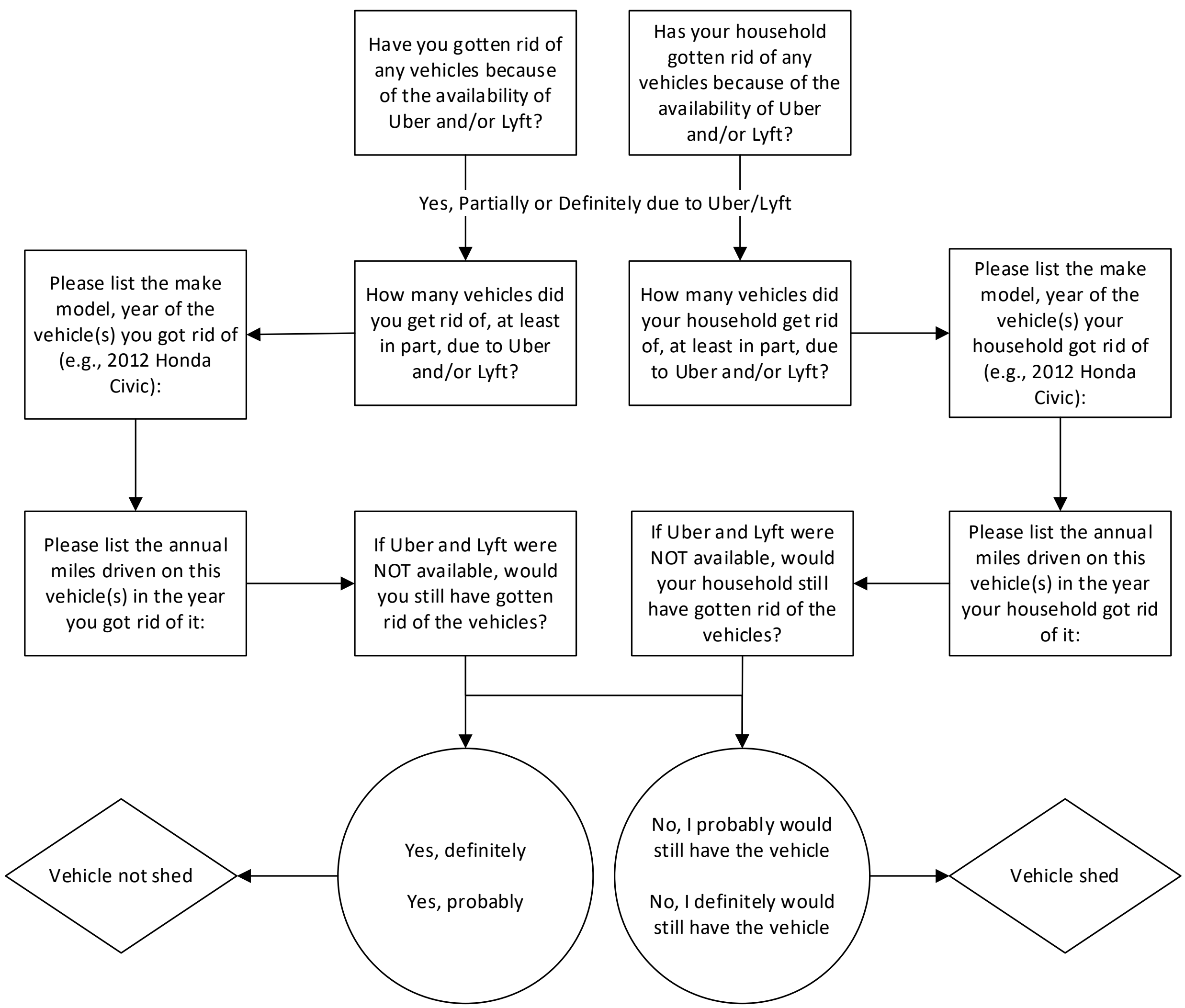
Additionally, the impacts of shedding, suppression, and acquisition as a result of Lyft and Uber were counted once for a respondent. That is, if a respondent indicated that Lyft and Uber caused more than one vehicle to be shed, suppressed, or acquired, only one was considered in the impacts. This too was in the interest of taking a more conservative assessment of Lyft and Uber impacts on vehicle ownership. This latter measure had a minimal impact on the results, in that the vast majority of respondents reported only one vehicle impact.

<u>Vehicle Shedding</u>

The survey explored the degree to which passengers of Lyft and Uber shed vehicles as a result of using the services. Some passengers may find that the mobility services and prices offered by Lyft and Uber are enough to motivate a reduction in vehicle ownership. These passengers decide that they can avoid the ownership costs of a vehicle and use Lyft or Uber to meet the essential mobility needs that were previously met by the personal vehicle. Those making this decision are a minority of the sample. The vast majority of passengers, even those who frequently use the service, did not decide to shed a personal vehicle due to the availability of Lyft and Uber.

The survey asked questions that evaluated whether the respondent shed a vehicle due to Lyft and Uber. Respondents first had to indicate that they "partially" or "definitely" shed a vehicle due to Lyft and Uber. If they did, they were asked to indicate details about the shed vehicle(s) including the number of vehicles; the make, model, and year; and the annual miles driven on each shed vehicle. Finally, respondents were asked a question confirming that they would not have discharged the vehicle if Lyft and Uber were not present. The flow and structure of the questions are presented in Figure 20 below, which shows two tracks of questioning depending on whether the respondent was classified as a household or an individual. The responses to vehicle shedding were weighted, as described previously, to account for the difference in the frequency of use of the sample versus the overall passenger population in each CBSA.

Figure 20. Personal Vehicle Shedding Question Structure



Overall, Lyft and Uber were having a small but measurable effect on vehicle holdings. Table 18 shows vehicle shedding as a result of Lyft and Uber. The results show the weighted count of respondents who reported shedding a vehicle either partially or definitely because of TNC availability. We reduced this total to the number of owners who verified that they would have held on to their vehicle if Lyft and Uber did not exist. Finally, Table 18 shows the number of vehicles shed as a percentage of respondents within each market and across all markets. The proportion of respondents who shed a vehicle is approximately 2.5 percent. This low proportion may be due to the transactional barriers to a vehicle sale. Weighted values produce estimates that are not whole numbers. For simplicity, the values within each in cell are rounded to the nearest whole vehicle and then summed. Results are presented this way in Table 18 as well as subsequent results within this section.

Table 18. 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
San Francisco	141	58	199	83	3.1%
Los Angeles	80	60	140	80	2.6%
Washington, D.C.	124	31	155	49	1.7%
Total (3 Markets)	345	149	494	212	2.5%

As indicated in Figure 20, respondents were asked to report the specific vehicle that they got rid of due to Lyft, Uber, or both. Not every respondent who reported shedding a vehicle also reported a specific make, model, and year. Table 19 below shows a selection of 200 of the specific vehicles that were reported as shed.

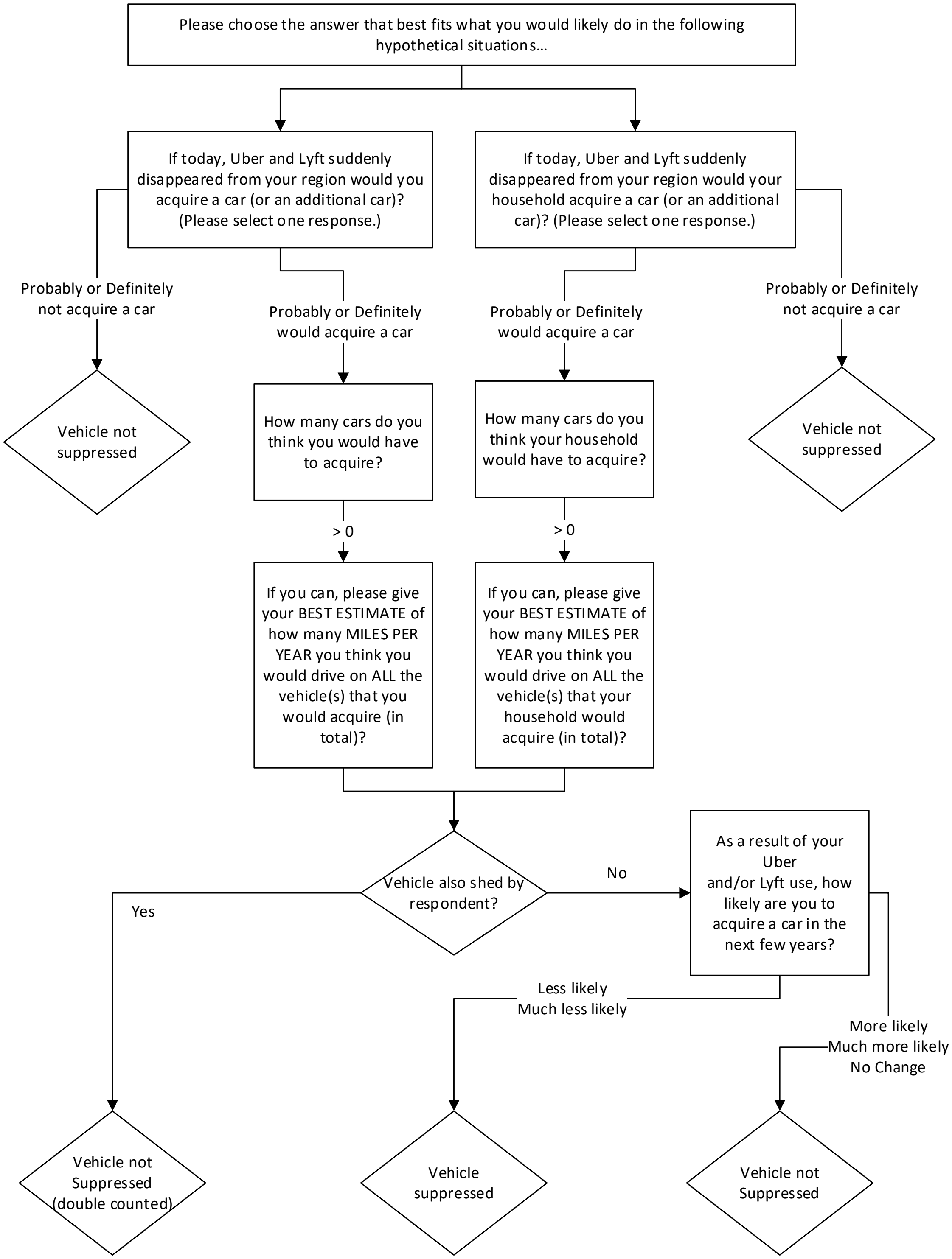
Table 19. Selected Vehicles Reported Shed by Respondents

2009 BMW M3	2011 Honda Civic	2000 GMC Jimmy	2005 Chevy Monte Carlo
2008 Honda Civic	1995 Honda Accord	2000 Mazda Miata	2010 Nissan Altima
2006 Toyota Prius	2000 Volvo S40	2008 Hyundai Tiburon	2009 Honda Civic
2009 Mazda 3	2008 Ford Escape	2001 Honda Civic	2014 Toyota RAV4
2012 BMW 335	2004 Jeep Cherokee	2013 Mercades C250	2002 Toyota Tacoma
2008 Volvo S60	2011 BMW 328i	2000 VW Beetle	2014 Mini Countryman
2005 Toyota Camry	2014 Toyota Corolla	2005 Chevy Cavalier	2008 BMW 330i
2013 Jeep Grand Cherokee	2014 Mercedes C250	2014 Honda Civic	1992 Honda Civic
1988 Acura Integra	1998 Ford Expedition	1988 Honda Civic	2005 Honda Civic
1996 Honda Accord	2006 Kia Spectra	1968 Mercury Cougar	2001 Volkswagen Jetta
2009 Audi A4	2012 Scion iQ	2014 Ford Focus	2013 BMW X3
2007 Toyota RunX	2013 Honda CRV	2003 Mitsubishi Eclipse	2009 Honda Fit
2004 Porsche 911	2014 Nissan Sentra	2010 Toyota Camry	2010 Toyota Camry
2008 Toyota Camry	2005 Hyundai Accent	2009 VW Jetta	2003 Honda Accord
2014 Nissan Versa	2010 Honda Accord	2008 Ford Escape	2004 Ford Escape
2015 Ford Focus	2009 Nissan Sentra	1996 Mazda MX6	2001 Hyundai Accent
2003 Honda Civic	2010 Honda CR-V	2007 Volkswagen Jetta	2002 Infiniti Q45
2011 Mini Cooper	2013 VW Jetta	2002 Ford Taurus	2007 Saab 9-3
2010 BMW 3 series	2006 Audi A4	1996 Jeep Grand Cherokee	2008 Honda Civic
2001 Subaru Forester	2010 Nissan Altima	2006 Subaru Tribeca	2002 VW Cabriolet
2011 BMW 328i	2007 Nissan Altima	2013 Ford Focus	2007 VW Jetta
2012 Honda CRV	2012 Toyota Prius	2000 Toyota Camry	2012 Honda Civic
2006 Jeep Wrangler Rubicon	2007 Honda Civic	2013 Buick Enclave	2003 Mercedes CLK320
2003 Toyota Tacoma	2014 Ford Fiesta	2002 Dodge Neon	2009 Chrysler PT Cruiser
2007 Honda Accord	2008 Nissan Sentra	2011 Ford Fiesta	2005 Nissan Altima
1991 Toyota Camry	2003 VW Jetta	2010 VW GTI	2013 Ford Fusion
2006 Toyota 4runner	2006 VW Passat	2003 BMW X5	2007 Toyota Corolla
2008 Ford Fusion	2012 Nissan Altima	2010 Mazda 3	2012 Chevy Silverado
1990 Lexus es250	2010 Aston Martin	2002 Toyota Prius	2011 Jeep
2008 Ford Escape	2006 Nissan Maxima	2002 Acura TL	2005 Ford Taurus
2012 Toyota Corolla	2013 BMW 535	2013 Honda Accord	2010 Ford Escape
2010 Toyota Prius	2000 Mercedes	2009 Nissan Rogue	2004 Volkswagen Passat
2008 Volkswagen Rabbit	2002 Ford Escape	1989 Toyota Pickup	2011 Jeep Wrangler
2010 BMW 325	2003 Honda Civic	2000 Toyota Sienna	2012 Honda Accord
2009 Chevy Silverado	2000 BMW 328iC	2005 Nissan Sentra	2005 Toyota Corolla
2012 Toyota Matrix	2001 Toyota Echo	2006 MBZ E350	2004 Nissan XTerra
2001 Honda Civic	1999 Nissan Maxim	2000 Toyota Corolla	2007 Honda Truck
2000 Bmw 325i	2002 Volkswagen Golf	2008 Honda Civic	2006 Volvo Wagon
2012 Subaru Legacy	2001 VW Jetta	2012 Toyota 4Runner	2014 Honda Accord
2005 Nissan Altima	2013 Hyundai Genesis Coupe	1997 Yamaha Riva	2013 BMW 328i
2001 Dodge Stratus	2015 Audi A4	2007 Toyota Prius	2006 Mazda Sedan
2010 Renault Grand Classic	2004 Jeep Grand Cherokee	1970 Ford Boss 302	2013 Toyota Prius
1992 Honda Civic	2008 VW Jetta	2012 Toyota Corolla	1989 Subaru Forester
2010 Volkswagon Jetta	2005 Honda CR-V	2009 Kia Rio	1999 Ford Mustang
2011 Honda Civic	2015 Lexus 450H	2013 Porsche Macan	2012 Subaru Outback
2012 Mercedes E350	2015 Honda Fit	2001 Honda Civic	1998 Honda Civic
2003 Audi A4	2013 BMW 335i	1996 Volkswagen Golf	2010 BMW 328
2007 BMW 325i	2013 Hyundai Veloster	2008 Chevrolet Malibu	2001 Ford Taurus
2009 Honda Civic	1998 Buick LeSabre	2008 Toyota Avalon	2008 Toyota Camry

Vehicle Suppression

We explored vehicle suppression through a similar series of questions. Figure 21, below, shows the survey question structure. As with the shedding methodology, we framed this question differently based on whether the respondent was classified as an individual or a household.

Figure 21. Personal Vehicle Suppression Question Structure



As with vehicle shedding, vehicle suppression was evaluated with several questions confirming the presence of a suppression impact. Respondents were asked if they would have acquired a vehicle if Uber and Lyft suddenly disappeared. If they believed that they probably or definitely would, respondents were asked a series of questions assessing the number of vehicles that they would acquire and how far they would drive on them. Figure 21 then shows two decision pathways. If a respondent also shed a vehicle, then we only counted the vehicle shed and did not count the reported vehicle shed as suppressed. We employed this methodology to avoid double counting that would arise as a result of a respondent shedding a vehicle due to Lyft and Uber and then reporting that the vehicle would need to be reacquired if Lyft and Uber disappeared. Thus, the subsamples of respondents who shed vehicles and suppressed vehicles are mutually exclusive. If the respondent did not shed a vehicle, an additional question was applied to evaluate suppression. Respondents were asked how likely they were to acquire a car in the next few years as a result of Lyft or Uber use. If respondents reported "less likely" or "much less likely," then this was an indication of sustained suppression of the vehicle as a result of Lyft and Uber. This response, in combination with the more immediate suppression indicated by the questions above was used to affirm a vehicle suppression impact within the household.

The analysis of vehicle suppression followed the same weighting process as the analysis of vehicle shedding. Table 20 shows the suppression results for the weighted sample. The results show that vehicle suppression as a result of Lyft and Uber is more substantial than the impacts found with shedding. This outcome is somewhat expected, as it is easier to not acquire a vehicle than it is to shed one. This impact of avoiding a vehicle acquisition is an important one, as it lowers the dependency on personal vehicle ownership for a share of the TNC passenger population. This naturally displaces VMT, since a vehicle not acquired is not driven.

One interesting finding is the discrepancy of suppression percentages across the three markets, also shown in Table 20. Surprisingly, the effect is largest in Los Angeles, where the suppression rate is 9.2 percent. Within the other two markets, the suppression rate is between 6.4 percent and 7.8 percent. The higher impact in Los Angeles suggests that Lyft and Uber may be more effective at vehicle suppression in more auto-oriented environments. In such environments, which have relatively lower density, Lyft and Uber deliver mobility to passengers in a manner that is much more accessible than other shared mobility modes such as carsharing and bikesharing, which require fixed assets to be deployed and maintained. Lyft and Uber bring the shared mobility asset to the user. These results suggest that Lyft and Uber enabled a notable portion of respondents to remain carless or avoid the acquisition of an additional car. This prevention of vehicle acquisition has important impacts on congestion, VMT, and emissions.

Table 20. Personal Vehicle Suppression From Weighted Sample

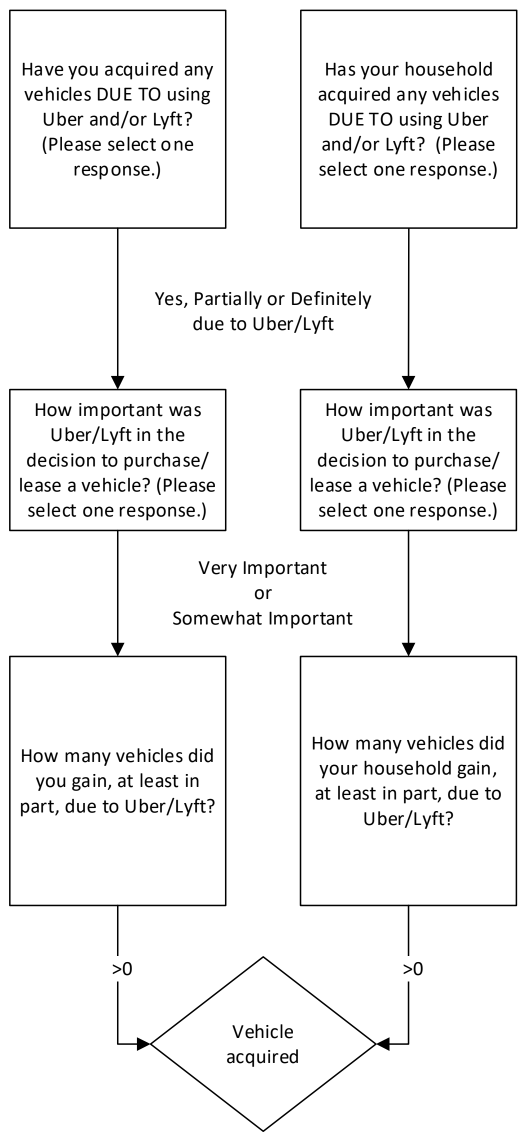
Vehicles Suppressed	Probably	Definitely	Total Due to Lyft/Uber	Total Sustained Suppression Due to Lyft/Uber	Vehicles Probably or Definitely Suppressed per Passenger
San Francisco	254	66	320	207	7.8%
Los Angeles	348	196	544	284	9.2%
Washington, D.C.	236	100	336	186	6.4%
Total (3 Markets)	838	362	1200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

The effects of suppression are even more pronounced in zero-car households, and this impact was quite prominent in Los Angeles. The suppression rate just among zero-car households was found to be 15 percent in San Francisco, 26 percent in Los Angeles, and 12 percent in Washington, D.C. In other words, Lyft and Uber enabled passengers to reduce personal vehicle ownership, but they more prominently enabled carless households to remain carless.

Vehicle Acquisition

While impact assessment of shared mobility generally focuses on the reduction of personal vehicles in households, our survey explored whether passenger survey respondents reported any increase in personal vehicle acquisition as a result of Lyft and Uber. This increase could happen for a number of reasons. For example, people who decide to drive for Lyft or Uber may acquire a vehicle for that purpose and then drive more overall. While this study administered a separate Driver Survey, respondents to the Passenger Survey were asked, "Have you ever been a driver for Uber or Lyft?" to provide appropriate background for other questions, such as this one. Additionally, exposure to automotive mobility may motivate some passengers to acquire a vehicle when they are able to. These reasons may be circumstantial, but to explore the magnitude and presence of these potential impacts, we asked a series of questions in our Passenger Survey to evaluate whether Lyft and Uber had caused respondents to acquire a vehicle (Figure 22).

Figure 22. Vehicle Acquisition Question Structure



Respondents had to report that they acquired a vehicle, and that it was "partially" or "definitely" due to Lyft and Uber. They also had to report that the TNC services were "very important" or "somewhat important" in the decision to purchase or lease the vehicle. Under the same weighted and active member criteria that were applied in the vehicle shedding and suppression analyses, we found that a small portion of respondents reported acquiring vehicles as a result of Lyft and Uber (Table 21).

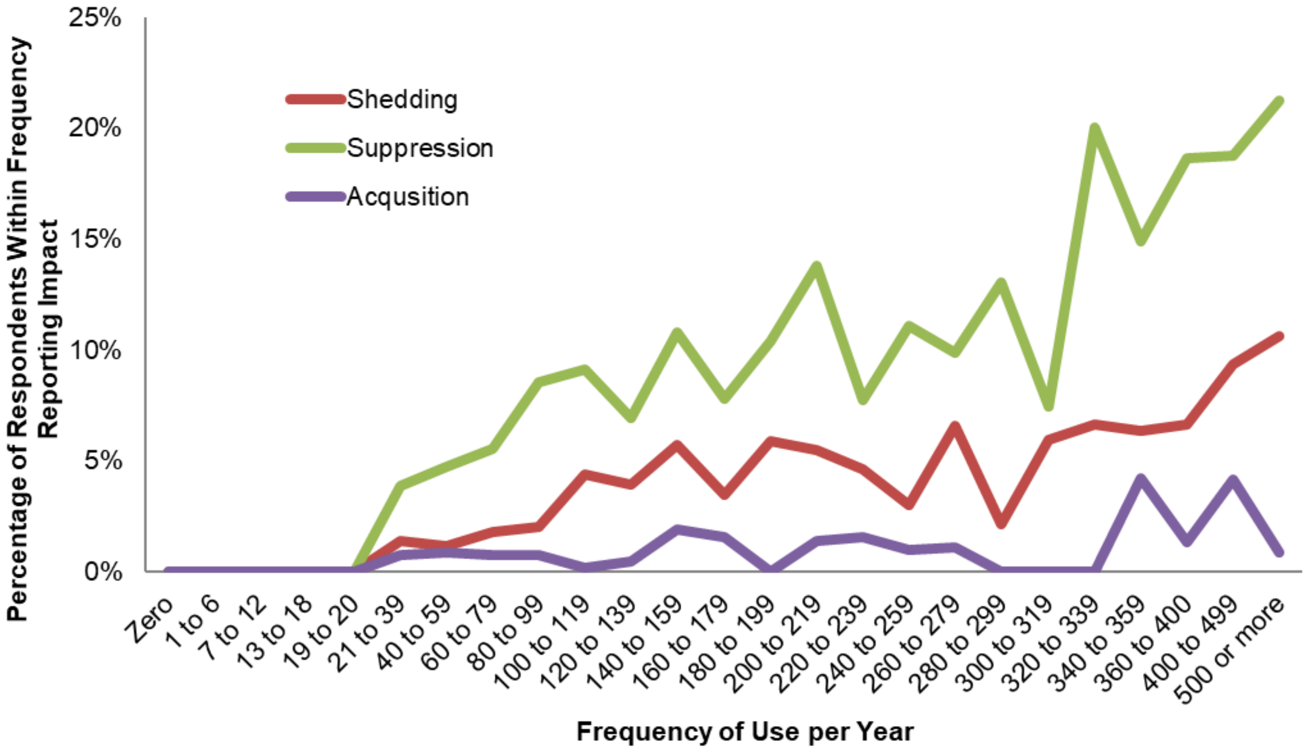
Table 21. Personal Vehicle Acquisition From Weighted Sample

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

We did not probe the exact reason for vehicle acquisition specifically, but we found that 18 respondents contributing to vehicles acquired were also Lyft or Uber drivers. Overall, vehicle acquisition does occur as a result of Lyft and Uber, but the percentages are much smaller than those observed relative to vehicle shedding and suppression.

Not surprisingly, usage frequency is positively correlated with the propensity to suppress and shed a vehicle. Figure 23 below shows the raw (unweighted) percentage of respondents reporting an impact of shedding, suppression, or acquisition as a function of usage frequency. These are "within category" percentages of respondents reporting an impact of a particular type. In the case of both shedding and suppression, the rates rise significantly as usage frequency increases, indicating that individuals who use Lyft and Uber at a greater frequency are more likely to perceive the service as a substitute for personal vehicle ownership. Notably, this trend does not exist for vehicle acquisition. This is perhaps expected, as a vehicle acquisition would reduce the need for Lyft and Uber. Comparing unweighted data underscores the need to consider how a sample is balanced with respect to usage frequency, particularly when evaluating the impacts of TNCs (as well as other shared modes) on the broader user population.

Figure 23. Percentage of Respondents Reporting Vehicle Impact as a Function of Usage Frequency (Unweighted)



<u>Summary of Vehicle Ownership Impact Findings</u>

Taking the results of Table 18, Table 20, and Table 21 together in combination, we evaluated the net vehicle change that occurred within the weighted sample (Table 22). There are impacts in both directions (increases and decreases), with vehicles shed and suppressed accounting for the reductions (negative) and vehicles acquired accounting for the gains (positive). Overall, the results show that while the majority of respondents experienced no impact on personal vehicle holdings due to availability of Lyft and Uber, TNCs have enabled some passengers to sell vehicles or forgo automobile ownership. The net vehicle change per respondent was found to be between –7.4 percent in Washington, D.C., and –10.9 percent in Los Angeles, the latter result owing to the high vehicle suppression rate reported in Los Angeles. Across all three markets, the average net change was about –9.6 percent. These results are among the key drivers of overall changes in VMT and emissions, which are discussed in depth in the next section.

Table 22. 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
San Francisco	-83	-207	13	-277	-10.4%
Los Angeles	-80	-284	29	-335	-10.9%
Washington, D.C.	-49	-186	19	-216	-7.4%
Total (3 Markets)	-212	-677	61	-828	-9.6%

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

The impact that Lyft and Uber have on VMT is a function of a number of behavioral changes that occur among service users. In addition to these behavioral changes, measuring shifts in VMT must also consider all Lyft and Uber vehicle activity on roads within their passenger markets, including the driving that occurs without passengers (also called deadheading). The net impact of Lyft and Uber is determined by these combined effects. The measurement of VMT impacts from TNCs ideally considers the visible behavioral change of passengers, the VMT that Lyft and Uber vehicles produce to facilitate that change, and the VMT that would have been logged had Lyft and Uber not been available. Measuring this change is an inherently challenging task that requires an estimate of the overall change in behavior and activity caused by the availability of Lyft and Uber.

To estimate the direction and magnitude of VMT impact from Lyft and Uber, this analysis measures four main components of passenger behavioral change. These are defined as follows:

> <u>Change in Personal Vehicle Use</u>: Access to Lyft and Uber services may change the amount of driving an individual does in a personal vehicle. For example, Lyft and Uber may substitute for driving to a social activity that would otherwise be undertaken in a personal vehicle. In this case, personal vehicle driving would still have occurred, even in the absence of Lyft and Uber. Therefore, this report analyzes the reduction in personal vehicle driving that passenger survey respondents report as a result of Lyft and Uber. Respondents could also report that Lyft and Uber caused them to increase their driving in personal vehicles, and this is included as well.
>
> <u>Change in the Number of Vehicles Owned or Leased (Personal Vehicles Shedding)</u>: The availability of Lyft and Uber services can make it easier for individuals to sell/shed a personal vehicle. In this case, we assume the costs of using Lyft and Uber (as well as other supporting modes, e.g., public transit) are a substitute for vehicle ownership costs. Among households that sell/shed a personal vehicle due to TNCs, the miles that would have been driven on those vehicles do not occur.
>
> <u>Change in the Number of Vehicles That Would Have Been Acquired (Personal Vehicle Suppression)</u>: Just as the availability of Lyft and Uber enable some households to sell/shed a personal vehicle, other households may be able to avoid the acquisition of one or more vehicles that would have been purchased or leased in the absence of TNCs. Naturally, a vehicle not acquired is a vehicle not driven. Vehicle suppression is more common than vehicle shedding, since the latter entails the initiative to sell a vehicle and the former simply requires inaction. Lyft and Uber prevent a household from transitioning to personal vehicle reliance (or additional personal vehicles) for mobility.
>
> <u>Change in Use of Other Shared Vehicle Modes (e.g., taxi, carsharing, car rental, etc.)</u>: Lyft and Uber provide access to a shared mode on a short-term basis, similar to other shared mobility options. Using these services instead of taxis is one of the more common substitution patterns reported by Lyft and Uber passengers. If a trip taken with Lyft or Uber would otherwise have been taken using a taxi instead, then the net VMT impact of Lyft and Uber for this specific trip is likely negligible. In this case Lyft and Uber are not adding VMT or emissions because this vehicle activity would have also occurred in their absence and to a similar degree.

The measurement of these four changes—in personal vehicle use, vehicle shedding, vehicle suppression, and substitution of other shared modes—in passenger behavior drives the VMT change that is observed among respondents in the survey sample. The net positive, negative, or neutral VMT impacts of these measured changes are calculated and combined with the VMT of the two operators. All the data presented in this section are weighted using the same weights that were used in the vehicle ownership impact analyses. Recall that in this analysis we apply weights to adjust the sample to population-level frequency of use. This is because usage frequency plays an important role in the level of impact that a service can have. As shown in Figure 23 at the end of the vehicle impacts section, the suppression and shedding rates rise with increased usage frequency. Since people who use a service frequently are more likely to take a survey about it, a survey sample has a good chance of over-representing high-frequency users and overrepresenting the population-level impact. For the important vehicle and VMT measurements, where the net impacts measurement is important, the weights adjusted the sample impacts to better represent those reflected in the population. A limitation of this approach is that the weighting is unidimensional; it does not simultaneously adjust for other dissimilarities between the survey population and the overall population. Demographic deviations in the sample, for example, are not accounted for directly, in part because Census-like demographics for the Lyft and Uber population are unknown. Such departures may be indirectly adjusted via the frequency-of-use weighting, which we believe is one of the most important attributes affecting user impacts.

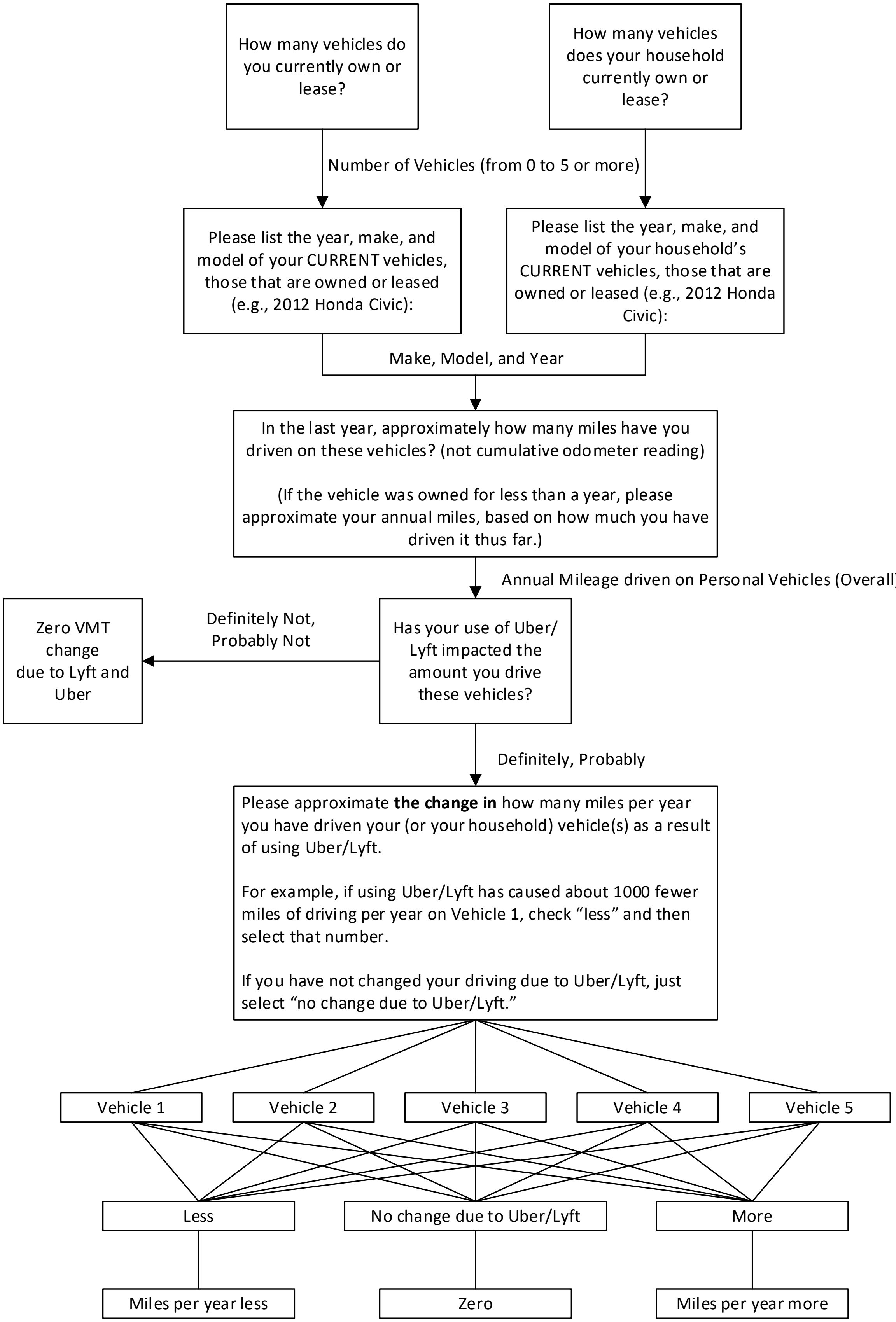
The change in miles traveled by the above-mentioned behaviors is facilitated and also substituted by Lyft and Uber use, which supplies automobility in place of auto ownership and use, for instance. These changes can also be translated into GHG emissions. We collected survey data on the make, model, and year of personal vehicles owned by passenger survey participants' households and mapped them to fuel economy factors as defined by the U.S. Environmental Protection Agency's fueleconomy.gov database. This permits a VMT translation to gasoline gallons consumed, which in turn can be used to estimate the resulting GHG emission change. In the sections that follow, we outline the distributions and average impacts found within each of these behavioral change components along the dimensions of VMT, followed by a discussion of the estimated net impacts. We then translate these impacts to net changes in GHG emissions.

Change in Personal Vehicle Use

We asked passenger survey respondents to assess whether their Lyft and Uber use had changed their personal vehicle use. For most respondents, when there was such a change, it was a decline in private auto use. However, some respondents reported that Lyft and Uber caused their driving of personal vehicles to increase, and we also considered this mileage.

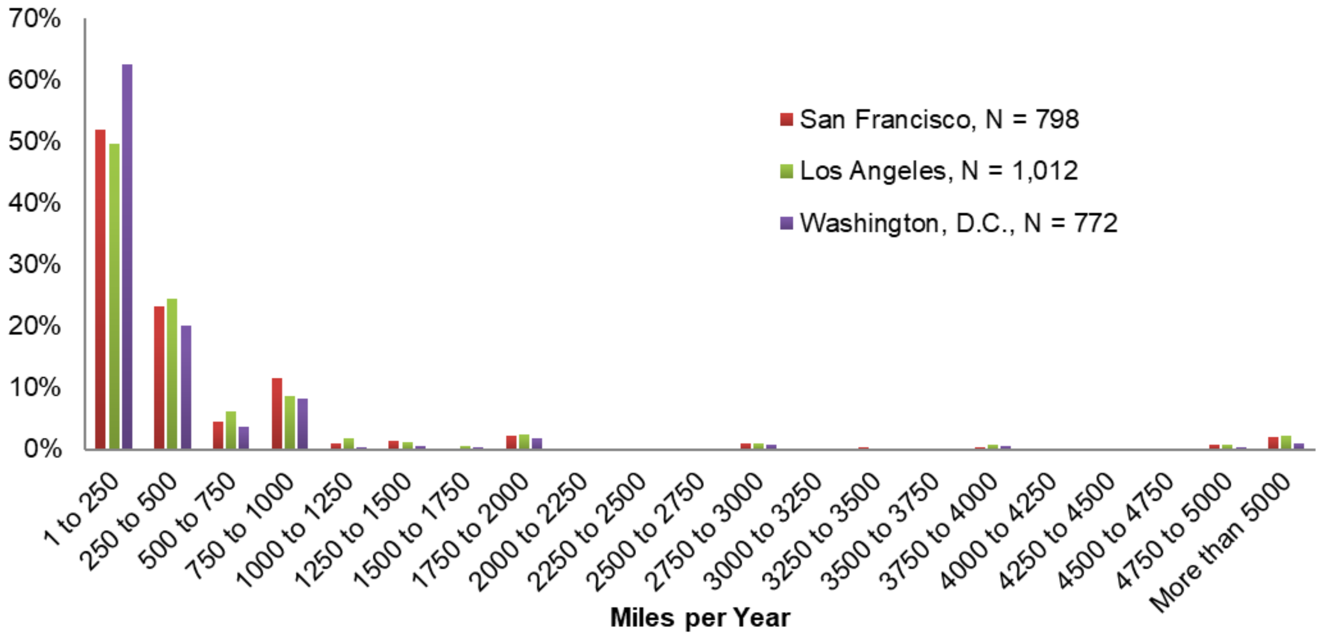
We evaluated the change in personal vehicle driving due to TNCs by employing a series of questions. First, we asked respondents to report which vehicles they (or their household) owned and how many miles they had driven during the past year in each vehicle. Then we asked respondents whether their Lyft and Uber use had impacted the amount that they drove their personal vehicles. Those reporting that TNCs had an impact were then asked questions to estimate the direction and magnitude of their change in personal vehicle driving. The structure and flow of these questions are outlined in Figure 24.

Figure 24. Question Structure of Vehicle Holdings and Driving Change



The responses to these questions provided a profile of the reported change in personal vehicle miles traveled (PVMT) that occurred as a result of using Lyft and Uber. Across all three markets, about 30 percent of passenger survey respondents reported driving their personal vehicles less as a result of Lyft and Uber. By market, these percentages were 30 percent in San Francisco, 33 percent in Los Angeles, and 27 percent in Washington, D.C. Figure 25 shows the distribution of responses just among those who reported driving less, across the three target markets. Recall that the total sample size (everyone) is 2,651 in San Francisco, 3,075 in Los Angeles, and 2,904 in Washington, D.C. Among those decreasing their PVMT due to TNCs, the weighted average of decline was 607 miles per year across all three markets.

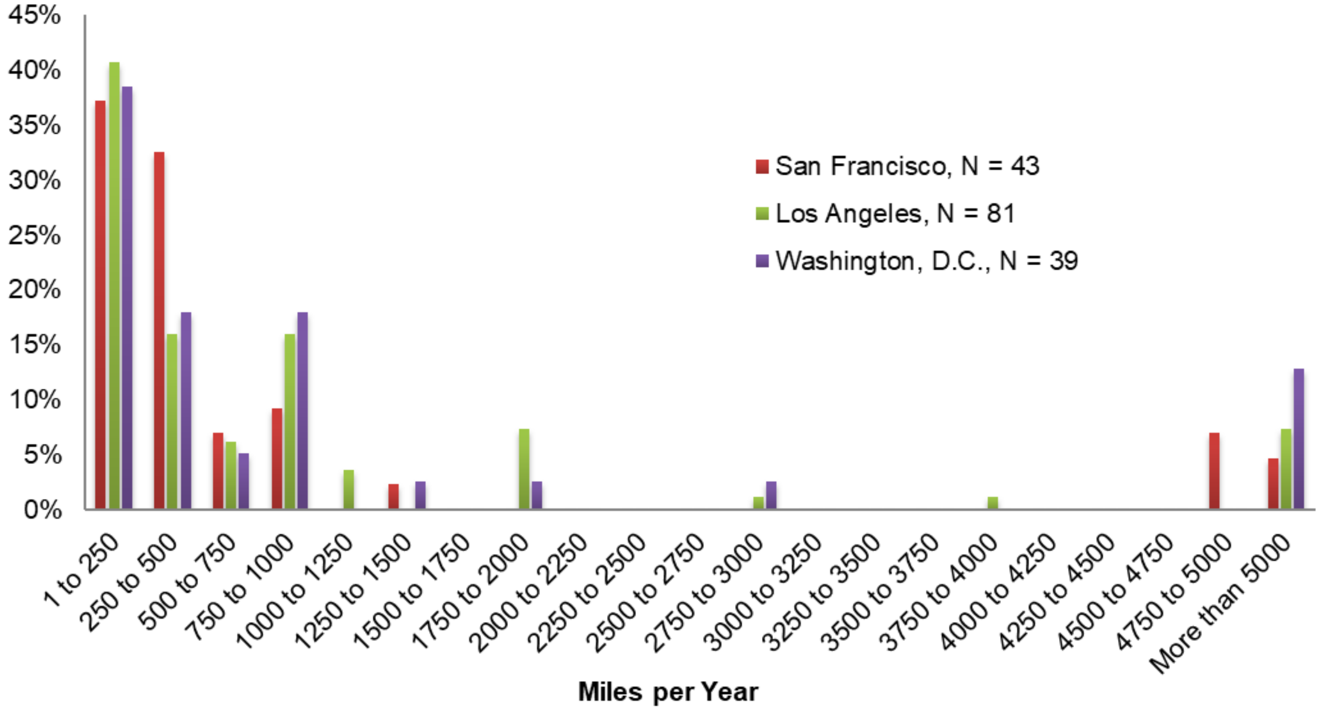
Figure 25. Distribution of Weighted Annual VMT Driving Less in Personal Vehicles Due to Lyft and Uber



A small portion of respondents reported driving their personal vehicles more due to Lyft and Uber. There could be a number of reasons for this. We hypothesize that at least some of these measurements consider additional driving by Lyft and Uber drivers among other lifestyle changes. To calculate the net change in personal vehicle driving due to TNCs, the increase in driving was subtracted from the reduction in driving shown in Figure 25.

Figure 26 shows the analogous distribution of reported increase in personal vehicle driving among passenger survey respondents due to Lyft and Uber. Two key attributes distinguish this distribution from that of Figure 25: The distribution has a larger variance, and the sample size is far smaller. Increases in personal driving were reported by 2 percent of the sample in San Francisco, 3 percent in Los Angeles, and 1 percent in Washington, D.C. However, among those increasing their personal vehicle driving, the average annual change in driving was considerably higher than it was among those decreasing their driving due to Lyft and Uber, with an overall weighted average of 1,311 additional miles per year driven per respondent in this subsample.

Figure 26. Distribution of Weighted Annual VMT Driving More in Personal Vehicles Due to Lyft and Uber



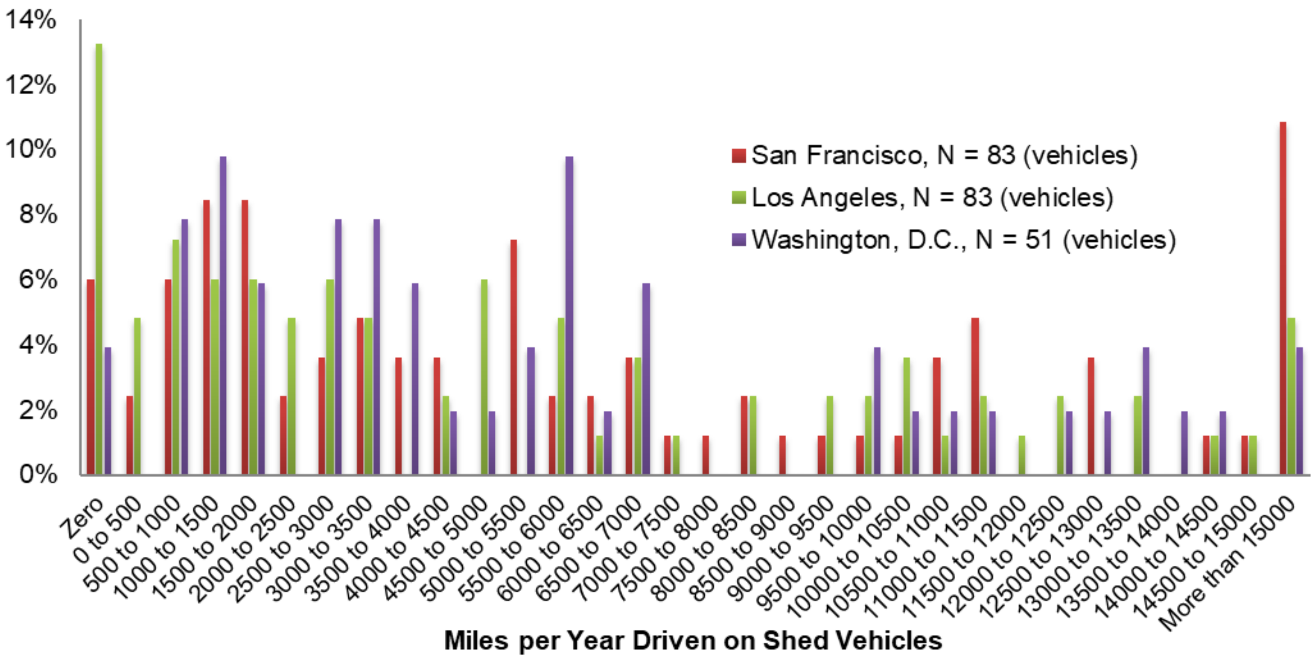
Across all passenger survey respondents, including those who exhibited no change in personal driving due to Lyft and Uber and those that did not own a personal vehicle, the weighted average change in personal vehicle driving was a reduction of 153 miles per year across all three markets. Within each market, this translated to a reduction of 164 miles per year in San Francisco, 194 miles per year in Los Angeles, and 100 miles per year in Washington, D.C. On balance, while Lyft and Uber facilitated some considerable reductions in personal vehicle driving among a minority of the survey population, the majority sample did not report a notable reduction in personal vehicle driving.

<u>Change in the Number of Vehicles Owned (Personal Vehicles Sold/Shed)</u>

The shedding of vehicles due to Lyft and Uber also reduces the amount an individual or a household chooses to drive. Unlike changes in personal driving, which can result in an increase or decrease of VMT among respondents, vehicle shedding exclusively results in a VMT reduction. Respondents who reported shedding a vehicle were asked to indicate the make, model, and year of the vehicle they shed, as well as the miles they drove annually in the vehicle when they had it. The structure of the survey questions we employed to collect this information was presented previously in Figure 20.

As noted earlier, vehicle shedding due to Lyft and Uber was found to be relatively limited within the overall sample. However, the VMT impacts from each vehicle shed was more substantive, as expected, since an entire vehicle is removed from the household fleet and no longer used. There are several ways to present these data. Figure 27 shows the distribution of the weighted miles driven on vehicles that were shed due to TNCs. This distribution shows the discrete number of vehicles reported shed by respondents in the sample (e.g., without weights on the counts); the weights are applied to the miles driven on these vehicles. For this reason, the count of vehicles shed as shown in Figure 27 differs from the weighted count shown in the vehicle impacts section in Table 18. It is important to note that the weights applied to the count of vehicles shed are the same as those applied to the miles of vehicles shed and to any other impact reported in this section. We cannot apply the weights twice (once to vehicles and again to miles), as this would overweight the impact. Since vehicles shed and suppressed have impacts both in units of vehicles and in units of miles, we could have applied the weights to one or the other. For example, we could have applied the weights to vehicles and then multiplied each weighted vehicle impact by the average change in VMT per respondent shedding a vehicle. The resulting computation would have produced the equivalent average. But this would not have worked for the VMT impacts related to changes in personal vehicle VMT; nor would this work for impacts related to shifts in taxi use or other personal vehicle modes, where mode use simply declined. For this reason, we applied the respondent weights to the units of miles driven and expressed the supporting counts in terms of the raw sample sizes (e.g., vehicles shed, respondents, etc.).

Figure 27. Distribution of Weighted Annual Miles Driven on Vehicles Shed



The weighted average annual miles driven on vehicles that were shed was about 6,308 per vehicle in San Francisco, 5,205 in Los Angeles, and 5,845 in Washington, D.C. Because the shedding of vehicles due to Lyft and Uber is rare within the sample, the average VMT impacts spread across the sample population are naturally much smaller. The average weighted annual miles reduced due to vehicle shedding per respondent was about 197 miles in San Francisco, 141 miles in Los Angeles, and 103 miles in Washington, D.C.

<u>Change in the Number of Vehicles That Would Have Been Owned (Personal Vehicle Suppression)</u>

One of the largest behavioral effects due to Lyft and Uber is personal vehicle suppression. This impact considers the annual miles that would have been driven in vehicles that were not purchased because Lyft and Uber provided enough mobility to make the acquisition unnecessary or not worth the expense. The question structure that identified personal vehicles suppressed was presented in Figure 21. As part of this multi-question structure, we asked passenger survey respondents to provide their best estimate of the miles that they would have driven on the vehicles that they would have acquired, if Lyft and Uber did not exist. This value, while hypothetical, provides an estimate based on multiple responses to different questions addressing the same impact.

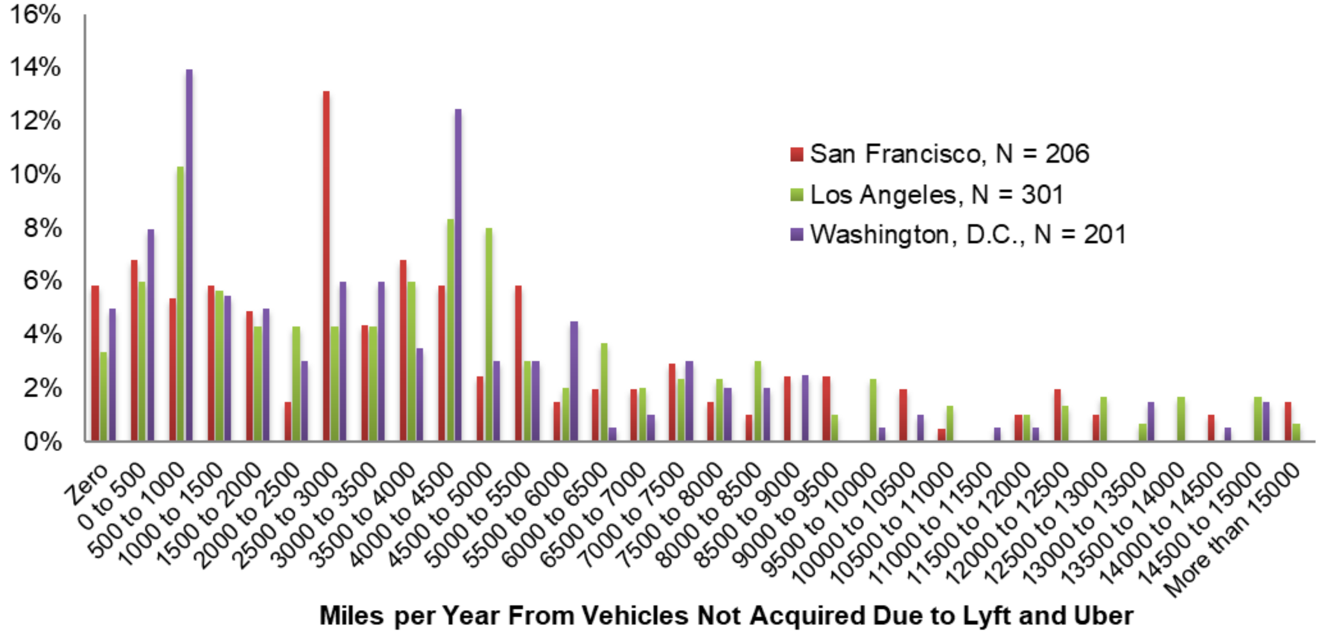
As noted previously, suppression is easier than selling/shedding a personal vehicle, since it is passive and involves taking no action. It is effectively the prevention of vehicle acquisition. Vehicle shedding, in contrast, requires a decision and action to get rid of a personal vehicle. Another aspect of personal vehicle suppression is the prospect of double counting these vehicles with those shed. As noted in the vehicle impacts section, if a respondent reported that he or she both shed and suppressed a vehicle, we considered the impact only of shedding a vehicle and did not count the reported suppression.

Figure 28 shows the distribution of the weighted annual miles that were reported by passenger survey respondents who indicated that Lyft and Uber caused personal vehicle suppression. The sample size shown is the unweighted count of respondents reporting personal vehicle suppression as a result of Lyft and Uber. Note that this distribution only shows vehicle suppression due to TNCs. It does not include those reporting no vehicle suppressed; all of those respondents would pile into the category of zero miles driven in Figure 28. We applied two assumptions to mileage suppression. First, some households reported the suppression of two vehicles, but this analysis counts only one vehicle per household, a conservative assumption. Second, although relatively high mileage reductions were uncommon, there were a few; we set an upper boundary for unweighted suppressed vehicle mileage at 20,000 miles per year.

Altogether, we developed an estimated average weighted mileage per suppressed vehicle of about 5,286 miles per year in San Francisco, 5,097 miles per year in Los Angeles, and 4,375 miles per year in Washington, D.C. Below we display the distribution of weighted miles only, as discussed above. The distribution comprises the weighted average of annual miles that respondents estimate would have been driven per year on vehicles they would have acquired in the absence of Lyft and Uber. It is not surprising that the average mileage is relatively low. Vehicles suppressed by any one shared mobility service are vehicles that, given the right portfolio mix of travel options, people can live without. But the automobility provided by shared services can be critical for personal vehicle suppression. Without it, Lyft and Uber passengers could be more compelled to acquire a personal vehicle to meet certain essential automotive needs. This in turn locks in the high ownership costs and lower marginal cost for using the automobile, which in turn could transition the owner to relying on a personal vehicle even more. This potentially larger impact is ultimately speculative, however, and there is a limit to the precision with which a hypothetical alternative future can be measured.

Still, the impact of personal vehicle suppression is an important one, and the survey indicates that a measurable minority of the survey sample (8 percent in San Francisco, 9 percent in Los Angeles, and 6 percent in Washington, D.C.) would choose not to purchase a vehicle because they had access to Lyft and Uber and would sustain that suppression in the near future. These respondents ultimately would not drive their estimated annual mileage on that personal vehicle. We present the distribution of reduced VMT due to personal vehicle suppression in Figure 28.

Figure 28. Distribution of Weighted Annual VMT Reduced From Personal Vehicle Suppression



Change in Use of Other Shared Vehicle Modes (e.g., taxi, carsharing, car rental, etc.)

It has been documented in this research and a number of previous studies that Lyft and Uber substitute for a notable portion of trips that would have otherwise been taken by a taxi. Lyft and Uber also compete with other shared passenger vehicle modes, including rental cars and roundtrip or one-way carsharing.

If a Lyft or Uber passenger would have used a taxi had the TNC services not been available, then the presence of Lyft and Uber is not increasing VMT relative to what would have occurred in a taxi. The same is true if a TNC passenger would have taken a rental car or a carsharing vehicle in the absence of TNCs (although rental cars and carsharing have less deadheading mileage, i.e., travel without passengers). Through substitution of trips that would have been made with other shared vehicle modes, Lyft and Uber are not reducing VMT, but at the same time, they are not substantively increasing it.

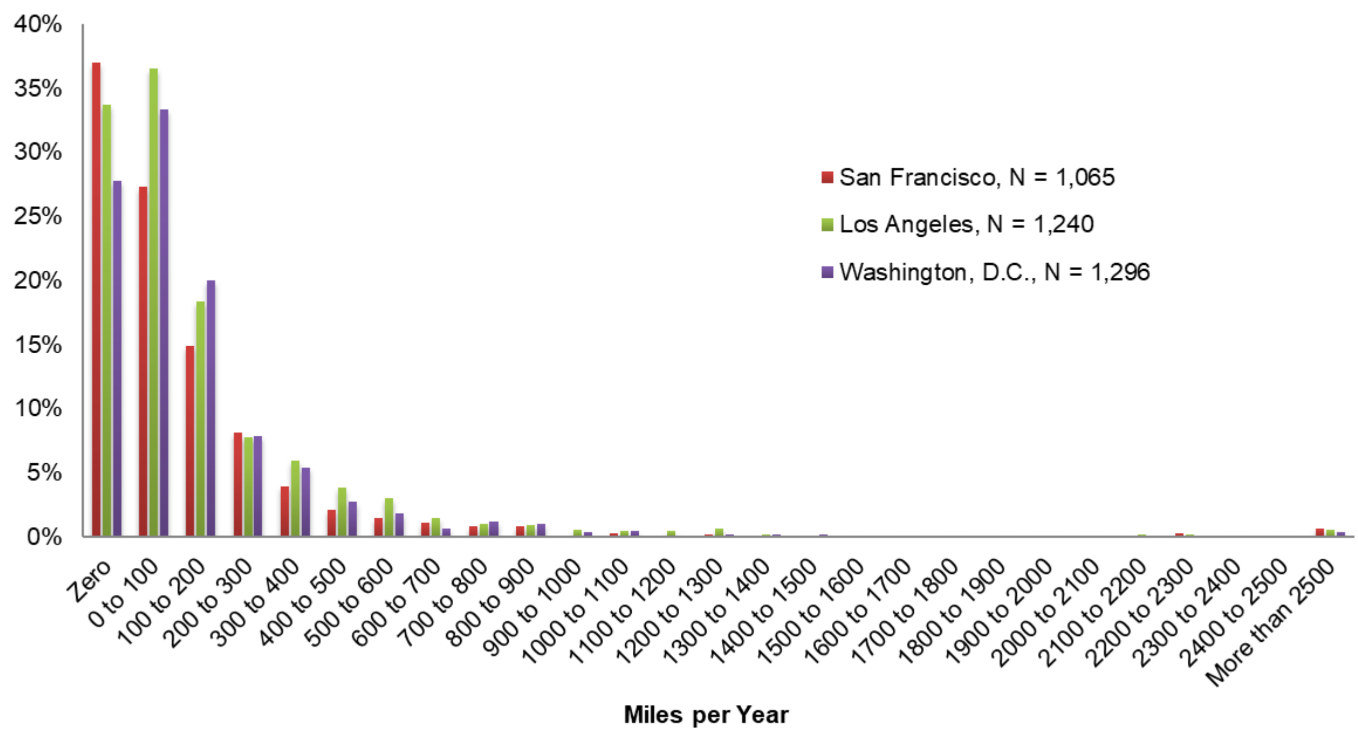
In considering the VMT per person driven by Lyft and Uber vehicles, we had to account for this substitution by subtracting out the VMT that would have occurred anyway. We considered the VMT reduction that respondents reported for taxis and carsharing vehicles in much the same way as we considered the reduction in personal vehicle miles as a result of Lyft and Uber.

We employed a question structure to evaluate the change in these modes similar to the one that we applied to modal shift. Because VMT produced by these less frequently used modes could be somewhat difficult to estimate in aggregate, we asked the survey question in terms of average miles per trip and then aggregated the travel to miles per year using the respondent's reported usage frequency. We also accounted for the deadheading mileage inherent in each of these modes. We increased each respondent's reported change in taxi miles per year by 45 percent to account for taxi deadheading (SFCTA 2017). We also increased both carsharing and rental car change in miles per year by 5 percent to account for re-positioning mileage.

We added a further constraint to the VMT reduction from these modes. Since the substitution of Lyft and Uber for taxis, carsharing, and rental cars is approximately one-to-one in terms of trip-based VMT, we did not permit the estimation of VMT reductions from the substitution of these modes to exceed the estimated combined VMT traveled on Lyft and Uber. That is, the VMT on Lyft and Uber was an upper bound of possible reductions in trip-based VMT from the substitution of these modes. We created this estimate for each respondent using the covariate variables that characterized the total fare distance traveled by the respondents on both systems. Since fare distances are mutually exclusive miles, these could be directly added across Lyft and Uber. We included deadheading miles per year attributed to these three modes after applying the trip-based VMT constraints, since deadhead miles are not accounted for in fare distances.

Figure 29 shows the distribution of the estimated mileage reduction (or substitution) in taxi, rental car, and carsharing use due to Lyft and Uber. The distribution shows that the reduction in use was generally limited. A majority of respondents who indicated that their taxi use changed due to Lyft and Uber reported no major change in mileage. For example, respondents could indicate that their mileage in taxis was currently "About the same" as before, which was effectively translated to a zero-mile change. A small number of respondents, 14 within each market, reported some increase in these modes due to Lyft and Uber. Overall, based on respondent estimates and the constraints defined above, the average net change in taxi, rental car, and carsharing mileage was a VMT reduction of 57 miles per year per respondent in San Francisco, 85 miles per year per respondent in Los Angeles, and 79 miles per year per respondent in Washington, D.C. About 70 percent of this reduction was from taxi mileage substitution, 20 percent was from rental car mileage substitution, and the remaining 10 percent was from carsharing reductions.

Figure 29. Distribution of Weighted Miles of Estimated Reduction in Taxi, Rental Car, and Carsharing Use



<u>Summary of Average VMT Change Impacts</u>
Each of the four components of VMT impact exhibits a different magnitude of change across the three studied markets. Table 23 presents a summary of the changes measured in the form of weighted

average change per passenger, shown rounded to the nearest tenth. The negative values reflect a VMT reduction. We note that these impacts are derived from the passenger survey, which was deployed in July and August 2016, and weighted by TNC activity data collected from the preceding year (June 1, 2015 to May 31, 2016).

Table 23. Summary of Average Changes in VMT (Miles per Passenger per Year)

VMT Change Due to Behavioral Change	Average Change Due to PVMT	Average Change Due to Vehicle Shedding	Average Change Due to Vehicle Suppression	Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift	Average Change in Weighted VMT per Passenger per Year
San Francisco	-163.9	-197.5	-424.5	-56.9	-842.7
Los Angeles	-194.2	-140.5	-511.1	-85.0	-930.8
Washington, D.C.	-100.2	-102.7	-303.8	-78.5	-585.2

As noted in the discussion above, the largest component of VMT change is from vehicle suppression, the estimated miles that would have been driven on vehicles not acquired. While the averages of each change are spread across all respondents, vehicle ownership impacts, such as vehicle suppression and vehicle shedding, are derived from only a minority of respondents (as noted above with suppression).

Because these values are derived from a sample, they have standard deviations, and thus confidence intervals. The confidence intervals provide a measure of uncertainty to the sample as drawn and measured in this way. The 99 percent confidence intervals in this sense convey the uncertainty associated with the sample drawn during the survey, and its representativeness of the true population mean as measured using these four components and the questions deriving their survey measurement. Statistics are shown in Table 24.

Table 24. Confidence Intervals of the Mean VMT Change

VMT Change Due to Behavioral Change	N	Standard Deviation	Sample Mean Margin of Error	Average Change in Weighted VMT per Passenger per Year and 99% Confidence Interval About the Sample Mean
San Francisco	2,651	2,909	145.5	-843 (-998, -697)
Los Angeles	3,075	2,753	127.9	-931 (-1059, -803)
Washington, D.C.	2,904	2,150	102.8	-585 (-688, -482)

The data in Table 23 and Table 24 show that the mobility provided by Lyft and Uber are facilitating behavioral changes and decisions that reduce or substitute driving within their user population. But the net impact must account for the VMT that is driven by the Lyft and Uber vehicles facilitating this change. The VMT from the Lyft and Uber vehicles are not considered in the values above.

Miles Driven by Lyft and Uber Vehicles

Lyft and Uber provided researchers with metrics on annual miles per passenger in each of the three markets. This amounted to total miles traveled by all Lyft and Uber vehicles in the three markets during the study year divided by all qualifying passengers in the markets during the study year (i.e., those who met the minimum trip criteria for taking the survey). These operator-provided values had to be combined (summed) into a single miles-per-passenger measurement.

Operators agreed that miles driven to fetch passengers and carry them to their destination were mutually exclusive. But a third phase, called the open miles phase in this study, was not considered to be mutually exclusive. This is the period in which the driver is "open" to receiving a passenger and has opened the driver app, which is recording its vehicle activity. During this period, a driver who drives for both Lyft *and* Uber may be simultaneously open to passengers on both platforms. If that driver is moving, then both apps would record that information, resulting in a double counting of miles. The operators agreed that this double counting was occurring, but only during the open phase of activity. It was challenging to determine how large the issue was, however, since each operator sees only the activity reported through its own platform.

The higher the overlap in activity, the greater the number of double-counted miles, and the greater the discount that would need to be applied to estimate the actual VMT traveled. We made a baseline assumption that this overlap applied to 20 percent of the open miles driven. This assumption is derived from TNC data obtained by the California Air Resources Board (CARB) encompassing all TNC activity in California during March 2019. The CARB data show that 18 percent of open miles overlapped between operators during this time (CARB 2019). Based on these data, we conservatively round up our assumption of open mile overlap to 20 percent. We evaluated the influence of open mile overlap rates in a sensitivity analysis, which showed that its impact was relatively small.

The passenger population also has a degree of overlap. That is, passengers within one operator's quotient were known to also be part of the other operator's quotient. We combined these values using a method that effectively assumed that each operator's value was a linear equation that produced a sum of the two operator-supplied values. Each of the operator-supplied values was multiplied by a coefficient. The coefficients were a function of the percentage of the respondents that used each of the services. Since this percentage differed between the operators (that is, the percentage of Lyft passengers using Uber was not the same as the percentage of Uber passengers using Lyft), the coefficients had different values for each operator-supplied value. These coefficients were estimated using survey data and used to solve the equation for the combined value of miles per passenger per year.

Finally, we took measurements from the driver survey to scale these values and account for driving that was done while the app was off. This sometimes called "Period 0" of TNC vehicle driving. Drivers were asked, for an average month, "Approximately how many miles have you driven specifically due to driving with Uber and Lyft?" They were then asked, "If you can, please estimate what percent of these miles is driven with both apps off (going to and from markets or not looking for passengers)." The response to this question was used to inform the relative percentage of app-off driving due to Lyft and Uber. The responses averaged 18 percent to 19 percent of driving with the app off, as reported by the drivers. Due to app-off driving, we scaled up measured operator mileage by 19 percent in San Francisco, 19 percent in Los Angeles, and 18 percent in Washington, D.C.

The result of these computations produced a combined set of measurements of miles driven by Lyft and Uber vehicles per passenger per year, as shown in Table 25. This estimate includes passenger (fare) miles, fetch miles, open miles, and app-off miles per qualified passenger (the passenger survey population).

Table 25. Combined Estimated Miles per Passenger per Year by Operator Given Baseline Assumptions

CBSA	Combined Miles per Qualified Passenger During Survey Year + Unmeasured Driving
San Francisco	1,077
Los Angeles	1,173
Washington, D.C.	502

The combination of miles per passenger plus the estimated unmeasured driving in each market suggests that Lyft and Uber vehicles drove about 1,077 miles per passenger per year in San Francisco, 1,173 miles in Los Angeles, and 502 miles in the Washington, D.C. market.

The percentage of open phase miles driven is an influential part of overall operator miles, and the operators provided their calculations of open phase driving as a percentage of all driving. Across the markets and operators, the measurements of open miles were an average of 34 percent, ranging from 24 percent to 46 percent. Open miles and fetch distances are also called deadheading collectively. Both involve driving without a passenger, but the two phases differ in that fetch distances are traveled with a dedicated passenger assigned.

The assumption that is applied to the percentage overlap of open miles across operators is an important one. Because this overlap in mileage may vary over time and across geographies, it is imperative to illustrate how the values under the baseline assumption vary with changes in the overlap percentage. Recall that the lower the overlap, the higher the estimated VMT traveled per passenger, since higher overlap means a greater degree of double counting miles that are independently measured. This sensitivity analysis is shown in Table 26.

Table 26. Sensitivity of Miles per Passenger per Year Estimate to Percentage of Open Miles Overlap

CBSA	0%	5%	10%	15%	20%	25%	30%	35%	40%
San Francisco	1,148	1,130	1,112	1,095	1,077	1,059	1,042	1,024	1,007
Los Angeles	1,257	1,236	1,215	1,194	1,173	1,152	1,131	1,110	1,089
Washington, D.C.	517	513	510	506	502	498	495	491	487

Table 26 shows that the percentage of overlap matters to a degree of about 100 to 200 miles per passenger per year in the California markets. The range for the Washington, D.C. market is considerably smaller, since the percentage of overlap applies to fewer miles. The values for the baseline assumption of 20 percent overlap are highlighted in orange.

Net Change in VMT at Baseline Assumption (20 Percent)

The operator-derived VMT represents the population-level estimate of vehicle driving by Lyft and Uber per passenger for the measured year. The average weighted change in VMT of respondents represents the estimated behavioral and vehicle holdings change per passenger of the population enabled by the presence of Lyft and Uber for the measured year. The estimated net change in VMT is the difference between these two values in each market. We note that while the VMT calculations are in units of VMT per passenger per year, this does not mean that each additional passenger increases VMT per year in each market by the specified amounts shown in Table 27. The measurements of operator VMT and VMT change due to behavioral change are static and were measured using survey and activity data sources from 2015 and 2016. Both mileage and behavioral impact trends could change over time, and thus VMT (and GHG) impacts presented in this section do not necessarily scale linearly with each new TNC passenger added.

Recall that we apply the weighting of VMT so that the survey sample measurements better reflect TNC use by the study population. But since the average is a sample average, it is subject to sampling uncertainty and the confidence intervals as defined in Table 24. The difference between our sample change in VMT and the population-level operator VMT is tested using the 1-tailed t-test based on the direction of change. This test gives us an indication as to whether the difference between the values is large enough to exceed the variation that would be expected to naturally occur with sampling. The net difference in VMT per passenger per year rounded to the nearest whole number is shown in Table 27.

Table 27. 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 Significant?	t-statistic	p-value (1-tailed)
San Francisco	–843	1,077	+234	Increase	Yes (1% level)	4.149	0.000
Los Angeles	–931	1,173	+242	Increase	Yes (1% level)	4.881	0.000
Washington, D.C.	–585	502	–83	Decrease	Yes (5% level)	–2.084	0.019

Based on the collective measurements applied in this analysis, the net differences in Table 27 suggest that Lyft and Uber increase VMT in San Francisco and Los Angeles by a degree that is statistically significant at the 1 percent level. We found a decline in net VMT in Washington, D.C., that is also statistically significant at the 5 percent level for the 1-tailed test.

Each market exhibits unique qualities that likely drive their respective results. In general, Los Angeles had the highest average impacts from behavioral change across all components except for vehicle shedding. At the same time, Lyft and Uber vehicles drove more within this market to deliver these benefits than in any of the other markets studied. The results from the San Francisco and Los Angeles markets suggest that Lyft and Uber are increasing VMT. Among the three markets, San Francisco had the highest impact from vehicle shedding but a smaller impact from vehicle suppression relative to Los Angeles. These results, coupled with a higher estimated amount of driving, yielded an increase in net VMT within the two California markets.

Washington, D.C., exhibited impacts suggesting a slight net VMT decline as a result of Lyft and Uber. The impacts of Lyft and Uber on behavior were the smallest in D.C. of the three markets. But the mileage driven by Lyft and Uber vehicles to enable that behavioral change was also found to be significantly lower, which resulted in a net VMT reduction. This is possibly due to land use and the built environment impacts on travel demand in the D.C. area.

Finally, it is important to note that these results already reflect the impact that Lyft Shared rides and UberPOOL had on VMT. That is, the shared services of the operators reduced the VMT they would otherwise have driven had everyone required a single passenger car for their trip. In other words, Lyft Shared rides and UberPOOL act as suppression for operator VMT. We evaluated the percentage reduction that resulted from these activities in the section discussing recent trip activities, and using these data, we quantify the possible VMT impact from Lyft Shared rides and UberPOOL later in this section.

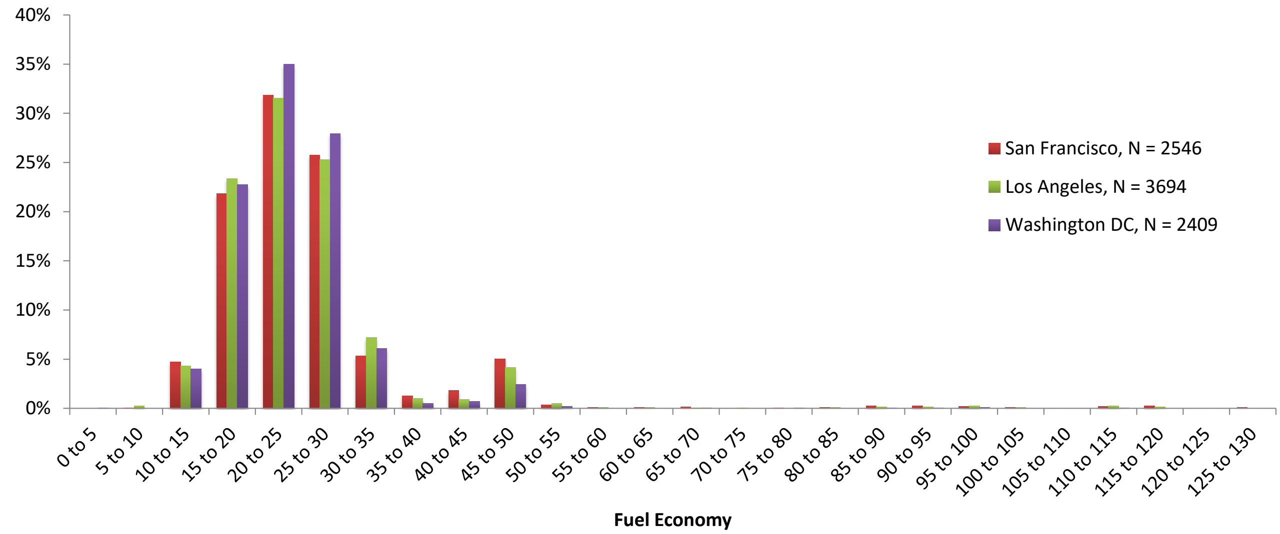
Change in Resulting GHG Emissions from Lyft and Uber

The change in VMT can be translated to GHG emissions by applying fuel economy factors to the specific components of VMT impact among passengers as well as to the operator fleet. We collected information in the survey on the make, model, and year of the vehicles owned by households, as well as the vehicles shed. In addition, operators provided information on the fuel economy of their operating fleets. We applied assumptions to generate the fuel economy factors for other components, such as vehicle suppression and substitution from other modes, such as taxis, where the exact vehicle driven was not known. We linked all make, model, and year data to the combined fuel economy as defined by the Environmental Protection Agency database derived from www.fueleconomy.gov.

The fuel economy factors permitted a translation of VMT to fuel consumption, which in turn was used to estimate GHG emissions. We assumed all fuel burned was gasoline and applied the factor of 8.887 kg of carbon dioxide (CO_2) per gallon to estimate GHG impacts of the change in fuel consumption. This is the simplified mile-dependent factor recommended in the latest published EPA methodology (EPA, 2018).

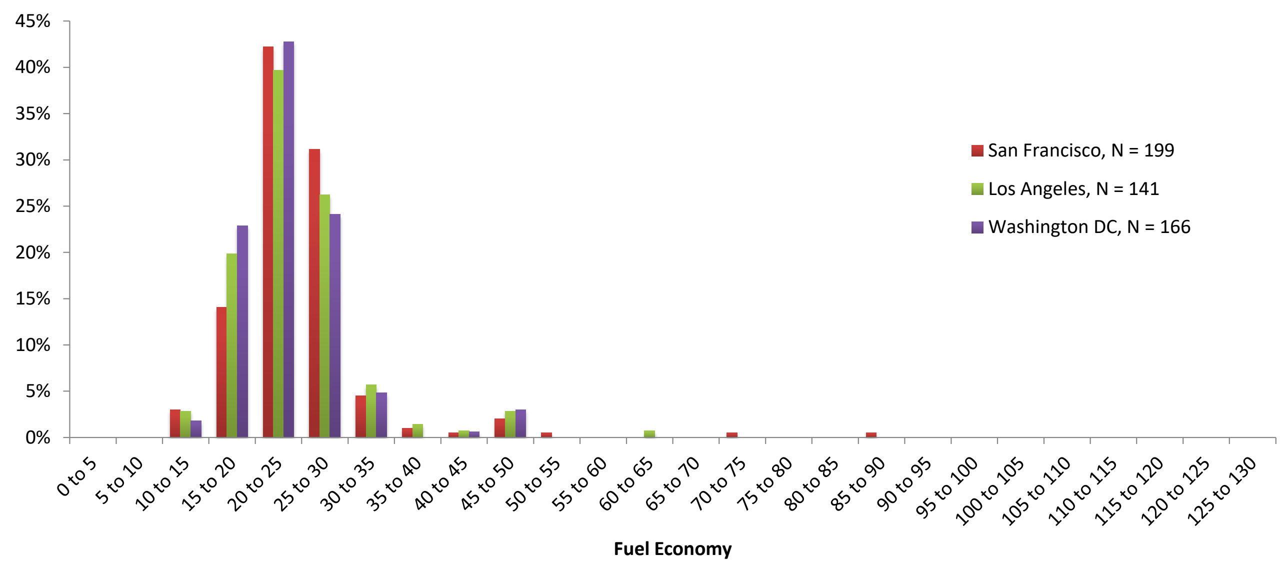
We computed the average fuel economy of household vehicles in each market via these data. There was very little difference across the markets. In San Francisco, the average (harmonic mean) of fuel economy for household vehicles was 23.2 mpg, in Los Angeles it was 23.0 mpg, and in Washington, D.C., it was 22.5 mpg. The distribution of fuel economy of household vehicles is presented in Figure 30.

Figure 30. Distribution of Household Vehicle Fuel Economy



The fuel economy of vehicles shed by respondents generally followed the same distribution, as shown in Figure 31. The average (harmonic mean) of fuel economy for shed vehicles across these markets was found to be 23.3 mpg in San Francisco, 23.2 mpg in Los Angeles, and 22.7 mpg in Washington D.C.

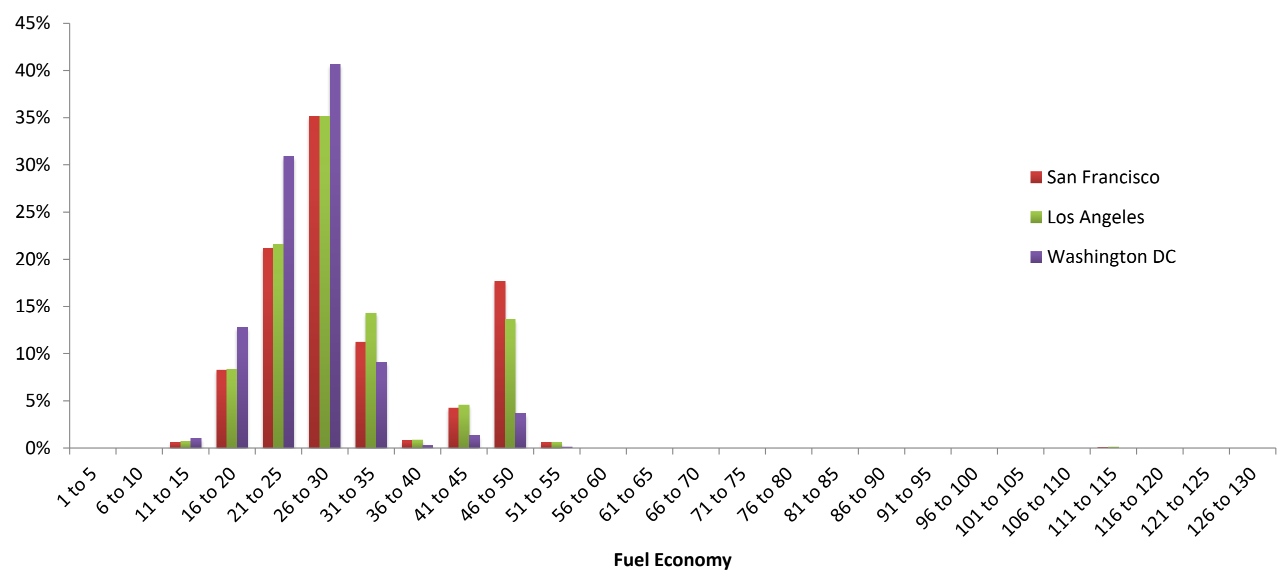
Figure 31. Distribution of Fuel Economy for Vehicles Shed



Suppressed vehicles are future vehicles that are not purchased. We assigned a fuel economy value of 31 mpg for suppressed vehicles. We were provided data on Lyft and Uber fleets in two different forms. One operator provided a distribution by fuel economy, and the other provided make, model, and year of each vehicle along with the percentage of total miles driven by that vehicle. We linked the make, model, and year information to fuel economy factors, as described above. The combination of these data suggested that Lyft and Uber vehicles had a harmonic mean fuel economy of 28 mpg in San

Francisco, 28 mpg in Los Angeles, and 25 mpg in Washington, D.C. We do not know the exact average across all the fleets since the balance of the fleet size is unknown across the two operators. However, the fuel economy averages hold to these integers, assuming that Uber comprises 50 percent to 80 percent of the fleet. We approximated the combined distribution of fuel economy for fleet vehicles by applying an assumption within this range of fleet composition, as shown in Figure 32.

Figure 32. Approximate Distribution of Fuel Economy of Lyft and Uber Fleet



With these fuel economy factors known for all components of the VMT impact, we estimated the change in CO_2 emissions from Lyft and Uber. Table 28 shows a summary of the components of GHG impact for the passengers of Lyft and Uber in units of metric tons per passenger per year. As expected, the results show a similar pattern of impact from behavioral change as observed with VMT change above.

Table 28. 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	Average Change Due to PVMT*	Average Change Due to Vehicle Shedding*	Average Change Due to Vehicle Suppression*	Average Change Due to Taxi, Rental Car, and Carsharing Mode Shift*	Average Change in Weighted GHG per Passenger per Year*
San Francisco	–0.066	–0.083	–0.122	–0.016	–0.287
Los Angeles	–0.072	–0.060	–0.147	–0.024	–0.303
Washington, D.C.	–0.039	–0.050	–0.087	–0.022	–0.199

*Units of metric tons (t) of CO_2 per passenger per year

As with the VMT change, the estimated GHG emission changes are subject to some sampling uncertainty. The margin of error and 99 percent confidence intervals are presented in Table 29.

Table 29. Confidence Intervals of the Mean GHG Change

GHG Change Due to Behavioral Change	N	Standard Deviation	Sample Mean Margin of Error	Average Change in Weighted GHG per Passenger per Year and 99% Confidence Interval About the Sample Mean
San Francisco	2,651	1.0	0.049	–0.287 (–0.336, –0.237)
Los Angeles	3,075	0.9	0.041	–0.303 (–0.344, –0.261)
Washington, D.C.	2,904	0.8	0.036	–0.199 (–0.234, –0.163)

The operator miles were translated to metric tons of GHG impact using the fuel economy factors defined above. These differences follow a similar pattern of impact across the markets. The results show that the fuel economy factors are important and influence the magnitude of some of the impacts.. For personal vehicle miles traveled and vehicles shed, less efficient miles are generally being replaced with slightly more efficient miles via Lyft and Uber. The direction of the emissions change is the same as the direction of VMT change across all three markets. As with the VMT change, we evaluated the difference using the 1-tailed t-test, and we found that the emissions increase in San Francisco is statistically significant at the 5 percent level. The emissions increase found in Los Angeles remains statistically significant at the 1 percent level, while the decrease in emissions found in Washington, D.C. was found to be significant for the 1-tailed test at the 5 percent level.

Table 30. 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)
San Francisco	–0.287	0.338	0.051	Increase	Yes (5% level)	1.930	0.027
Los Angeles	–0.303	0.374	0.071	Increase	Yes (1% level)	3.259	0.001
Washington, D.C.	–0.199	0.179	-0.020	Decrease	Yes (5% level)	-2.097	0.018

*Units of metric tons (t) of CO_2 per passenger per year

It is important to note that these results are sensitive to assumptions about fuel economy, particularly for suppressed vehicles. For example, if we assumed the suppressed vehicles had a fuel economy of 40 mpg, the results would look less favorable. Los Angeles and San Francisco would show statistically significant increases in emissions. Washington, D.C., would still show a decrease in emissions, but it would be statistically insignificant.

The estimated changes in emissions from travel behavior and vehicle ownership decisions compensate for the estimated miles per operator within the three markets. While the net emissions changes are generally statistically significant, this reflects sampling certainty rather than measurement certainty. The results can flip direction with changes in some key assumptions. In the San Francisco and Los

Angeles markets, the operators appeared to perform less favorably, with a likely, but modest, increase in VMT and emissions on a per passenger basis. The results are more favorable in the Washington, D.C. market. While the impacts of Lyft and Uber are smaller in this market, along with operator vehicle driving, they yield a slight net reduction in VMT and emissions.

Broadly, the results suggest that when it comes to passenger behavior, there are substantive reductions in VMT that result from Lyft and Uber use. However, the VMT and emissions from Lyft and Uber vehicles, which enable those changes, are canceling or exceeding a significant portion of those reductions. This analysis does not find Lyft and Uber to be drivers of GHG reductions, but it also does not find that they are drivers of large GHG increases on a per passenger basis.

These results suggest a need for careful measurement in the future of the range of impacts that are enabled by Lyft and Uber and the operator activity conducted to facilitate them. In the sections that follow, we explore the impact of pooled TNCs on VMT and GHG emissions. More immediately, we evaluate the sensitivity of the results above to the key parameter of personal vehicle suppression and changes in operator mileage.

Sensitivity Analysis of Changes in Vehicle Suppression and Operator Miles

Table 27 and Table 30 presented the estimated net changes in VMT and emissions that were caused by Lyft and Uber during the period of study. The results from this analysis suggest that Lyft and Uber do facilitate behavioral changes that result in substantive reductions in VMT and GHG emissions among the passenger population. At the same time, the driving by Lyft and Uber vehicles broadly negates and overwhelms the major impacts from these changes. The analysis does not produce conclusive evidence that Lyft and Uber reduce transportation emissions.

Critical parameters that inform this result are subject to change over time. Building on the data collected and the resulting insights, we now proceed to review how certain changes to calculations can alter the results and conclusions. This analysis may serve as a guide for future work and evaluation as these systems and their impacts evolve over time.

Two of most critical components of the evaluated impact of Lyft and Uber found above were vehicle suppression and operator miles per passenger. The suppression of personal vehicle ownership was the largest component of behavior shifts that reduce emissions, accounting for 50 percent to 55 percent of the emissions impact across the three markets. If the magnitude of personal vehicle suppression changes over time, with no commensurate change in operator miles, it would significantly impact the conclusions regarding the net impact of Lyft and Uber on emissions. Similarly, should the vehicles of Lyft and Uber begin to deliver services with reduced or increased annual miles per passenger, this would also impact key conclusions regarding whether Lyft and Uber increase or decrease emissions.

This analysis further shines a spotlight on the issue of measurement for vehicle suppression. Personal vehicle suppression is challenging to measure, and it is also potentially quick to change under shifting economic conditions. The circumstances defining what vehicle suppression means can also shift depending on how it is explored within a survey or data analysis, and how it is defined can impact its measurement. In this study, we evaluated vehicle suppression using a two-question measurement, with one question examining current suppression and another evaluating the expectation of sustained suppression in the near future. A respondent who affirmatively reported that Lyft and Uber suppressed their need for a personal vehicle in both questions was counted.

The degree to which changes in personal vehicle suppression and operator miles impact conclusions is presented in the following tables. Table 31 shows how estimates of net VMT impacts would change in the face of changes in the personal vehicle suppression rate and in operator miles for San Francisco. The estimated suppression rate as derived from the weighted survey data is 7.8 percent and highlighted in orange. The corresponding operator mileage is 1,077 per passenger per year and highlighted in gray. Considering this and the four components of VMT impact, the net impact, an increase of 234 VMT per passenger per year, is highlighted with bold borders. Note that Table 31 shows changes in net impacts, holding all other impacts equal (i.e., ceteris paribus). This is at least a modest departure from reality, in that we expect that some substitution of PVMT and taxi miles would likely change with increases or decreases in operator miles.

The changes in the net impact are shown within each colored cell. Table 31 shows that in San Francisco, the results are rather sensitive to changes in either parameter. Should operator miles per passenger per year increase by 20 percent, personal suppression rates would have to rise to about 12 percent to offset the increase in miles by operator vehicles. Furthermore, if personal vehicle suppression rates were lower than the estimated 7.8 percent, then the net VMT change would quickly transition to a more significant increase in VMT. Operator VMT would need to fall below 80 percent of its reported value to yield a VMT reduction at the reported vehicle suppression rate.

Table 31. Sensitivity of Personal Vehicle Suppression and Operator Miles per Passenger per Year in 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
16.0%	-1071	-855	-640	-424	-209	7	222	437	653	868
17.0%	-1125	-909	-694	-479	-263	-48	168	383	599	814
18.0%	-1179	-964	-748	-533	-317	-102	113	329	544	760
19.0%	-1233	-1018	-802	-587	-372	-156	59	275	490	705
20.0%	-1288	-1072	-857	-641	-426	-210	5	220	436	651
21.0%	-1342	-1126	-911	-696	-480	-265	-49	166	382	597
22.0%	-1396	-1181	-965	-750	-534	-319	-103	112	327	543
23.0%	-1450	-1235	-1019	-804	-589	-373	-158	58	273	489
24.0%	-1504	-1289	-1074	-858	-643	-427	-212	3	219	434
25.0%	-1559	-1343	-1128	-912	-697	-482	-266	-51	165	380

Table 32 shows the same analysis for Los Angeles. The net VMT change found in the suppression rate of 9.2 percent yields an increase in overall VMT. Similar to San Francisco, reductions in operator miles per passenger per year to around 80 percent would begin to yield VMT reductions at this suppression rate. At the reported operator miles, this analysis finds that suppression rates need to increase to at least 14 percent to yield net VMT reductions.

Table 32. Sensitivity of Personal Vehicle Suppression and Operator Miles per Passenger per Year in 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
16.0%	-1070	-835	-601	-366	-131	103	338	572	807	1042
17.0%	-1125	-890	-656	-421	-187	48	283	517	752	986
18.0%	-1180	-946	-711	-477	-242	-7	227	462	697	931
19.0%	-1236	-1001	-766	-532	-297	-63	172	407	641	876
20.0%	-1291	-1056	-822	-587	-353	-118	117	351	586	821
21.0%	-1346	-1112	-877	-642	-408	-173	61	296	531	765
22.0%	-1402	-1167	-932	-698	-463	-229	6	241	475	710
23.0%	-1457	-1222	-988	-753	-518	-284	-49	185	420	655
24.0%	-1512	-1278	-1043	-808	-574	-339	-104	130	365	599
25.0%	-1567	-1333	-1098	-864	-629	-394	-160	75	309	544

Finally, the sensitivity analysis of these parameters in Washington, D.C. shows that the results yield a VMT reduction. At the estimated suppression rate of 6.4 percent, Table 33 shows that around a 2 percent reduction in suppression or a 20 percent increase in operator miles per passenger would shift the estimated net impact into positive territory.

Table 33. Sensitivity of Personal Vehicle Suppression and Operator Miles per Passenger per Year in Washington, D.C.

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
16.0%	-939	-839	-738	-638	-537	-437	-337	-236	-136	-35
17.0%	-987	-886	-786	-685	-585	-484	-384	-284	-183	-83
18.0%	-1034	-934	-833	-733	-632	-532	-431	-331	-231	-130
19.0%	-1081	-981	-880	-780	-680	-579	-479	-378	-278	-178
20.0%	-1129	-1028	-928	-827	-727	-627	-526	-426	-325	-225
21.0%	-1176	-1076	-975	-875	-774	-674	-574	-473	-373	-272
22.0%	-1223	-1123	-1023	-922	-822	-721	-621	-521	-420	-320
23.0%	-1271	-1170	-1070	-970	-869	-769	-668	-568	-468	-367
24.0%	-1318	-1218	-1117	-1017	-917	-816	-716	-615	-515	-415
25.0%	-1366	-1265	-1165	-1064	-964	-864	-763	-663	-562	-462

The sensitivity analyses of suppression and operator miles per passenger per year show that changes in either component would have significant implications for the conclusions of the study. This is important to understand in light of the fact that vehicle suppression is a challenging component to measure, and operator miles per passenger per year may change over time as algorithms change or drivers alter their level of activity relative to passenger demand. The analysis above shows that in all cases suppression miles must be considered for Lyft and Uber to result in any reductions in VMT or emissions. If the suppression impacts are ignored, this analysis would find that Lyft and Uber would appear to significantly increase VMT and emissions in every market.

Analysis of the Most Recent TNC Trip and Associated Travel Impacts

We asked respondents of the passenger survey about their most recent trip using a Lyft or Uber service (the most recent trip at the time of the survey). This allowed us to ask more detailed questions due to the recallable nature of a recent TNC experience. It also allowed us to conduct analysis based on this sample of most recent travel activity. Questions prompted respondents to recall the day, time, distance, and duration of their latest trip, as well as the specific TNC service they used. We also asked respondents what transportation mode they would have used if Lyft or Uber had not existed. One unique aspect of these data is that they enable us to look at differences in behavior between those who used a private versus pooled TNC service. Where relevant, we split impacts by Lyft Shared rides and uberPOOL as compared with private Lyft and Uber services.

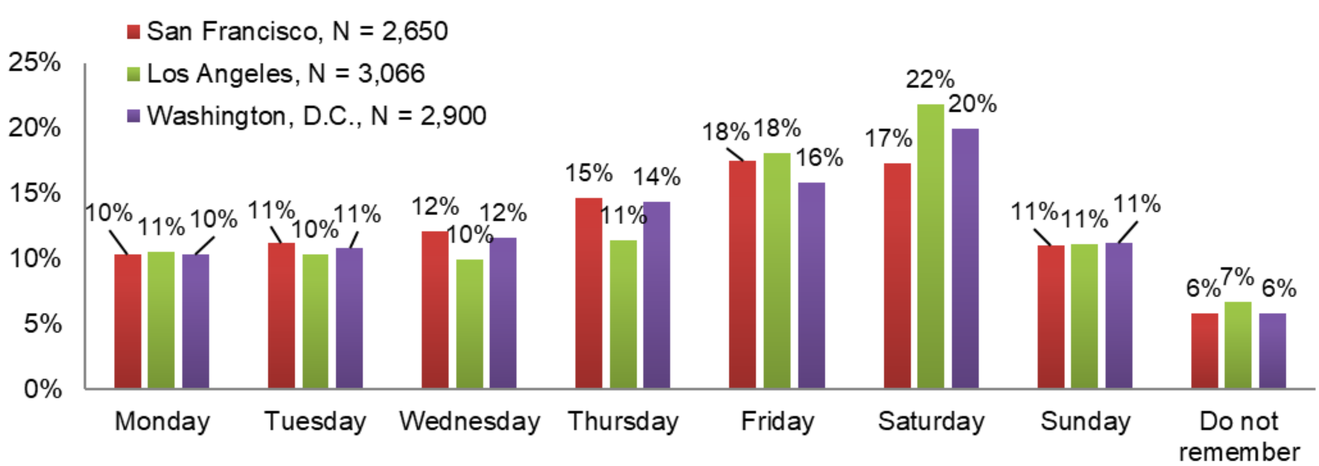
In this section, the topics we explore with respect to the respondents' most recent trip include day and time, trip purpose, trip distance, pooled and private Lyft and Uber analysis, trip occupancy and matching success, mode substitution, implications of Lyft Shared rides and uberPOOL on TNC VMT and GHG emissions, and first- and last-mile travel to public transit using TNCs.

<u>TNC Trips: Day and Time</u>

We asked respondents to recall the day of the week and approximate time of day of their most recent trip with Lyft or Uber. To mitigate bias in responses that might arise if respondents were asked on only one particular day about their most recent trip, we coordinated with the operators to spread the launch of the survey evenly across five weekdays. For example, had the entire survey population been surveyed on a Monday, the responses would be heavily biased to reflect weekend behavior. By spreading the survey launch across five weekdays, we captured the broader distribution of recent trip attributes more accurately.

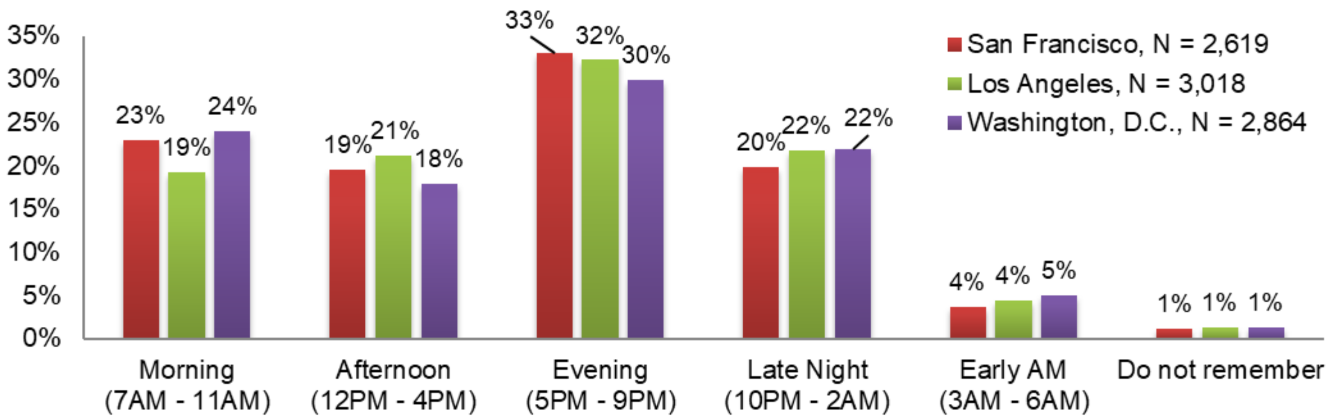
Figure 33 shows the distribution across the days of the week for the most recent trip using a Lyft or Uber service. Fridays and Saturdays are the most popular days for TNC trips, making up 35 percent of the most recent trips in San Francisco, 40 percent in Los Angeles, and 36 percent in Washington, D.C. After Friday and Saturday, Thursday is the next most popular day for TNC trips, while Sunday and other weekdays account for 10 percent to 12 percent of trips each, depending on the CBSA. Between 6 percent and 7 percent of respondents across CBSAs do not remember what day of the week they made their most recent Lyft or Uber trip.

Figure 33. Most Recent Trip: Day of Week



We also asked respondents to estimate the time of day of their last TNC trip to the nearest hour. Figure 34 displays the time of day that respondents took their most recent Lyft or Uber trip, aggregated across all days of the week. The evening time frame (5–9 p.m.) was the most common in all three of the study CBSAs, constituting 30 percent to 33 percent of all rides, depending on the market. The morning, afternoon, and late-night time frames contained similar trip proportions for all three CBSAs, and the early-morning (3–6 a.m.) time frame encompassed only about 4 percent to 5 percent of all trips, depending on the market. Around 1 percent of respondents did not remember the time of day of their most recent TNC trip.

Figure 34. Time of Most Recent Trip, Across All Days



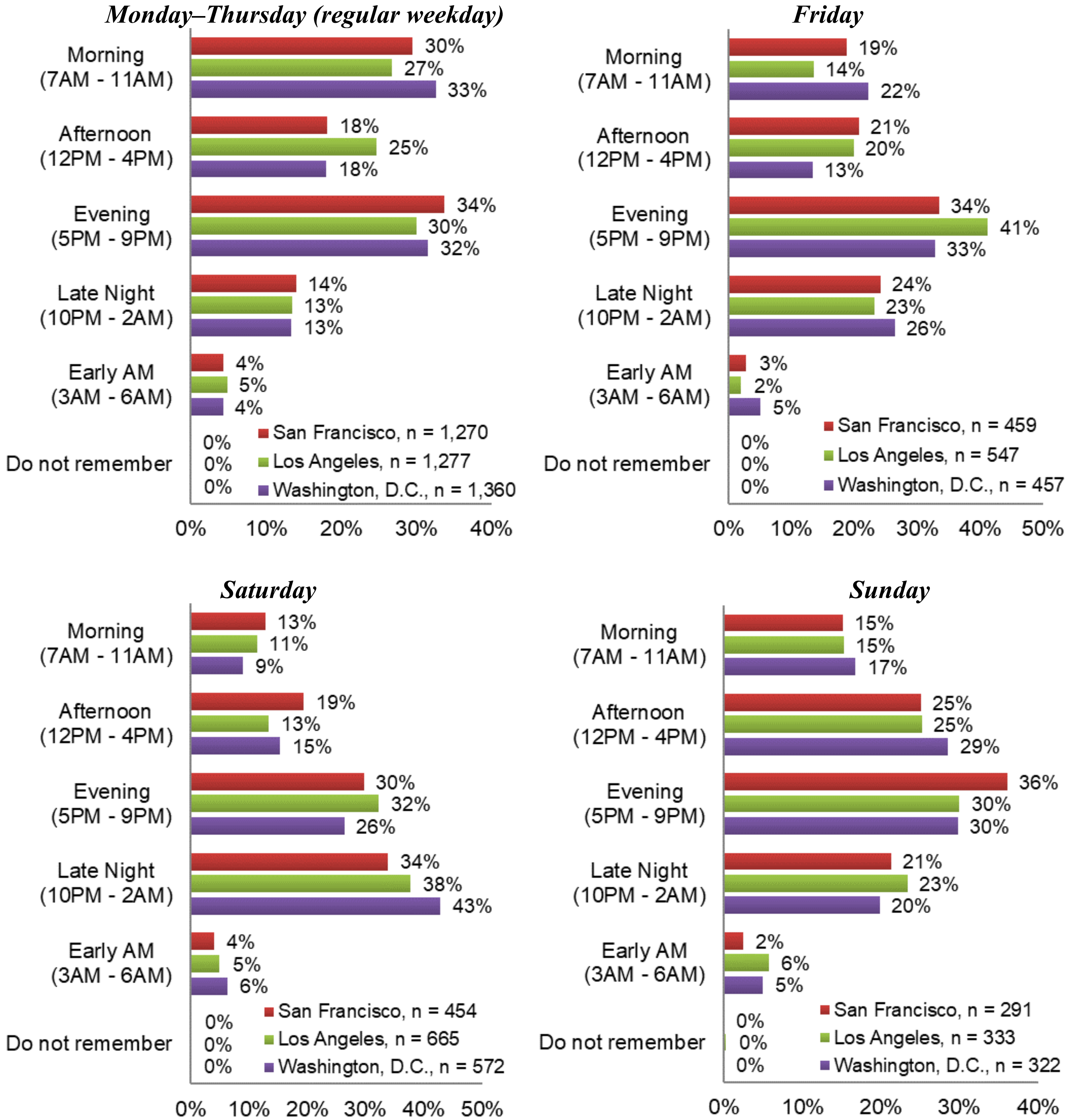
When examining most recent trip times by day of the week, distinct patterns emerge. Figure 35 shows trip time distributions broken out over four categories: Monday through Thursday (regular weekday), Friday, Saturday, and Sunday. We combined Monday through Thursday into one category because the individual distributions for these days were very similar.

We found that regular weekday distributions are quite similar across CBSAs as well. On regular weekdays (Monday through Thursday), there were clear peaks in the morning (7–11 a.m.) and evening (5–9 p.m.), with 63 percent of trips in San Francisco, 57 percent in Los Angeles, and 64 percent in Washington, D.C., occurring during one of these two periods. In Los Angeles, there is a slightly higher share of afternoon (12–4 p.m.) trips and a slightly lower portion of morning and evening trips relative to the other two markets.

Time of day distributions on Friday are similar to regular weekday distributions but with higher proportions of late-night (10 p.m.–2 a.m.) trips and lower proportions of morning trips. This is likely due to nightlife activity that is more typical on Fridays than on other weekdays.

On Saturdays, evening and late-night trips account for more than two-thirds of the most recent trips across all three markets. This is again likely due to dining, nightlife, and other social activities that more commonly occur on Fridays and Saturdays compared with other days of the week. Respondent trip distributions on Sundays are more evenly spread across the day than during other parts of the week, and they also display the largest proportions of afternoon trips (12–4 p.m.) out of all four categories across all CBSAs, at one-fourth or more of all Sunday trips.

Figure 35. Time of Most Recent Trip by Day of Week Category



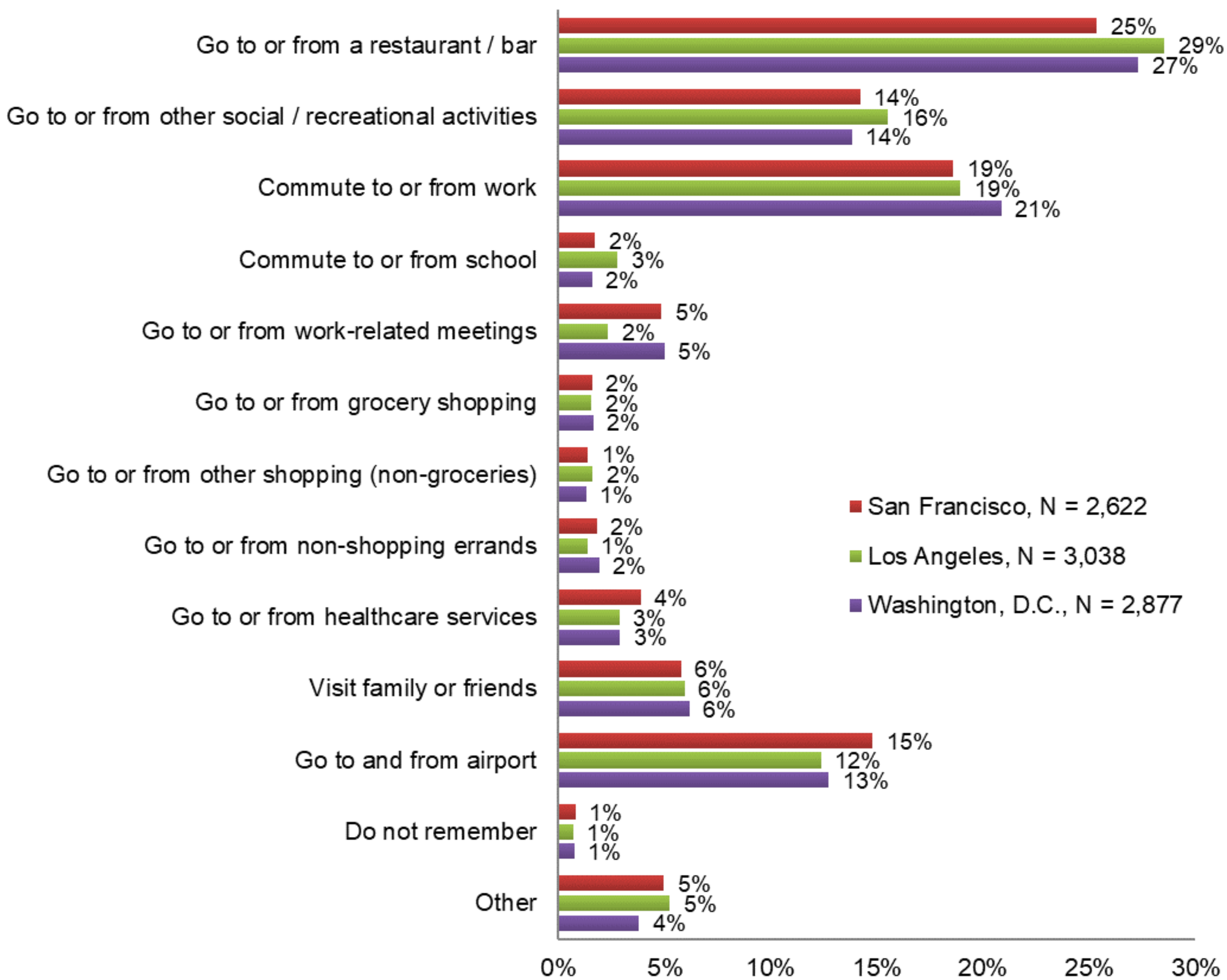
Overall, our findings match closely with the trip time and day-of-week distributions found in other studies. Like other studies focused on day-of-week distributions (SFCTA 2017; Feigon and Murphy 2018), we also find that trip volumes are highest on Fridays and Saturdays. The passenger survey time of day distributions match up fairly closely with those found in a previous study of TNC trips in San Francisco in late 2016 (SFCTA 2017). The Feigon and Murphy (2018) study concluded that TNC use in five U.S. cities peaks on weekends and evenings, as opposed to during rush hours, when public transit use is highest. While our distributions show substantial TNC trips on Saturdays and evening/late-night periods as well, we also find significant TNC use during regular weekday morning and evening peak periods, suggesting a fair amount of workday-related trip purposes.

Thus, although our data reflect a survey sample and may not be totally representative of the overall TNC trip distribution in the CBSAs, the similarity of our findings to those of other studies that use trip activity data (as opposed to survey data) suggest a fairly representative distribution of trip-making among the passenger survey respondents' most recent trips.

Trip Purpose

We asked passenger survey respondents to categorize the purpose of their most recent Lyft or Uber trip. Results are displayed in Figure 36. We find very similar trip purpose distributions across the three markets. Going to or from a restaurant or bar is the most common TNC trip purpose among respondents in each of the three CBSAs. These trips, combined with the similar answer option of going to or from other social/recreational activities, represent 40 percent of the most recent trips in San Francisco, 44 percent in Los Angeles, and 41 percent in Washington, D.C. In addition, a notable portion of respondents' most recent trips are to commute to/from work or school, making up 20 percent of trips in San Francisco and 22 percent in both Los Angeles and Washington, D.C. Airport trips are fairly common as well, making up 15 percent of the most recent trips in San Francisco, 12 percent in Los Angeles, and 13 percent in Washington, D.C. Shopping (grocery and non-grocery) trips and errands are less common TNC trip purposes, constituting only 5 percent of trips in all three CBSAs. Note that not all percentages add exactly to 100 percent due to rounding.

Figure 36. Trip Purpose Distribution



When considering trip purposes of those who used Lyft Shared rides (formerly Lyft Line) or uberPOOL for their last trip, we found certain purposes were more common than others. Commute trips (to work or school) were slightly more likely to be made with a pooled TNC service than the average TNC trip, across all three CBSAs. On the other hand, respondents going to/from an airport were slightly less likely to use pooled TNC services for this trip purpose. This is probably due to time sensitivity and luggage requirements. Table 38 in a subsequent section covers pooled TNC trip purpose in more detail.

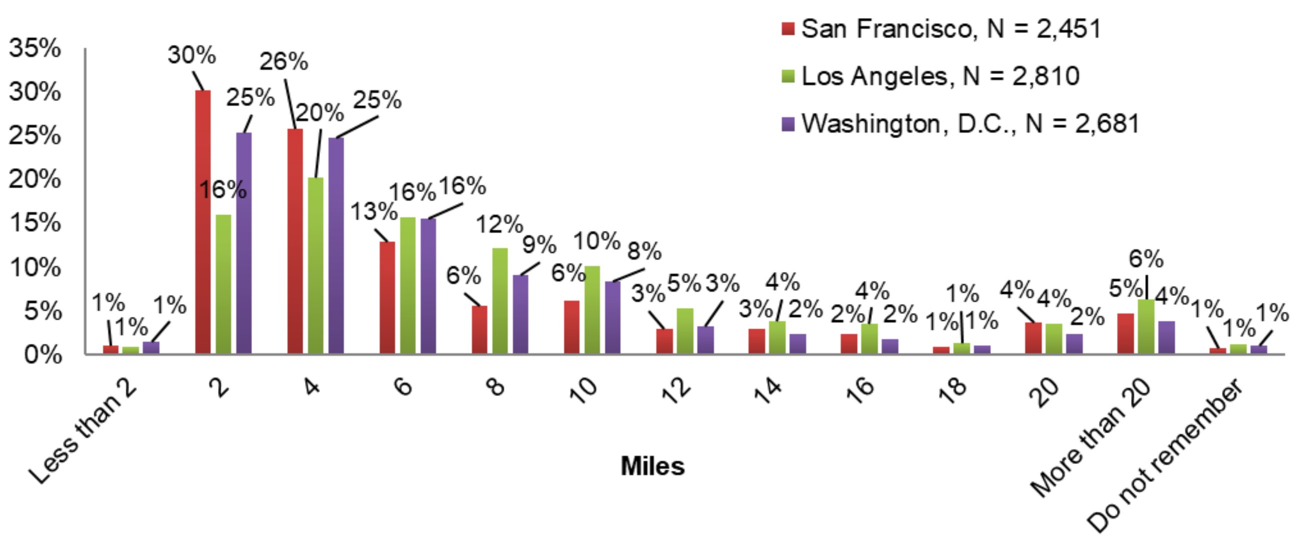
Trip Distance

We asked respondents to estimate the miles they traveled during their most recent Lyft or Uber trip to the nearest two miles.[8] While these data are only estimates, they provide valuable insights into differences in TNC trip distances across the three CBSAs. Figure 37 shows the distribution of estimated trip distances. The average estimated trip distance was 7.0 miles in San Francisco, 8.8 miles

[8] These data reflect estimated distances traveled only while the respondent was in the vehicle; they are not estimates of overall driving by TNC vehicles.

in Los Angeles, and 6.9 miles in Washington, D.C. The majority of trips in San Francisco and Washington, D.C., were 4 miles or less (57 percent and 52 percent, respectively), while only 37 percent of trips in Los Angeles were 4 miles or less. It is not surprising that respondents in Los Angeles made longer TNC trips on average than those in the other two markets, since Los Angeles is a larger and more sprawling CBSA than San Francisco and Washington, D.C. While most TNC trips were fairly short distances, there was a notable portion that reflected longer distances. Fifteen percent of trips in San Francisco, 19 percent in Los Angeles, and 11 percent in Washington, D.C., were 14 miles or longer. One percent of respondents in each market did not remember the distance of their last Lyft or Uber trip.

Figure 37. Passenger Estimated Recent Trip Mileage Distribution



In considering trip mileage across trip purposes, we found that some purposes had comparatively longer trip distances than others, on average. Table 34 below shows the average estimated trip mileage by trip purpose across the three markets. We aggregated similar trip purposes (e.g., work and school commuting). Across all three CBSAs, airport trips had the longest average trip distances (13.6 to 16.7 miles on average, depending on the market), and shopping/errands had the shortest average trip distances (5.0 to 5.8 miles on average, depending on the market). The more popular trip purposes such as going to/from a restaurant or bar, social activities, and work or school commute trips had slightly shorter average trip distances than the average distance across all trips in each corresponding CBSA. In San Francisco, restaurant, social, and commute trips were slightly longer than 5 miles, on average. In Los Angeles and Washington, D.C., there was more variability in the distance of these common trip purposes. Social trips in Los Angeles (8.8 miles, on average) were slightly longer than restaurant/bar and commute trips in the CBSA. In Washington, D.C., commute trips (6.4 miles, on average) were a little longer than the average restaurant/bar or social activity trip across the market. The mileage variations suggest that land-use context has an effect on TNC trip behavior across markets.

Table 34. Average Estimated TNC Trip Mileage by Purpose

Trip Purpose	San Francisco	Los Angeles	Washington, D.C.
Go to or from a restaurant/bar	5.3 (n = 610)	7.1 (n = 787)	5.5 (n = 733)
Go to or from other social/recreational activities	5.2 (n = 344)	8.8 (n = 426)	5.6 (n = 370)
Commute to or from work or school	5.2 (n = 488)	7.6 (n = 591)	6.4 (n = 582)
Go to or from work-related meetings	5.3 (n = 116)	11.3 (n = 64)	6.0 (n = 129)
Go to or from shopping or errands	5.0 (n = 116)	5.8 (n = 128)	5.3 (n = 122)
Go to or from health care services	5.0 (n = 94)	10.1 (n = 81)	5.9 (n = 80)
Visit family or friends	5.7 (n = 143)	8.9 (n = 157)	6.2 (n = 161)
Go to or from airport	16.7 (n = 365)	14.7 (n = 349)	13.6 (n = 337)
Other	7 (n = 122)	9.0 (n = 149)	6.3 (n = 106)

Pooled and Private Lyft and Uber Analysis

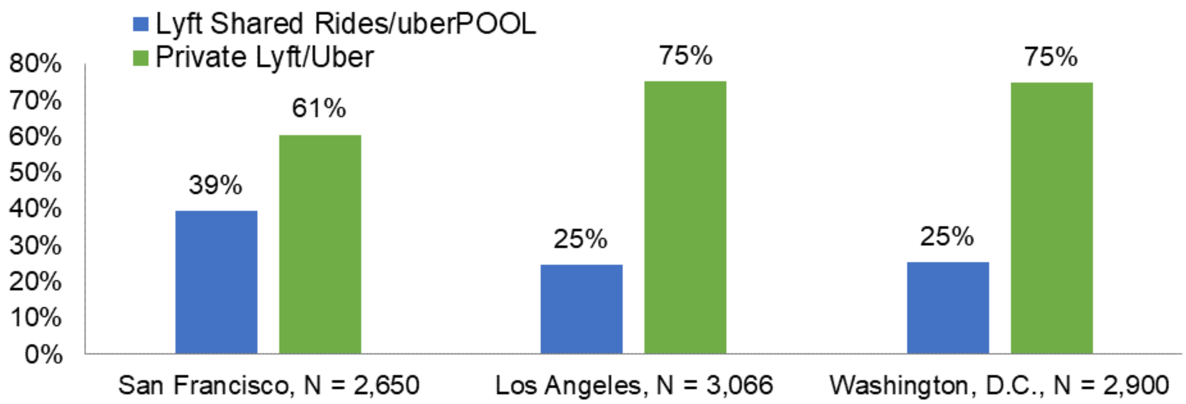
In this section, we compare and contrast attributes of trips made using pooled and private TNC services. The results presented here reflect the analysis of pooled services as they operated before the pandemic. The degree to which such findings extend to the future will depend on how pooling options are re-introduced to cities, which has begun to occur.

In the survey, we asked some additional follow-up questions to those who had used either of the two pooled TNC services, Lyft Shared rides (formerly Lyft Line) or uberPOOL, for their latest trip. We asked respondents about the specific Lyft or Uber service they had used for their most recent trip. Based on the available Lyft and Uber services at the time of our survey, answer options for Uber included: uberPOOL, uberX, uberXL, uberSELECT, uberBLACK, uberSUV, and uberTAXI. Service options for Lyft included Lyft Line (now called Lyft Shared rides), Lyft, Lyft Plus, and Lyft Premier. Respondents were also able to indicate that they did not remember what specific service they had used. The overwhelming share of most recent trips were made with uberPOOL, uberX, Lyft Line, or Lyft, accounting for more than 90 percent of respondents' trips. About 1 percent of respondents in each market did not remember what particular service they had used.

Share of Pooled Versus Private TNC Trips

The portion of most recent trips made at the time of the survey with pooled TNC services among passenger survey respondents is displayed in Figure 38. In San Francisco, 39 percent (n = 1,045) of respondents used a pooled TNC service for their most recent trip, while 25 percent of respondents did the same both in Los Angeles (n = 758) and in Washington, D.C. (n = 732). These shares are expected to change over time. The higher rate of pooled trips in San Francisco may indicate this effect since San Francisco was the first market in which both companies deployed pooled TNC services. We also noted that 10 percent to 14 percent of most recent trips had three passengers or more from the start of the trip, which meant they had too many passengers to request Lyft Shared rides or uberPOOL. Moreover, while Figure 38 shows the portion of rides in each market where respondents chose a pooled TNC option, it does not indicate the portion of rides that were successfully matched. We explore the rates of successfully matched pooled rides further in the sections that follow.

Figure 38. Passenger Requested Pooled vs. Private TNC by CBSA (Before Matching)



Reasons for Not Using a Pooled TNC Service

As shown in Figure 38, the majority of respondents' most recent trips in each market were made using private Lyft and Uber services as opposed to pooled services. To understand why some respondents did not use pooled TNCs for their last trip, we asked those who used a private service to tell us the main reason for their decision not to use a pooled service. Some respondents who used private Lyft and Uber services had too many passengers to request a pooled service (three or more), so we omitted these respondents from Table 35 and considered only those with two passengers or fewer for their most recent trip. More than 80 percent of respondents in each market who used a private Lyft or Uber service had two passengers or fewer for their last TNC trip.

Of respondents who used a private Lyft or Uber service and could have used a pooled service for their last trip, the most common reason for not using one, across all three CBSAs, was: "I needed to get to my destination as quick as possible." More than 40 percent of respondents in each market chose this answer option, signaling that time constraints are a major reason why people do not choose a pooled TNC service.

Interestingly, the next most popular answer in all three markets was: "I am not comfortable with sharing my ride," accounting for 15 percent of respondents in San Francisco, 23 percent in Los Angeles, and 21 percent in Washington, D.C. This finding highlights a distinction between how people perceive drivers versus how they view other passengers. Although drivers and matched passengers are most likely strangers to someone using Lyft and Uber services, some respondents are comfortable getting a ride from a stranger (the driver) but not comfortable sharing a ride with other strangers (matched passengers). This study did not investigate possible reasons for this effect, but we hypothesize that it may be related to space considerations (passengers may be comfortable with a driver in the front seat because they sit in the back, while they may not be comfortable sharing the back seat with other passengers) or safety perceptions (passengers may perceive that drivers have undergone more extensive background checks and vetting than other passengers), among other potential reasons. It is important to note that sentiments toward sharing rides may change over time as shared mobility services mature and expand.

Most respondents knew of Lyft Shared rides (formerly Lyft Line) and uberPOOL; only 2 percent or less had not heard of the services across the three CBSAs. However, 5 percent to 8 percent of respondents (depending on the market) knew of the services but had never tried them. Five percent to 11 percent of respondents across the three markets said they did not have a particular reason for choosing a private Lyft or Uber instead of a pooled service. Six percent to 10 percent of respondents across the CBSAs chose a reason outside of the given answer options for why they did not use a pooled service. Popular "other" answers included that 1) respondents had luggage, 2) an employer paid for the trip, 3) they'd had an unpleasant prior experience with Lyft Shared rides or uberPOOL, 4) they did not think the price savings was worth the extra time, 5) they had a ride credit, or 6) they were on a date and wanted privacy.

Table 35. Reasons for Not Using a Pooled TNC Service

What was the main reason you did not choose the shared ride option during this last Uber or Lyft trip (UberPOOL or Lyft Line)?	**San Francisco, n = 1,321**	**Los Angeles, n = 1,849**	**Washington, D.C., n = 1,805**
I am not comfortable with sharing my ride.	15%	23%	21%
I was not the one who called the Uber/Lyft.	3%	2%	2%
I needed to get to my destination as quick as possible.	53%	41%	48%
It was not an option in the area where I called the trip.	6%	6%	2%
I have heard of these services, but I have not tried them.	5%	8%	7%
I am unaware of what UberPOOL/Lyft Line are.	0.5%	2%	0.2%
I tried to call an uberPOOL/Lyft Line but the request took too long.	1%	1%	1%
I cannot remember.	1%	1%	0%
No particular reason	5%	11%	8%
Other	10%	6%	9%

Trip Occupancy and Matching Success

In this section, we discuss matching success among most-recent pooled TNC trips and present distributions and average occupancy rates for pooled, private, and overall (combined) TNC trips. When they operated pre-pandemic, pooled TNC services (Lyft Shared rides and uberPOOL) were requested with the understanding that the user may be matched with one or more other passengers prior to or during the trip. As mentioned above, pooled TNC services could be requested by up to two passengers. If there were three or more initial passengers, then they had to request a private TNC service. Of respondents who requested a pooled TNC service for their most recent trip, the majority—72 percent to 77 percent—were by themselves.

Table 36 shows how many other passengers were matched with respondents using pooled TNCs for their most recent trip. Pooled TNC requests that are not matched with other passengers are still fulfilled but have effectively the same routing and occupancy as a private TNC trip. The matching rates varied by city, with 72 percent of pooled TNC trips successfully matched in San Francisco, 49 percent matched in Los Angeles, and 57 percent matched in Washington, D.C. The difference in matching rates may be partially dependent on how long these services have existed in each CBSA; San Francisco was the first market with TNC pooling for both companies as noted earlier. The matching success rates were likely also correlated with the share of pooled TNC trip requests, since a greater density of pooled requests will create more opportunities for successful matching of rides. Another factor that may affect matching success is land-use context. Los Angeles has many areas that are less dense than the other two markets and also had the lowest matching success rate out of the three. However, matching rates were likely very fluid over time, and more detailed data would be needed to fully investigate the factors affecting pooled TNC matching success.

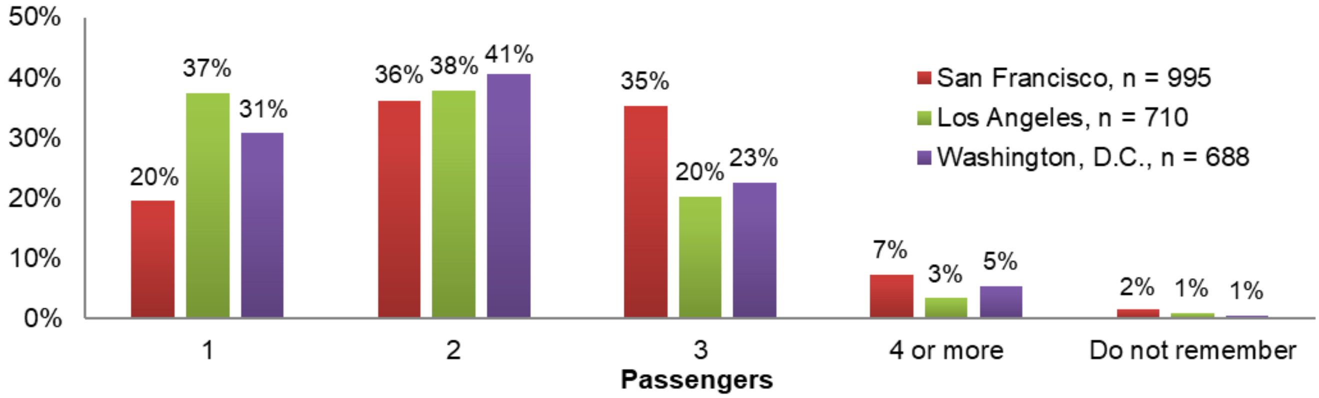
Table 36. Pooled TNC Matching Success by CBSA

Were you matched with other passengers during your ride?	San Francisco, n = 1,045	Los Angeles, n = 756	Washington, D.C., n = 732
No	26%	49%	42%
Yes, one other passenger	45%	37%	38%
Yes, two other passengers	25%	12%	18%
Yes, more than two other passengers	2%	1%	2%
I do not remember	2%	1%	1%

Passenger occupancy distributions for respondents' most recent trips varied by pooled versus private TNC options and by CBSA. Figure 39 shows the distribution of occupancy for respondents' most recent Lyft Shared rides or uberPOOL trip. For estimation purposes, we consider additional matched passengers when calculating pooled TNC trip occupancy. For example, if a respondent requests a one-passenger Lyft Shared ride or uberPOOL and is matched with two other passengers, the ride is considered a three-passenger trip. This methodology produces a slight overestimate of actual mile-weighted occupancy rates, since the vehicle traveled some distance before picking up the matched passengers and also after dropping off the first set of passengers. Since this distance is unknown, this approach provides the closest estimate of pooled TNC trip-based occupancy possible with this data.

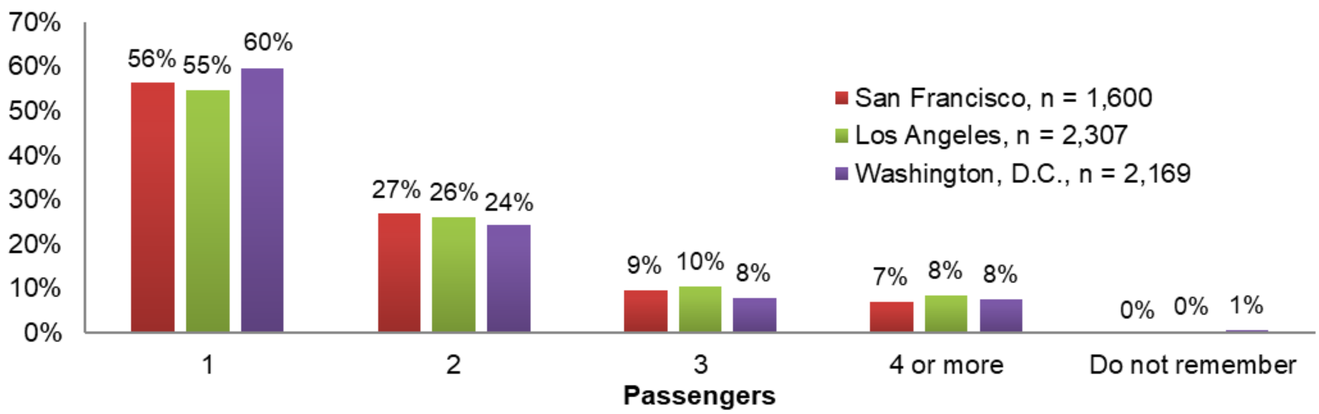
Due to its higher rate of matching success, San Francisco had higher pooled TNC trip occupancies than the other two study CBSAs, on average. In San Francisco, 43 percent of pooled trips had three or more passengers, compared with only 24 percent in Los Angeles and 28 percent in Washington, D.C. It is interesting to note that although pooled TNC passengers were willing to share a ride, many pooled TNC trips happened to be unmatched single-occupant trips. Pooled TNC trips with one passenger made up only 20 percent of pooled trips in San Francisco, but 37 percent in Los Angeles and 31 percent in Washington, D.C. Since matching and occupancy rates are very likely to change over time, more data would needed to assess longitudinal changes in TNC metrics of any future pooling services.

Figure 39. Lyft Shared Rides and uberPOOL Trip Occupancy Distribution



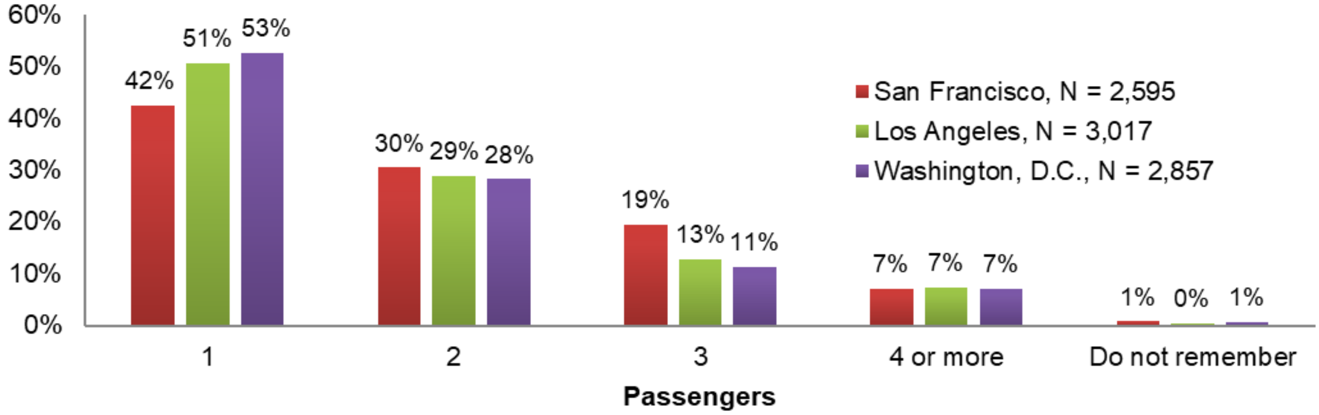
Unlike the pooled trip occupancies, the private Lyft and Uber trip occupancy distributions (in Figure 40, below) were fairly similar across the three target markets. More than half of all private TNC trips were single occupant in each of the three CBSAs. Around one-quarter of the private Lyft and Uber trips had two passengers, and between 15 percent to 19 percent have three or more occupants, depending on the market. Again, note that rounding causes slight misalignment of percentages in the figure.

Figure 40. Private Lyft and Uber Trip Occupancy Distribution



Examining overall trip occupancies by combining pooled and private TNC trips, we see in Figure 41 that San Francisco's higher share of pooled trips and more successful matching rate leads to higher overall trip occupancies than the other study CBSAs. Fifty-one percent of overall trips in Los Angeles and 53 percent in Washington, D.C., were single occupant, while this proportion was 42 percent in San Francisco. Twenty-eight percent to 30 percent of trips had two occupants, depending on the market. More than one-quarter of the most recent trips in San Francisco had three or more passengers, while this proportion was 20 percent in Los Angeles and 18 percent in Washington, D.C.

Figure 41. Overall Lyft and Uber Trip Occupancy Distribution (Pooled and Private Combined)



Using these occupancy distributions, we calculated the average occupancy of most recent trips using pooled and private services, as well as an overall (combined) measurement of trip-based occupancy for each CBSA. Table 37 contains average occupancies for Lyft Shared rides and uberPOOL trips, private Lyft and Uber trips, and overall trips for each of the target markets. As expected, the average occupancies for pooled service trips were higher than for private TNC trips in each of the three CBSAs. San Francisco pooled TNC trips had the highest average occupancy of the three markets at 2.31 passengers, and Washington, D.C., private Lyft and Uber trips had the lowest, at 1.67 passengers. Out of the three markets, Los Angeles had the lowest Lyft Shared ride and uberPOOL average trip occupancy at 1.90 passengers but the highest private TNC trip occupancy at 1.76 passengers, on average. Overall combined average trip occupancies (pooled and private combined) were highest in San Francisco at 1.93, followed by Los Angeles at 1.79 and Washington, D.C., at 1.76 passengers.

For comparison, the average occupancy of privately owned vehicles in the United States is 1.67 persons per vehicle mile (NHTS 2017). Note that the National Household Travel Survey measures occupancy in persons per vehicle mile (distance-based occupancy), while our methodology estimates TNC passengers per trip (trip-based occupancy) due to data limitations. While the average occupancies of pooled TNC trips across all three markets are slightly higher than the average vehicle occupancy in the United States, the average occupancies of private TNC trips are about the same, and the overall (combined) average TNC occupancies are only slightly higher in all three study markets. However, considering that deadheading makes up a significant portion of overall TNC miles (at an average of 34 percent across the three markets, as outlined in the VMT and GHG impacts section), distance-based TNC occupancies very likely have been lower than the U.S. average distance-based vehicle occupancy of 1.67 passengers per vehicle mile. For example, vehicles traveling with an occupancy of 1.93 per passenger mile would have to have a percentage of deadheading miles to be no greater than 16% to be roughly equivalent to this US average (not counting the driver). We present trip-based occupancy rates in this section as opposed to distance-based occupancy rates, which is a different measure.

While we do not assess the impact of TNCs on traffic congestion in this study, occupancy is one of the metrics to consider when evaluating the effect Lyft and Uber have on regional transportation networks. Combined with mode replacement behavior of those now making trips with TNC services (explored later within this section), an analysis of occupancy provides insight into important issues regarding TNC impacts on VMT and GHG emissions.

Table 37. Average Passenger Trip Occupancy by Service Type and Market

TNC Service Model	San Francisco	Los Angeles	Washington, D.C.
Lyft Shared rides/UberPOOL	2.31	1.90	2.03
Private Lyft/Uber	1.69	1.76	1.67
Overall (Pooled and Private)	1.93	1.79	1.76

Average Occupancy by Trip Purpose

Although the use of pooled versus private services in general has an impact on TNC occupancies, certain trip purposes are more likely than others to have higher average trip occupancies. Table 38 displays average overall trip occupancies (pooled and private services combined) and the percentage of respondents who used pooled TNCs for their most recent trip, broken out by trip purpose. It is important to note that even though a given trip purpose may have a relatively high average occupancy, this does not necessarily correlate with a high percentage of trips made using pooled TNC services.

The highest average trip occupancies occurred during restaurant/bar and social/recreational trips, ranging from 2.0 to 2.3 passengers across the three CBSAs, on average. This effect is due to the fact that restaurant and social trips are more often made with friends, relative to other trip purposes. However, restaurant/bar and social/recreational trips did not exhibit high percentages of pooled service use relative to other trip purposes. For example, in Los Angeles, only 17 percent of restaurant/bar and 24 percent of social/recreational trips were made using a pooled TNC service.

Conversely, commute trips to or from work or school exhibited some of the lowest average overall occupancies by trip purpose, even though they displayed some of the highest proportions of pooled TNCs for respondents' most recent trips. For example, in Washington, D.C., work and school commute trips had one of the lowest average passenger occupancies out of all trip purposes in the market (1.4 passengers), while the portion using pooled services is the second highest in the market, at 35 percent of most recent commute trips. This pattern is due to very low occupancies (close to one passenger, on average) for private Lyft and Uber work or school TNC commute trips. Given these results, should pooling options return to market, policies that aim to increase average TNC occupancies of commute trips by encouraging the use of pooled over private TNC service options may be an effective way to increase TNC occupancies not just for commute trips but overall. In summary, the results displayed in Table 38 show that trip purpose is a key factor in average TNC trip occupancy rates.

Table 38. Average Trip Occupancy (Overall) and Percentage Who Used Pooled Services by Trip Purpose

	Average Occupancy (Overall)			% Who Used Pooled Service for Last Trip		
Trip Purpose	*San Francisco*	*Los Angeles*	*Washington, D.C.*	*San Francisco*	*Los Angeles*	*Washington, D.C.*
Go to or from a restaurant/bar	2.3	2.2	2.2	37%	17%	20%
Go to or from other social/recreational activities	2.1	2.1	2.0	41%	24%	25%
Commute to or from work or school	1.7	1.4	1.4	53%	37%	35%
Go to or from work-related meetings	1.6	1.3	1.4	31%	26%	20%
Go to or from shopping or errands	1.9	1.7	1.6	46%	40%	32%
Go to or from health care services	1.5	1.4	1.5	36%	25%	27%
Visit family or friends	1.8	1.5	1.7	52%	34%	36%
Go to and from airport	1.7	1.6	1.5	21%	12%	16%
Other	1.8	1.6	1.6	40%	28%	21%

<u>Mode Substitution</u>

We asked passenger survey respondents what transportation mode they would have used in place of their most recent trip if TNC services (both Lyft and Uber) had not been available. The results presented in this section provide a snapshot of mode substitution behavior among respondents in the three CBSAs. This analysis is distinct from the modal shift sections of this report because those sections assess the general direction and magnitude of changes in the use of other modes due to TNCs, whereas this section compares the portion of Lyft and Uber trips that draw from other specific transportation modes in each market. By analyzing responses regarding a discrete and recallable recent event (the respondent's last TNC trip at the time of the survey), we are able to generate distributions of mode substitution in each CBSA. These distributions allow us to comparatively examine which transportation modes were more commonly being replaced by TNCs.

<u>Pooled Versus Private TNC Mode Substitution</u>

Respondents who had used a pooled TNC service for their last trip were able to indicate whether they would have used another Lyft or Uber service if neither Lyft Shared rides nor uberPOOL had been available. Forty-two percent of those who had selected a pooled service during their last trip in San Francisco, 45 percent in Los Angeles, and 48 percent in Washington, D.C., reported that they would have used another Lyft or Uber service if pooled TNCs were not available. These respondents were then asked what transportation mode they ultimately would have used if no Lyft or Uber services existed. Respondents who used a private Lyft or Uber service for their last trip were simply asked what transportation mode they would have used if TNCs were not available.

Mode substitution results differed among respondents who had used pooled TNCs for their last trip as compared with those who had used a private Lyft or Uber service. Results also varied across the three CBSAs. The mode substitution distributions, broken out by pooled and private TNC services, are displayed in Table 39. Note that the subsamples represented in each market are mutually exclusive. Each column adds to 100 percent, but the percentages are rounded to the nearest whole, so some totals do not appear to equal exactly 100 percent.

Table 39. Mode Substitution by Pooled vs. Private TNCs

If Lyft and Uber were not available, how would you have made your most recent trip instead?	***San Francisco***		***Los Angeles***		***Washington, D.C.***	
	Lyft Shared rides / uberPOOL, n = 1,036	Private Lyft/Uber, n = 1,584	Lyft Shared rides / uberPOOL, n = 752	Private Lyft/Uber, n = 2,288	Lyft Shared rides / uberPOOL, n = 725	Private Lyft/Uber, n = 2,149
Would not have taken	7%	4%	11%	7%	5%	3%
Driven alone	9%	11%	13%	19%	4%	7%
Rode in a car with friend/family	6%	8%	14%	22%	5%	7%
Bus	34%	18%	31%	14%	23%	11%
Rail or subway	12%	9%	6%	3%	30%	20%
Walk	10%	9%	9%	6%	8%	7%
Bike	2%	1%	2%	2%	1%	0%
Bikesharing	0%	0%	0%	0%	1%	1%
Carsharing vehicle	0%	1%	1%	0%	0%	1%
Taxi	15%	33%	11%	25%	21%	42%
E-Hail taxi	2%	4%	1%	0%	1%	0%
Other	2%	2%	2%	2%	1%	1%

Across all three CBSAs, respondents using pooled TNCs most frequently reported using those pooled services instead of public transit modes (bus and rail combined); 46 percent of respondents in San Francisco, 37 percent in Los Angeles, and 53 percent in Washington, D.C., who used Lyft Shared rides or uberPOOL for their last trip would have used some form of public transit if no TNC services had been available. For Lyft Shared rides and uberPOOL passengers in San Francisco and Los Angeles, bus was the most common mode that would have been used if TNC services did not exist. In Washington, D.C., the most common replacement mode for pooled TNC passengers was rail or subway.

Among respondents who used private Lyft and Uber services for their most recent trips, the most common replacement mode in San Francisco and Washington, D.C. was a taxi or E-Hail taxi; 37 percent of private Lyft and Uber respondents in San Francisco and 42 percent in Washington, D.C. would have used a taxi or E-Hail taxi in place of their last TNC trip. In Los Angeles, driving or riding in a personal vehicle was the most frequent replacement mode for private Lyft and Uber respondents, with about 40 percent claiming they would have used a personal vehicle had TNCs not been available.

We found that the induced demand effect was slightly greater among respondents who had used a pooled TNC service for their last trip. In San Francisco, 7 percent of Lyft Shared rides and uberPOOL passengers would not have taken their last trip if TNCs did not exist, while only 4 percent of private Lyft and Uber passengers would not have made their trip. Eleven percent of pooled TNC passengers in Los Angeles versus 7 percent of private service passengers would not have taken their last trip, and 5 percent of pooled compared with 3 percent of private TNC passengers in Washington, D.C., would not have made their most recent trip if TNCs were not available. A slightly higher proportion of pooled than private TNC respondents would have used an active mode (walk, bike, or bikesharing) for their last trip, although this difference was 3 percentage points or less across all three markets.

In general, private Lyft and Uber services drew a greater proportion of passengers from taxis and personal vehicles than Lyft Shared rides and uberPOOL, while pooled TNC services pulled more heavily from public transit. In San Francisco, about 55 percent of those who used private Lyft and Uber services would have taken a taxi or used a personal vehicle if TNCs had not been available, compared with only 32 percent of pooled TNC passengers who would have done the same. In Los Angeles, 66 percent of private Lyft and Uber passengers, but only 39 percent of pooled TNC passengers would have used a taxi or personal vehicle for their last trip. A similar pattern exists in Washington, D.C. Conversely, a greater proportion of respondents who used Lyft Shared rides or uberPOOL for their last trip would have used public transit compared with private Lyft and Uber passengers. In Washington, D.C., 53 percent of pooled TNC respondents would have used public transit (bus or rail) if TNC services did not exist, compared with 31 percent of private Lyft and Uber respondents who would have done so. Similar effects exist in San Francisco and Los Angeles, where 46 percent and 37 percent of pooled service respondents would have used public transit for their last trip. In contrast, just 27 percent of private Lyft and Uber respondents in San Francisco and 17 percent in Los Angeles would have substituted modes similarly.

In summary, the mode substitution profiles were quite different among pooled versus private TNC passengers. These differences are important when considering the overall impact of Lyft and Uber on the transportation network. Although average passenger occupancies were indeed higher for pooled TNC services, as shown in the preceding section, these services drew a greater proportion of passengers from high-occupancy public transit modes than did private Lyft and Uber services, which tended to compete more often with taxis and driving. These mode substitution differences may be partially due to demographic factors like personal vehicle ownership, age, and income. Nonetheless, there were clear distinctions in mode substitution profiles among those using pooled versus private TNC services.

Vehicle Owner Versus Non–Vehicle Owner Mode Substitution

Mode substitution results also vary by whether a respondent owned one or more household vehicles. Table 40 displays mode substitution results for all respondents, for personal vehicle owners, and for those without a household vehicle, across the three CBSAs. All distributions sum to 100 percent, but rounding to the nearest percent causes a few distributions to be off by 1 or 2 percent.

Table 40. Mode Substitution by All Respondents, Vehicle Owners, and Non–Vehicle Owners

If Lyft and Uber were not available, how would you have made your most recent trip instead?	*San Francisco*			*Los Angeles*			*Washington, D.C.*		
	Total, N = 2620	Vehicle owner, n = 1766	No vehicle, n = 847	Total, N = 3040	Vehicle owner, n = 2436	No vehicle, n = 591	Total, N = 2874	Vehicle owner, n = 1800	No vehicle, n = 1065
Would not have taken	5%	4%	7%	8%	8%	8%	4%	4%	4%
Driven alone	10%	14%	1%	17%	21%	3%	6%	10%	1%
Rode in a car with friend/family	7%	8%	5%	20%	22%	12%	6%	8%	4%
Bus	24%	19%	36%	18%	13%	41%	14%	10%	21%
Rail or subway	10%	10%	12%	4%	3%	7%	22%	20%	26%
Walk	10%	8%	13%	7%	6%	10%	7%	6%	9%
Bike	2%	2%	2%	2%	1%	5%	0%	0%	1%
Bikesharing	0%	0%	0%	0%	0%	0%	1%	1%	1%
Carsharing vehicle	1%	0%	1%	1%	0%	1%	1%	0%	1%
Taxi	26%	29%	18%	21%	24%	10%	36%	40%	31%
E-Hail taxi	3%	3%	4%	0%	0%	1%	0%	0%	0%
Other	2%	2%	2%	2%	2%	1%	1%	1%	1%

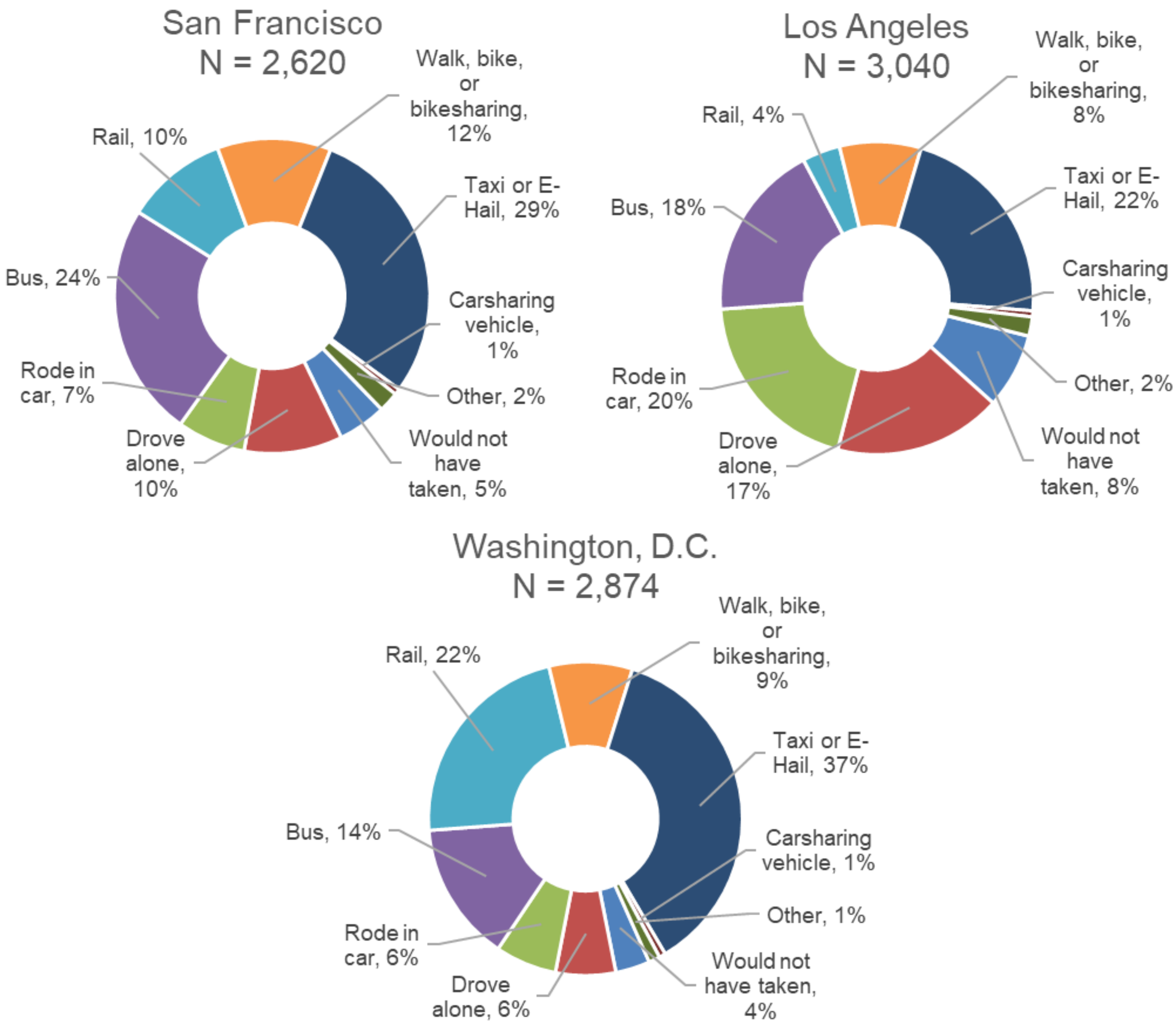
Unsurprisingly, vehicle owners were more likely to have driven alone had Lyft and Uber not been available for their most recent trip than non-vehicle owners, although there were small proportions (3 percent or less across all markets) of non-owners who claimed they would have driven alone if TNCs had not been available, possibly by borrowing a car from friends or family members. Vehicle owners were also more likely than non-owners to receive a ride in the absence of TNCs, likely due to other members of their household owning private vehicles. Mode substitution with taxis was also more common among vehicle owners than among non–vehicle owners. In San Francisco, 32 percent of car owners would have used a taxi or E-Hail taxi, while 22 percent of those without a personal vehicle would have done the same if TNCs did not exist. Similar patterns in taxi mode substitution existed in Los Angeles and Washington, D.C. Respondents without a personal vehicle were more likely to substitute TNCs for public transit than were vehicle owners, with this effect being most pronounced in Los Angeles. In Los Angeles, 48 percent of respondents without a vehicle would have used public transit (bus or rail) if TNCs had not been available, compared with only 16 percent of car owners. In addition, a slightly greater proportion of non–vehicle owners would have used active modes (walk, bike, or bikesharing) for their last trip than vehicle owners across all three CBSAs.

These results show that in addition to TNC service type, mode substitution results also varied depending on household vehicle ownership. Vehicle owners were more likely to substitute TNC trips for other auto-based modes, like driving alone or getting a ride with a friend or in a taxi. Conversely, the majority of non-vehicle owners in all three CBSAs substituted TNC trips for public transit or active transportation modes. In the following section, we discuss overall mode substitution results (across all respondents) and how they differ across our three study markets.

<u>*Overall Mode Substitution Across CBSAs*</u>

In Figure 42, we display mode substitution results among all respondents and for all TNC service types by CBSA. For simplicity, we aggregated similar mode choice options, including active modes (walk/bike/bikesharing) and use of taxis (taxi/E-Hail). The same results, disaggregated by each individual mode, are presented in the "Total" columns of Table 40 for reference.

Figure 42. Mode Substitution Among All Respondents by CBSA



Taxis and E-Hail taxis were the most common TNC mode substitution among all respondents in the three markets, at 29 percent of all respondents in San Francisco, 22 percent in Los Angeles, and 37 percent in Washington, D.C. However, the overall mode substitution profiles differed across the CBSAs. In San Francisco and Washington, D.C., there were greater proportions of respondents who substituted TNCs for public transit (bus and rail) than for driving or riding in a personal vehicle. In addition, heavier bus substitution occurred in San Francisco (about 35 percent of all respondents substituted for public transit, with 24 percent for bus specifically), while a more rail-heavy shift existed in Washington, D.C. (about 37 percent of all respondents substituted for public transit, with 22 percent for rail specifically). The relatively larger proportion of respondents who substituted for rail in Washington, D.C., may partially be due to the disruptive SafeTrack rail maintenance program that occurred at the time of our passenger survey, as mentioned previously.

Conversely, in Los Angeles, driving or getting a ride in a personal vehicle was a more common substitute for TNCs than was public transit. Thirty-seven percent of all respondents in Los Angeles would have driven or ridden in a personal vehicle, compared with 22 percent who would have used public transit (18 percent bus, 4 percent rail) if TNCs had not been available for their last trip. Interestingly, a slightly greater portion of respondents in Los Angeles would have gotten a ride with a friend or family member (20 percent) than would have driven alone if TNCs did not exist.

Induced demand due to TNCs was higher in Los Angeles than in the other two CBSAs, as 8 percent of respondents claimed they would not have made their most recent trip if Lyft and Uber did not exist, compared with only 5 percent in San Francisco and 4 percent in Washington, D.C. Granted, TNCs may have been providing important mobility benefits for some of these respondents who otherwise would not have made their last trip entirely, if TNCs were not available. The shift in active modes was ordered differently, as 12 percent of all respondents in San Francisco, 8 percent in Los Angeles, and 9 percent in Washington, D.C., would have walked, biked, or used bikesharing for their most recent trip if TNCs had not been available.

In summary, these results show that TNC mode substitution is very location dependent and unique to each individual market. In San Francisco and Washington, D.C., about two-thirds or greater of all respondents would have used public transit or taxis in place of their most recent TNC trip, while in Los Angeles less than half of all respondents would have used these modes. Los Angeles experienced more significant TNC mode substitution from personal vehicle driving than the other two markets, as more than two times the proportion of respondents there claimed they would have driven or ridden in a car if TNC services had not been available, relative to San Francisco, and more than three times the proportion relative to Washington, D.C. These mode substitution distinctions across CBSAs are likely due to variations in land-use contexts, overall mode shares, vehicle ownership rates, and demographic makeup across the study markets. As a relatively new entrant into an existing ecosystem of transportation mode options, TNC trips substitute for the more commonly used modes in each market. The San Francisco and Washington, D.C., core urban areas are denser and have higher proportions of public transit trips than in Los Angeles. Therefore, it is fairly intuitive that TNCs more commonly substitute for public transit in these two markets and more commonly substitute for driving in personal vehicles in Los Angeles.

Implications of Lyft Shared rides and uberPOOL on TNC VMT and GHG Emissions

A key question among policymakers is whether pooled TNC services are increasing or decreasing VMT and GHG emissions. Answering this question is challenging due to data limitations, and the results are dependent on a number of factors that can change from market to market and over time. The results presented here are estimates based on available data and were informed by a few key assumptions. Again, these results reflect findings as related to pooled services in operation prior to the pandemic.

First, it is useful to explain how we consider pooled rides to reduce VMT and GHG emissions. Pooling reduces private TNC VMT and GHG emissions only if matching actually occurs and the modes displaced are not more VMT efficient than the pooled ride. The amount of VMT increase or decrease relative to the substituted modes depends on the degree to which rides are matched. Naturally, if all passengers elect to use shared rides but no one is matched, there is no difference between shared rides or pooling and private Lyft and Uber rides. And for rides that are matched, additional information is needed on the distance of that ride as well as the mode substitution. If passengers of shared or pooled rides would otherwise have walked, bicycled, or used public transit, for instance, no emissions are saved. Under such circumstances VMT and emissions may in fact increase as a result of pooling because the more affordable shared rides can induce additional automobile travel. This can result in competition with other modes, like walking, biking, and public transit, which have little to no increase in marginal emissions (as discussed in the previous section). However, if pooled rides are drawing from personal vehicles, taxis, or private Lyft or Uber rides, then there is an emission reduction that is directly the result of pooling.

Measuring this is difficult because it requires data not only on match rates but also on trip distances and mode substitution. Simultaneously obtaining all this information for the entire passenger population would be very difficult in the present day, but our sample survey data on passengers' most recent trip contains this information. We applied it here to generate an estimate of the impact of pooling on private TNC VMT and GHG emissions. Changes in these parameters would shift the degree to which pooling would impact VMT and emissions.

We have analyzed the changes in VMT and GHG emissions produced by pooled TNC services relative to a hypothetical scenario in which only private Lyft and Uber services exist. Note that this analysis considers the change in TNC VMT per passenger (VMT/pax) only and is not intended as an evaluation of the overall change in transportation system VMT due to TNCs. This evaluation aims to offer some insight into the potential mitigation effects that pooled TNCs, in particular, has on the VMT and GHG emissions produced by private TNC services. An examination of TNC impacts on overall VMT and GHG emissions is presented in other sections of this report.

We first compared the VMT/passenger (pax) of the respondent's most recent trips both with Lyft Shared rides and uberPOOL and, in a hypothetical scenario, without Lyft Shared rides and uberPOOL. Then we calculated a change and percentage change in VMT/pax of TNC services due to Lyft Shared rides and uberPOOL. Again, note that this calculation examines only the impact that pooled TNCs have on mitigating the VMT/pax of private Lyft and Uber services and does not evaluate the broader impact of TNC VMT on the transportation system as a whole.

The data show that the presence of Lyft Shared rides and uberPOOL decreased the overall VMT/pax of private Lyft and Uber services in each of the three study CBSAs. The results are displayed in Table 41 and Table 42, below, and suggest that at the calculated parameters, San Francisco had a 10 percent reduction, Los Angeles a 1 percent reduction, and Washington, D.C. a 4 percent reduction in VMT/pax from pooling.

Impacts differ by market due to three factors: differences in mode substitution of pooled TNC trips, the proportion of respondents' last trips that were made with Lyft Shared rides or uberPOOL as opposed to a private TNC service, and the pooled service matching effectiveness in each CBSA. All of these factors are subject to change and not expected to be static over time. San Francisco experienced the greatest reductions mainly due to more successful matching rates and thus higher Lyft Shared rides and uberPOOL occupancies than in the other two cities. In addition, almost 40 percent of San Francisco respondents' last trips were made with Lyft Shared rides or uberPOOL. This contributed to the larger magnitude of VMT/pax reduction in San Francisco than in Los Angeles and Washington, D.C.; in each of the latter cities, pooled TNC trip requests achieved a 25 percent share. Los Angeles also yielded a lower VMT/pax reduction from Lyft Shared rides and uberPOOL because of the smaller jump in average occupancy between its private TNC (1.76) and pooled (1.90) services. Table 37, discussed above in the vehicle occupancy section, displays average occupancies for Lyft Shared rides and uberPOOL and the private TNC services across each market.

The percentage change in GHG emissions per passenger (GHG/pax) were very similar to the VMT/pax reductions in each corresponding market, with a 10 percent reduction in San Francisco, a 2 percent reduction in Los Angeles, and a 4 percent reduction in Washington, D.C. Los Angeles had a slightly greater percentage GHG/pax reduction than its corresponding VMT/pax reduction mainly because a proportionally larger share of pooled TNC trips would have been made in a personal vehicle (12 percent) than in the other two markets (7 percent in San Francisco and 5 percent in Washington, D.C., see Table 42). Since the average fuel economy of respondents' personal vehicles was lower than the fuel economies of Lyft and Uber vehicles (discussed earlier), the relatively higher proportion of vehicle trip substitution in Los Angeles leads to a slightly higher percentage GHG/pax reduction than the corresponding VMT/pax percentage reduction. These calculations, methodologies, and their limitations are discussed in the remainder of this section.

Table 41. Percentage Change in TNC VMT/pax and GHG/pax Due to Lyft Shared Rides and UberPOOL

Metric	San Francisco	Los Angeles	Washington, D.C.
Percentage Change in VMT/pax	–10%	–1%	–4%
Percentage Change in GHG/pax	–10%	–2%	–4%

<u>*Change in TNC VMT/pax and GHG/pax Calculations*</u>
Formulas (1), (2), and (3) and Table 42, Table 43, and Table 44 (presented below) detail the algorithms used to calculate the percentage change in TNC VMT/pax and GHG/pax due to pooled TNCs displayed in Table 41. We calculated change in TNC VMT/pax due to Lyft Shared rides and uberPOOL by measuring VMT and the number of passengers across three distinct subpopulations within our sample, by CBSA. VMT and passengers were measured empirically by using stated survey responses for the private and pooled TNC subpopulations and the mode substitution for the pooled TNC subpopulation. VMT and passenger occupancies of those who used private Lyft and Uber services and those who used Lyft Shared rides and uberPOOL for their last trip were empirically measured using responses from our survey. VMT was measured among both these subpopulations by summing the most recent trip mileages given in the survey (distribution shown in Figure 37) across each market. The number of passengers in the private Lyft and Uber subpopulation was calculated by summing the last trip occupancies, by CBSA (distribution shown in Figure 40). The number of passengers served in the Lyft Shared rides and uberPOOL subpopulation was calculated by summing the stated original occupancy (either one or two passengers) and adding the number of passengers that were matched (if any) with the respondent during his or her last trip, as outlined in prior sections (distribution shown in Figure 39).

The third subpopulation includes the hypothetical VMT that would have been produced by a passenger vehicle (either a private Lyft or Uber, taxi, personal vehicle, or carsharing vehicle) if Lyft Shared rides and uberPOOL did not exist. Both VMT and passengers served were calculated by examining the mileage and occupancy implications of the transportation mode that each pooled TNC respondent would have used (as outlined in Table 44). As shown in Table 42, almost half of the respondents (between 42 percent and 48 percent, depending on the market) in each CBSA would have used a private Lyft or Uber service if Lyft Shared rides and uberPOOL did not exist. This substitution represents a VMT and emission reduction as a result of shared rides with Lyft and Uber when passengers requesting pooled trips were successfully matched with other passengers. Additionally, 11 percent to 16 percent would have used a taxi or driven/ridden in a personal vehicle, and this substitution also results in VMT and emission reductions when successful matching occurred. Finally, between 24 percent and 31 percent of respondents, depending on the market, would have used some form of public transit (bus or rail).

Table 42. Mode Substitution of Pooled TNC Respondents

If UberPOOL and Lyft Line (both shared ride services) did not exist in your area, how would you have made this trip instead?	San Francisco, n = 1,040	Los Angeles, n = 755	Washington, D.C., n = 727
Would not have taken	4%	7%	3%
Some other Lyft/Uber service	42%	45%	48%
Driven alone	4%	6%	2%
Rode in a car with friend/family	3%	6%	3%
Bus	23%	20%	13%
Rail or Subway	8%	4%	18%
Walk	6%	6%	5%
Bike	2%	1%	0%
Bikesharing	0%	0%	1%
Carsharing vehicle	0%	0%	0%
Taxi	6%	4%	6%
E-Hail taxi	1%	0%	0%
Other	1%	1%	0%

Using the VMT and passenger totals of these three subpopulations, we calculated the VMT/pax observed in our survey and the total VMT/pax that would have occurred if Lyft Shared rides and uberPOOL did not exist. These calculations are displayed in formulas (1) and (2), below. We calculated the observed VMT/pax by adding the VMT of private and pooled TNC passenger trips and dividing that total by the passengers served by these two services (formula (1)). Then, we calculated the hypothetical VMT/pax if pooled TNCs did not exist (formula (2)). This was done by summing the VMT of private Lyft and Uber respondents and the VMT produced by the modes that pooled service respondents *would have used* if Lyft Shared rides and uberPOOL did not exist. This VMT was divided by the sum of the passengers served by private Lyft and Uber and the passengers hypothetically served by substituted modes for Lyft Shared rides and uberPOOL. This resulted in the VMT/pax that would have occurred if pooled TNC services did not exist, as outlined in formula (2). Finally, as shown in formula (3), we calculated the percentage change in TNC VMT/pax due to Lyft Shared rides and uberPOOL by using the VMT/pax of observed trips and the VMT/pax if Lyft Shared rides and uberPOOL did not exist, as calculated in the previous two formulas.

(1) $\frac{VMT}{pax}$ $of\ Observed\ Trips =$

$$\frac{(VMT\ of\ Private\ Lyft\ and\ Uber\ Trips) + (VMT\ of\ Lyft\ Shared\ rides\ and\ Trips)}{(Pax\ of\ Private\ Lyft\ and\ Uber\ Trips)\ + (Pax\ of\ Lyft\ Shared\ rides\ and\ uberPOOL\ )}$$

(2) $\frac{VMT}{pax}$ $if\ Lyft\ Shared\ rides\ and\ uberPOOL\ did\ not\ exist =$

$$\frac{(VMT\ of\ Private\ Lyft\ and\ Uber\ Trips) + (VMT\ of\ Modes\ Substituted\ for\ Lyft\ Shared\ and\ uberPOOL\ Trip)}{(Pax\ of\ Private\ Lyft\ and\ Uber\ Trips) + (Pax\ of\ Modes\ Substituted\ for\ Lyft\ Sharedand\ uberPOOL\ Trip)}$$

(3) $\%\ Change\ in\ TNC\ \frac{VMT}{pax}\ due\ to\ Lyft\ Shared\ rides\ and\ uberPOOL =$

$$\frac{\frac{VMT}{pax}\ of\ Observed\ Trips\ - \frac{VMT}{pax}\ if\ Lyft\ Sharedand\ uberPOOL\ did\ not\ exist}{\frac{VMT}{pax}\ if\ Lyft\ Shared\ rides\ and\ uberPOOL\ did\ not\ exist}$$

We calculated GHG/pax using a methodology similar to the one outlined above, by considering the emission implications of each observed TNC trip as well as the emissions that would have occurred on modes substituted for Lyft Shared rides or uberPOOL trips. Using data provided by both operators, we assumed Lyft and Uber vehicles have a fuel economy of 28 miles per gallons (mpg) in San Francisco, 28 mpg in Los Angeles, and 25 mpg in Washington, D.C. We assumed that carsharing vehicles and taxis have fuel economies of 28 mpg, which we chose as a conservative estimate based on TNC vehicle mpg. We also used the fuel economies of respondents' vehicles for those respondents who would have used a personal vehicle for their last pooled TNC trip. Considering the fuel economies of observed TNC trips and hypothetical modal trips, we then used the stated mileage of each respondents' last trip to determine the tons of CO_2 that were produced under each scenario. Once we summed aggregate GHG emissions among our three subpopulations, we computed GHG/pax in the same way as VMT/pax, as described previously. The detailed calculations for each market are outlined in Table 43.

Table 43. Calculations for Change in VMT/pax and GHG/pax Due Strictly from Passenger Mode Shift to Lyft Shared Rides and UberPOOL

Metric Category	Metric	San Francisco	Los Angeles	Washington, D.C.
Private Lyft and Uber Trips	VMT of Private Lyft and Uber Trips	11888	18678	14300
	GHG of Private Lyft and Uber Trips (tons CO_2)	3.77	5.93	5.08
	Passengers of Private Lyft and Uber Trips	2685	4021	3577
Lyft Shared rides/uberPOOL Trips	VMT of Lyft Shared rides and uberPOOL Trips	5062	5266	3646
	GHG of Lyft Shared rides and uberPOOL Trips (tons CO_2)	1.61	1.67	1.30
	Passengers of Lyft Shared rides and uberPOOL Trips	2232	1294	1378
Mode Substitution for Lyft Shared rides/uberPOOL Trips	VMT of Modes Substituted for Lyft Shared rides and uberPOOL Trips	2970	3328	2254
	GHG of Modes Substituted for Lyft Shared rides and uberPOOL Trips (tons CO_2)	0.95	1.09	0.79
	Passengers of Modes Substituted for Lyft Shared rides and uberPOOL Trips	1194	810	805
VMT/pax	VMT/pax of Observed Trips	3.45	4.50	3.62
	VMT/pax if Lyft Shared rides and uberPOOL Did Not Exist	3.83	4.56	3.78
GHG/pax	GHGs/pax of Observed Trips	0.001094	0.001430	0.001287
	GHGs/pax if Lyft Shared rides/ uberPOOL Did Not Exist	0.001218	0.001452	0.001341
Final Percentage Changes (also shown in Table 41*)*	% Change in TNC VMT/pax due to Lyft Shared rides/uberPOOL	**–10%**	**–1%**	**–4%**
	% Change in TNC GHG/pax due to Lyft Shared rides/uberPOOL	**–10%**	**–2%**	**–4%**

<u>Change in TNC VMT/Pax and GHG/Pax Assumptions and Limitations</u>
There are a number of assumptions made when calculating the impact of Lyft Shared rides and uberPOOL on TNC VMT/pax and GHG/pax, as well as limitations that arise due to these assumptions and the precision of available data. The VMT and passengers of the hypothetical Lyft Shared rides and uberPOOL subpopulation were calculated using the assumptions outlined in Table 44 below.

Table 44. Mileage and Passenger Assumptions for Trip Substitution

Mode Substitution if Lyft Shared rides and uberPOOL Did Not Exist	*VMT Value—Substitute Mode*	*Passenger Value—Substitute Mode*
Would not have taken	0	0
Some other Lyft/Uber service	Trip Mileage	Starting occupancy
Driven alone	Trip Mileage	1
Rode in a car with friend/family	Trip Mileage	2
Bus	0	Starting occupancy
Rail or Subway	0	Starting occupancy
Walk	0	1
Bike	0	1
Bikesharing	0	1
Carsharing vehicle	Trip Mileage	Starting occupancy
Taxi	Trip Mileage	Starting occupancy
E-Hail taxi	Trip Mileage	Starting occupancy
Other	N/A	0

To calculate the substituted mode VMT of Lyft Shared rides and uberPOOL trips, we used stated trip mileage if the respondent indicated she or he would have used some other Lyft or Uber service, driven alone, ridden in a car, used a carsharing vehicle, or used a taxi/E-hail taxi. We assumed the VMT to be zero if the respondent would not have taken the trip or would have used public transit (bus, rail or subway), walked, or biked. Zero VMT was assumed for public transit modes since these miles would have been produced regardless of the respondent's decision to use public transit. For calculating passengers served by the substituted modes for pooled TNC trips, we assumed zero passengers if the respondent would not have taken the trip; one passenger if the respondent would have driven alone, walked, or biked; and two passengers if the respondent would have ridden in a car with a friend or family member. We assumed the starting passenger occupancy (either one or two passengers for Lyft Shared rides and uberPOOL) if the respondent would have used some other TNC service; bus, rail or subway; a carsharing vehicle; or a taxi/E-hail taxi. We used these assumptions to calculate the VMT and passengers of substituted modes if pooled TNC services did not exist, which affected the VMT/pax without Lyft Shared rides and uberPOOL metric.

Other assumptions affected the methodology of calculating occupancy for pooled TNC trips. As explained in preceding sections, we made the simplifying assumption that matched passengers rode with each respondent for the entirety of the respondent's trip. In reality, most pooled TNC trips drive some distance before matching with other passengers. For this reason, our calculation of Lyft Shared rides and uberPOOL trip-based occupancies, when compared with distance-based occupancies, are likely overstated and therefore yield a conservative estimate of VMT/pax change. If the occupancy miles were precisely known, the VMT/pax of Lyft Shared rides and uberPOOL would be higher than calculated, and the impacts of pooling would look slightly less favorable than shown.

Other limitations of the Lyft Shared rides and uberPOOL impact on the VMT/pax calculation include the use of stated trip mileages as opposed to actual trip mileage data, and our inability to include non-trip miles (app open phase, fetch phase, and access to market miles, as described in the methodology section). In actuality, each TNC trip also produces some measure of zero-occupant miles while the driver is heading to his or her main market, driving around looking for a fare, and fetching a passenger. Omitting these zero-occupant miles due to data limitations leads to a VMT underestimate per trip. However, since this limitation is reflected in the VMT calculations for every subpopulation in this section, the calculation of change in miles from shared/pooled rides may not be impacted too heavily, since each subpopulation omits these miles. Differences in the portions of zero-occupant miles driven between private and pooled TNC services would affect the outcome of the change-in-miles calculation, but these data were not publicly available. Non-trip VMT is examined in this report's analysis of overall change in VMT due to TNCs, which used activity data obtained from both operators.

Impact of Pooled TNC on Overall VMT and GHG Change Per passenger

As outlined above, the net changes in VMT and GHG emissions due to Lyft and Uber already contain the impacts of the pooled TNC services (Lyft Shared rides and uberPOOL) and reflect the corresponding behavioral change among passengers. However, by applying the percentage change in VMT and GHG per passenger factors derived from the most recent trip section (see "Implications of Lyft Shared rides and uberPOOL on TNC VMT and GHG Emissions" subsection above), we can estimate what the net change in VMT and GHG emissions would be, if pooled TNCs did not exist.

By augmenting formula (3) in the "Change in TNC VMT/pax and GHG/pax Calculations" subsection of the most recent trip section (above), we can estimate a percentage increase in TNC VMT per passenger and GHG per passenger that would occur if Lyft Shared rides and uberPOOL did not exist. Using these data, we estimated that the following would have occurred as a result of mode substitution that would have happened in the absence of the shared/pooled services: 1) an 11 percent increase in VMT per passenger and GHG per passenger in San Francisco, 2) a 1 percent increase in VMT per passenger and a 2 percent increase in GHG per passenger in Los Angeles, and 3) a 4 percent increase in VMT and GHG per passenger in Washington, D.C. would have occurred without pooled services. These increases are shown in Table 45.

Table 45. Percent Change in VMT/pax/year and GHGs/pax/year Strictly from Passenger Mode Shift, if Lyft Shared Rides and uberPOOL Did Not Exist

Metric	San Francisco	Los Angeles	Washington, D.C.
Percent Change in VMT/pax/year	+11%	+1%	+4%
Percent Change in GHGs/pax/year	+11%	+2%	+4%

To find the operator VMT and GHG emissions that would have been produced from mode shift in the absence of pooled TNCs, we applied the percentage increases in VMT and GHG emissions per passenger per year from Table 41 to the operator VMT per passenger per year and operator GHG emissions per passenger per year for each market (from Table 25 and Table 30). Table 46 displays the estimated increase in operator VMT and GHG emissions per passenger that would have occurred if

Lyft Shared rides and uberPOOL did not exist. The increase in operator VMT per passenger per year across the three markets is small to modest, ranging from an increase of 13 miles per year per passenger in Los Angeles to an increase of 120 miles per passenger per year in San Francisco.

Table 46. Operator VMT and GHG Emissions per Passenger per Year, if Lyft Shared Rides and uberPOOL Did Not Exist

CBSA	Operator VMT per Passenger per Year	Percent Change in VMT/pax if Pooled TNCs Did Not Exist	Operator VMT per Passenger per Year if Pooled TNCs Did Not Exist	Operator GHG Emissions per Passenger per Year	Percent Change in GHGs/pax if Pooled TNCs Did Not Exist	Operator GHG Emissions per Passenger per Year if Pooled TNCs Did Not Exist
San Francisco	1,077	+11%	1,197	0.338	+11%	0.376
Los Angeles	1,173	+1%	1,186	0.374	+2%	0.379
Washington, D.C.	502	+4%	524	0.179	+4%	0.186

The impact of the Lyft Shared rides and uberPOOL do not significantly change the conclusions shown in Table 27. That is, if Lyft Shared rides and uberPOOL did not exist, there would still be increases in VMT per passenger in San Francisco and Los Angeles (since operator VMT would be higher). As shown in Table 47, with the absence of pooled TNCs, the net VMT change in San Francisco would increase from 234 to 354 miles per passenger per year and from 242 to 255 miles per passenger per year in Los Angeles, and the VMT reduction in Washington, D.C. would be dampened from –83 to –61 miles per passenger per year. This would reduce the statistical significance of the change in VMT for Washington, D.C. from the 5% to the 10% level. The findings suggest that Lyft Shared rides and uberPOOL are beneficial in reducing a portion of the overall VMT produced by TNCs, but their impact as measured in this analysis was not significant enough to substantively alter whether TNCs increases or decreases net VMT in any of the three markets at their current market shares.

Table 47. Net Change in VMT From Lyft and Uber by Market, if Lyft Shared Rides and uberPOOL Did Not Exist

VMT Change Due to Behavioral Change	Average Change in VMT per Passenger per Year (in Miles)	Operator VMT per Passenger per Year if Pooled TNCs Did Not Exist (in Miles)	Difference (Miles per Passenger per Year)	Change in VMT	Statistically Significant?	t-statistic	p-value (1-tailed)
San Francisco	–843	1,197	354	Increase	Yes (1% level)	6.2710	0.000
Los Angeles	–931	1,186	255	Increase	Yes (1% level)	5.1413	0.000
Washington, D.C.	–585	524	–61	Decrease	Yes (10% level)	–1.5344	0.063

We see similar impacts with GHG emissions resulting from Lyft Shared rides and uberPOOL. Table 48 shows that the change in GHG emissions remains directionally the same as in Table 30, with the San Francisco and Los Angeles markets experiencing an increase in GHG emissions per passenger per year and the Washington, D.C. market experiencing a decrease. Both the San Francisco and Los Angeles markets would have exhibited higher magnitude increases in GHG emissions per passenger per year had Lyft Shared rides and uberPOOL not existed. San Francisco would still exhibit an increase in GHG emissions without pooled services, although this increase would shift to being statistically significant at the 1% level. Similar to the net VMT change, Los Angeles would still yield a statistically significant increase at the 1% level. Washington, D.C. would still exhibit a reduction in GHG emissions, but as with VMT, this reduction would shift from the 5% to the 10% level without pooling.

Table 48. Net Change in GHG Emissions From Lyft and Uber by Market, if Lyft Shared Rides and uberPOOL Did Not Exist

GHG Change Due to Behavioral Change	Behavioral Change Per Respondent*	Operator GHG Emissions per Person if Pooled TNCs Did Not Exist*	Difference (t per Passenger per Year)*	Change in GHG	Statistically Significant?	t-statistic	p-value (1-tailed)
San Francisco	–0.287	0.343	0.056	Increase	Yes (1% level)	2.9528	0.002
Los Angeles	–0.303	0.348	0.045	Increase	Yes (1% level)	2.8298	0.002
Washington, D.C.	–0.199	0.177	-0.022	Decrease	Yes (10% level)	–1.5489	0.061

*Units of metric tons (t) of CO_2 per passenger per year

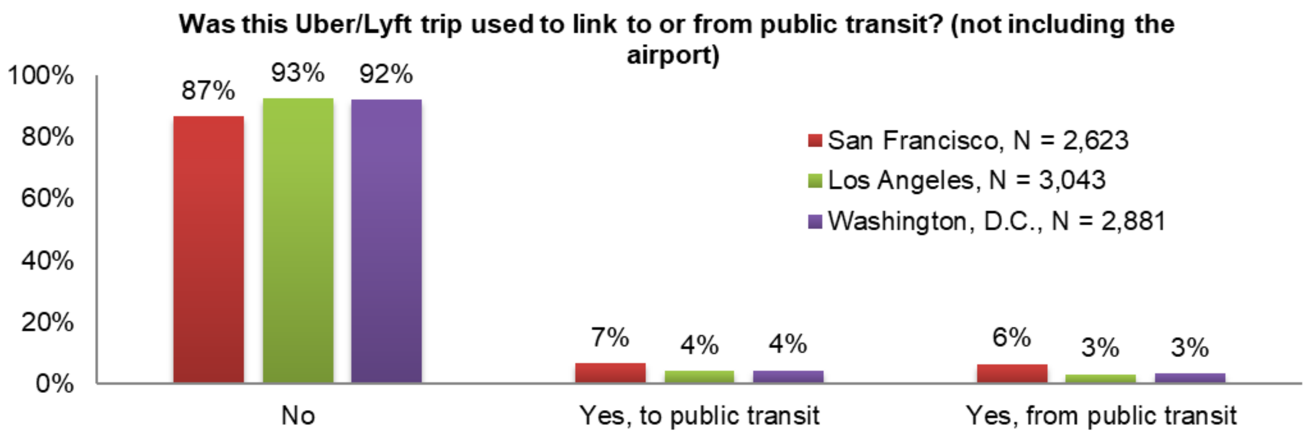
Based on the measurements taken in this study, pooled TNC services like Lyft Shared rides and uberPOOL have mitigating effects on TNC VMT and GHG emissions. The effect found here is relatively modest and does not impact whether TNCs increase overall VMT and GHG emissions. San Francisco experienced the most significant impact on VMT and GHG emissions per passenger per year due to pooled TNCs, with a savings of 120 miles per passenger per year, on average, due to Lyft Shared rides and uberPOOL. The greater savings in San Francisco is due to the city's relatively higher pooled TNC and matching rates compared with the other two markets.

It is very important to note that the impact of Lyft Shared rides and uberPOOL on overall VMT and GHG emissions, as they are returned to the TNC services post-pandemic, will very likely change over time and across markets. This will naturally depend on their popularity, matching effectiveness, route deviation, and public policy. As these services return, if they were to increase in use relative to the levels observed in this study, pooled TNC services could have a greater impact on mitigating overall TNC VMT. The increased use of pooled TNCs would have a positive effect on mitigating VMT and emissions produced by private TNC services, but a true measurement of its impact requires consideration of other factors such as mode substitution and, more ideally, routing patterns as matched with origin destination pairs.

First- and Last-Mile to Public Transit Analysis

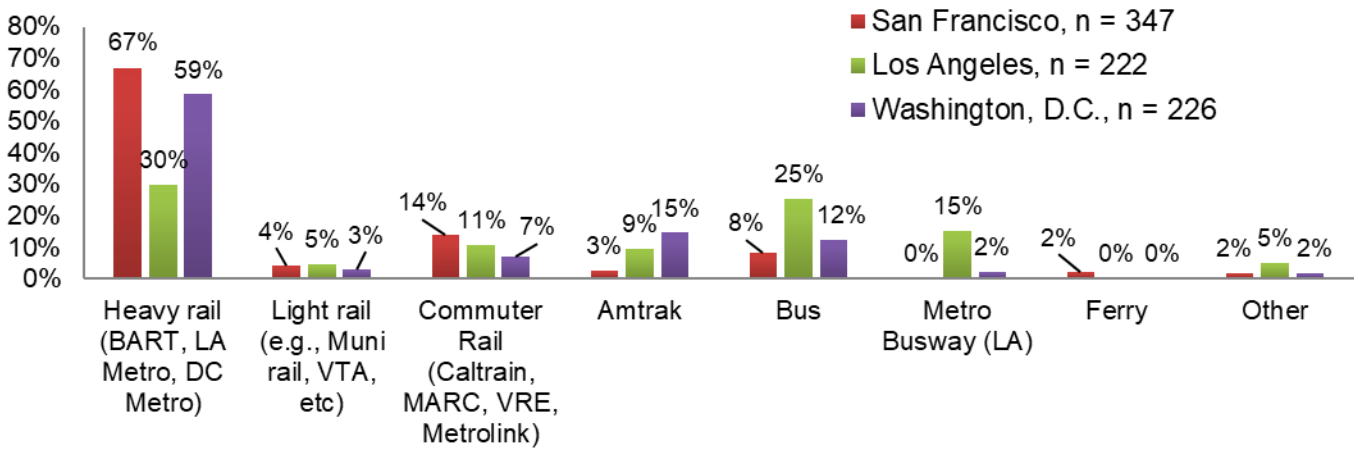
Survey responses allowed us to evaluate the degree to which TNC passengers employed Lyft and Uber as a first- or last-mile linkage to public transit. In the passenger survey, we asked respondents whether they had used their last TNC trip to travel to or from public transit (excluding the airport). Figure 43 below displays these results, showing that the vast majority of respondents did not take Lyft or Uber to access or egress public transit for their most recent trip. San Francisco had a slightly higher rate of first- and last-mile activity than the other two markets, as 13 percent of respondents' last trips served as a link to or from public transit. Seven percent connected to or from public transit in Los Angeles, and about 8 percent did so in Washington, D.C. There were slightly higher portions of respondents who took TNCs as a first-mile link to public transit for their most recent TNC trip in contrast to those who egressed from public transit.

Figure 43. First- or Last-Mile Public Transit Link for Most Recent TNC Trip



Of the trips that served as a first- or last-mile link to or from public transit, 46 percent of respondents in San Francisco, 31 percent in Los Angeles, and 28 percent in Washington, D.C., used a pooled TNC service. The respondents who indicated they used Lyft or Uber to access/egress public transit during their last trip were subsequently asked what public transit operator they employed. The results vary by CBSA and are shown in Figure 44, below. Linking to or from heavy rail operators (such as BART, LA Metro, or DC Metro) accounted for more than half of all first- and last-mile trips in San Francisco (67 percent) and Washington, D.C. (59 percent). However, heavy rail accounted for only 30 percent of first- and last-mile trips in Los Angeles, while buses (bus and Metro Busway combined) accounted for 41 percent of public transit access/egress activity. Bus linking is much less common in San Francisco, at 8 percent, and Washington, D.C., at 15 percent of most recent trips. Commuter rail and Amtrak combined accounted for 16 percent to 22 percent of first- and last-mile activity, depending on the market. Light rail constitutes 5 percent or less of the share of access/egress activity in each of the study CBSAs.

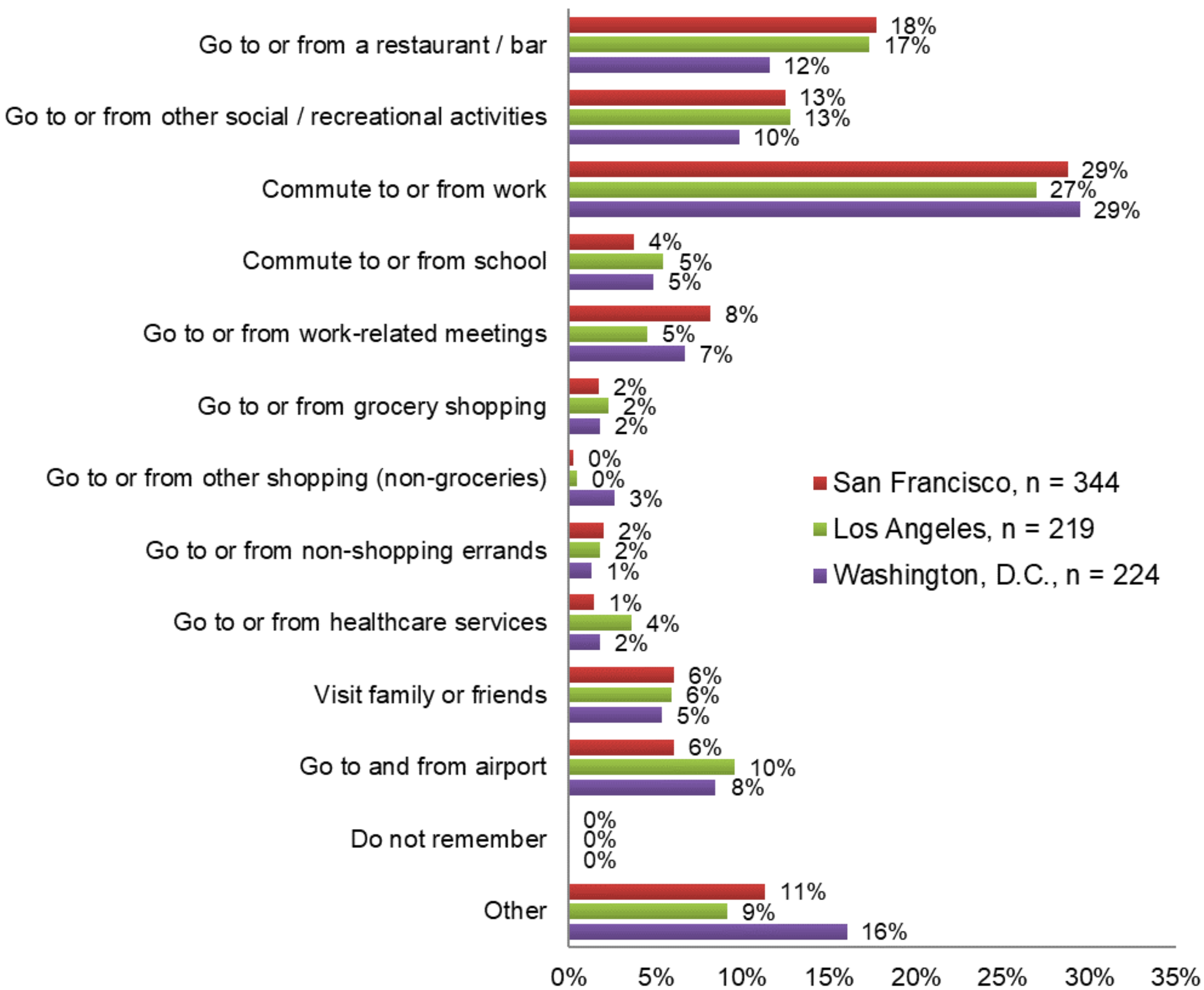
Figure 44. First- and Last-Mile Access to Public Transit With TNCs



<u>Trip Purpose and First- and Last-Mile Activity</u>

When we examine first- and last-mile activity to public transit and the corresponding trip purposes, we see that many of these trips were for work- or school-related purposes. As displayed in Figure 45, below, 41 percent of public transit access/egress trips in San Francisco, 37 percent in Los Angeles, and 41 percent in Washington, D.C., were for commuting to or from work or school or for work-related meetings. First- and last-mile public transit trips were also commonly made for traveling to or from a restaurant/bar or social activities, as these two trip purposes combined accounted for about 21 percent to 30 percent of this activity, depending on the CBSA. When compared with the overall trip purpose distribution (Figure 36), we see that first- and last-mile public transit trips constituted slightly higher portions of commute or work-related trips and lower portions of restaurant/bar and social trips.

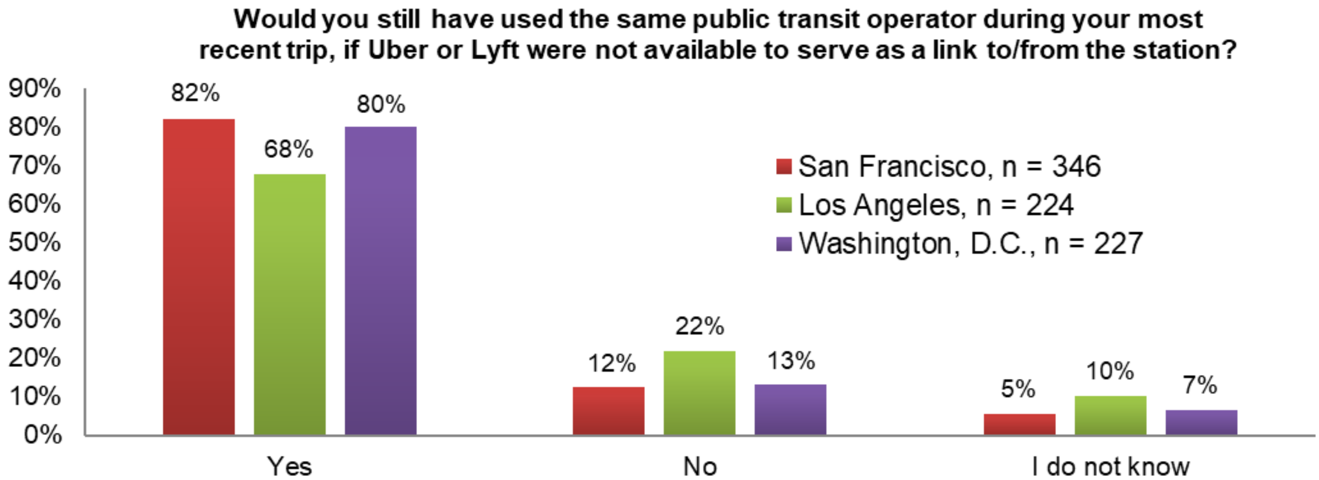
Figure 45. Trip Purpose Distribution of First- and Last-Mile Public Transit Trips



<u>*Mode Substitution for First- and Last-Mile to Public Transit Trips*</u>

We asked respondents who employed Lyft or Uber to access/egress public transit during their last trip whether they would have used the same public transit service if TNC services were not available. As shown in Figure 46, below, the majority of respondents in each market still would have used the same public transit service. Eighty-two percent of respondents in San Francisco, 68 percent in Los Angeles, and 80 percent in Washington, D.C. answered this way.

Figure 46. Necessity of TNC as a First- and Last-Mile Linkage to Public Transit



Of the respondents who still would have used the same public transit service if TNCs were not available (i.e., answered yes in Figure 46), bus was the most common mode in San Francisco and Los Angeles that would have been used to travel to or from the public transit station. Displayed in Table 49, 34 percent of these respondents in San Francisco, 42 percent in Los Angeles, and 31 percent in Washington, D.C. would have used a bus instead of Lyft or Uber to get to or from the public transit station. Taxis and E-Hail taxis were also a common alternative that would have been used to access/egress public transit, with 21 percent of these respondents in San Francisco, 16 percent in Los Angeles, and 34 percent in Washington, D.C. reporting they would have used a taxi/E-hail in place of TNCs. Between 14 percent and 23 percent of respondents would have walked, biked, or used bikesharing to access or egress the station if TNCs were not available, depending on the market.

These results suggest that a significant portion of TNC first- and last-mile activity probably would have occurred anyway, with either public transit or active modes. Considering all respondents who employed Lyft and Uber to access/egress public transit (not just those who still would have used the same operator without a TNC), 51 percent in San Francisco, 44 percent in Los Angeles, and 43 percent in Washington, D.C. would have used a different form of public transit or an active mode instead of TNCs. This mode substitution behavior is important to consider when examining the first- and last-mile effects of TNC services on public transit.

Table 49. Mode Substitution for Access or Egress to the Same Public Transit Operator

Without Uber or Lyft, how would you have gotten to/from the public transit station?	San Francisco, n = 284	Los Angeles, n = 152	Washington, D.C., n = 182
Would not have taken	3%	0%	2%
Driven alone	5%	9%	3%
Rode in a car with friend/family	4%	9%	5%
Bus	34%	42%	31%
Rail or Subway	5%	6%	8%
Walk	19%	13%	14%
Bike	4%	3%	0%
Bikesharing	0%	1%	0%
Carsharing vehicle	0%	0%	1%
Taxi	20%	16%	34%
E-Hail taxi	1%	0%	0%
Other	3%	1%	1%

We asked respondents who would not have used, or were not sure they would have used, the same public transit service that they accessed or egressed during their last TNC trip (i.e., answered no or "I do not know" in Figure 46) what mode they would have used in place of the combination of a TNC and public transit. Note that these are the public transit trips that might have been enabled by TNC availability. As shown in Table 50, below, the most common replacement modes for these enabled or induced public transit trips were driving or getting a ride in a personal vehicle, which accounted for 39 percent of these respondents in San Francisco, 46 percent in Los Angeles, and 37 percent in Washington, D.C. Taxis and E-hail taxis would also have been frequently used in place of a TNC and public transit, with 13 percent to 26 percent of these respondents, depending on the market, reporting that they would have used a taxi/E-hail for their entire trip instead of a TNC and public transit. Another prominent mode substituted was buses, with 10 percent of respondents in San Francisco, 21 percent in Los Angeles, and 16 percent in Washington, D.C., indicating that they would have used a bus to make their entire trip.

Table 50. Mode Substitution for First- and Last-Mile Public Transit Access/Egress That Might Not Have Occurred Without TNCs

If Uber or Lyft were not available, how would you have made this entire trip instead?	San Francisco, n = 61	Los Angeles, n = 72	Washington, D.C., n = 43
Would not have taken	11%	10%	7%
Driven alone	26%	31%	21%
Rode in a car with friend/family	13%	15%	16%
Bus	10%	21%	16%
Rail or Subway	5%	3%	7%
Walk	7%	6%	2%
Bike	0%	0%	2%
Bikesharing	0%	0%	0%
Carsharing vehicle	0%	1%	2%
Taxi	20%	13%	26%
E-Hail taxi	2%	0%	0%
Other	7%	1%	0%

Overall, the findings in Table 50 show that the majority of those who employed TNCs to access/egress public transit would have made their entire trip in a private vehicle or taxi if TNCs had not been available. However, the group of passengers who were enabled or induced to access/egress public transit due to TNCs constitutes a relatively small portion of total respondents, at 2 percent in San Francisco and Los Angeles and 1 percent in Washington, D.C.

Summary

The recent-trip survey analysis permitted a deep exploration of the attributes of TNC trips and the resulting impacts on mode substitution, pooling, and first- and last-mile connections to public transit. We found that Fridays and Saturdays were most popular for TNC trips, comprising 35 percent of respondents' most recent trips in San Francisco, 40 percent in Los Angeles, and 36 percent in Washington, D.C. The distribution of trips followed a common peak-travel profile during weekdays, with the majority of trips in each market made during the morning (7 to 11 a.m.) and evening (5 to 9 p.m.) periods, with a more evening-focused pattern on weekends.

The results show a wide range of trip purposes with Lyft and Uber, with similar distributions across the three CBSAs. A large portion of trips were to restaurant/bar or for social/recreational purposes, ranging from 40 percent to 44 percent of respondents' last trips, depending on the CBSA. Commuting to and from work or school was also a major TNC application, making up 20 percent to 22 percent of trips, depending on the market. TNC trips were generally short-distance in nature, with the majority of trips in San Francisco and Washington, D.C. and 37 percent of trips in Los Angeles traveling 4 miles or less. The average trip distance was higher in Los Angeles (8.8 miles) than in San Francisco (7.0 miles) and Washington, D.C. (6.9 miles), likely due to land-use context and built environment differences. Average distances also varied by trip purpose, with airport trips having the longest average distances and shopping/errands some of the shortest.

Table 51 displays key TNC pooling metrics found among the passenger respondents who used Lyft

Shared rides or uberPOOL for their most recent trip. As noted earlier, San Francisco exhibited a higher share of pooled trips requested, at 39 percent, whereas this share was 25 percent in Los Angeles and in Washington, D.C. The share of pooled TNC requests appear to affect the matching success in a given market, as almost three-quarters (72 percent) of pooled TNC trips were matched in San Francisco, but only about half (49 percent) were matched in Los Angeles and 57 percent were matched in Washington, D.C. The matching success rates impact the average occupancies of pooled TNC trips, with an average pooled TNC occupancy of 2.31 in San Francisco, 1.90 in Los Angeles, and 2.03 in Washington, D.C. The trip-based occupancy of TNC vehicles, which is pooled and private services combined and shown in Table 51 below, was slightly higher than measured occupancy in personal automobiles, which averages 1.67 persons per vehicle mile in the United States (NHTS 2017). It should be noted that these trip occupancy calculations do not consider vehicle deadheading before and after trips and between passengers, as discussed previously. Roughly speaking, if deadheading was any more than 16% of total miles, then the average occupancy of TNC vehicles (not including the driver) was probably lower the 1.67 persons per vehicle mile benchmark.

Table 51. TNC Pooling Metrics Summary

Metric	San Francisco	Los Angeles	Washington, D.C.
Percent of TNC Trips Requested as a Pooled Service	39%	25%	25%
Matching Success Rate of Pooled TNC Trips	72%	49%	57%
Average Occupancy of Pooled TNC Trips	2.31	1.90	2.03
Average Occupancy Overall (Pooled and Private Combined)	1.93	1.79	1.76

Mode substitution questions show how respondents would have traveled in the absence of TNCs. Substitution patterns, summarized in Table 52, reveal key differences among those who used a pooled versus private TNC services for their most recent trip. In general, the portion of those using pooled TNCs who would have substituted public transit (bus or rail) was greater than the portion of private TNC passengers who would have done the same. In contrast, private Lyft and Uber passengers were much more likely to substitute passenger vehicle modes (using a personal vehicle, taxi/E-hail taxi, or carsharing vehicle) for a TNC trip than were those who used pooled TNC services. These findings show that pooled and private TNCs may be drawing from a slightly different cross-section of travelers.

Table 52. Mode Substitution by Pooled TNCs, Private TNCs, and All Respondents

If Lyft and Uber were not available, how would you have made your most recent trip instead?	San Francisco			Los Angeles			Washington, D.C.		
	Lyft Shared Rides/ uberPOOL, n = 1036	Private Lyft/ Uber, n = 1584	Total, N = 2620	Lyft Shared Rides/ uberPOOL, n = 752	Private Lyft/ Uber, n = 2288	Total, N = 3040	Lyft Shared Rides/ uberPOOL, n = 725	Private Lyft/ Uber, n = 2149	Total, N = 2874
Would not have taken	7%	4%	5%	11%	7%	8%	5%	3%	4%
Passenger vehicle (drive alone, ride in car, taxi/E-hail taxi, carsharing)	33%	56%	47%	40%	66%	60%	31%	56%	50%
Public transit (bus or rail)	46%	27%	35%	37%	17%	22%	53%	31%	37%
Walk, bike, or bikesharing	13%	11%	12%	11%	8%	8%	10%	8%	9%
Other	2%	2%	2%	2%	2%	2%	1%	1%	1%

Mode substitution results also varied by CBSA. Among all respondents (both pooled and private TNC passengers) in San Francisco and Washington, D.C., around two-thirds or more would have used public transit or taxis in place of their last TNC trip. In Los Angeles, less than half of respondents would have used these modes for their most recent TNC trip. Respondents in Los Angeles were more than twice as likely to have chosen to drive alone or ride in a personal vehicle than in San Francisco or Washington, D.C., had TNCs not been available.

Findings from the most recent trip section reveal that a portion of TNC trips serve as a first- or last-mile link to public transit, as 13 percent of trips linked with public transit in San Francisco, 7 percent did so in Los Angeles, and 8 percent did so in Washington, D.C. As summarized in Table 53 below, the analysis also suggests that Lyft and Uber enabled some passengers to connect to public transit who would not have otherwise, but this effect was limited (2 percent of respondents or less across all markets). A larger proportion of all respondents would still have linked to or from the same public transit operator without TNCs (5 percent to 11 percent of all respondents, depending on the market), suggesting that a significant portion of public transit use probably would have occurred anyway. An even larger proportion, who did not link with public transit for their last trip, would have used some form of public transit instead of TNCs (19 percent to 34 percent of all respondents, depending on the market). This suggests that overall, along with other evidence in the survey, Lyft and Uber were probably drawing more from public transit use than they were adding to it.

Table 53. First- or Last-Mile Public Transit Linking and Mode Substitution Behavior Among All Respondents

	Those that Linked to/from Public Transit for Last Trip		**Those that Did Not Link to/from Public Transit for Last Trip**	
CBSA	*Linked to/from Public Transit Due to TNCs*	*Would Still Have Linked to/from Public Transit Without TNCs*	*Would Have Used Public Transit (Rail or Bus) Had TNCs Not Been Available*	*Would Not Have Used Public Transit (Rail or Bus) Had TNCs Not Been Available*
San Francisco	2%	11%	30%	57%
Los Angeles	2%	5%	19%	73%
Washington, D.C.	1%	6%	34%	58%

The analysis of shared rides and pooling facilitated by Lyft Shared rides and uberPOOL mitigates the VMT per passenger produced by private TNC services among the population. We found estimated this be about a 10 percent reduction of TNC VMT/pax in San Francisco, a 1 percent reduction in Los Angeles, and a 4 percent reduction in Washington, D.C. The degree to which private TNC VMT reduction occurs is dependent on the number of passengers requesting pooled TNC services, the matching success rate, and the mode substitutions enabled by pooled TNC options. San Francisco performed better than the other two regions, given the higher pooled TNC requests and match rates (39 percent and 72 percent, respectively, as shown in Table 51). In Los Angeles, where the TNC VMT reduction due to pooled options was found to be lower, the results were driven primarily by the relatively lower matching success rate (49 percent), which is likely due in part to land-use context and built environment factors. Regions like Los Angeles could may benefit more from pooling than could public transit-rich environments, given the high substitution of private vehicles that respondents reported in this market.

Overall, responses to the most recent trip section of the passenger survey provided the opportunity to conduct direct travel analysis based on a sample of trips. These and other insights are carried forward into the broader conclusions of this study.

Control Survey—Results and Discussion

In addition to surveying Lyft and Uber passengers, we conducted a control survey that allowed a comparative analysis of the respondents who had used Lyft or Uber during the year preceding the survey versus those who had not. The control survey panel was drawn to match the demographic attributes of gender, age, race/ethnicity, income, and education as closely as possible to the general population of each respective CBSA. To provide a baseline for comparison in each of the three markets, we present control survey findings alongside distributions of each CBSA population within the three studied markets, as reported by the ACS 2016 five-year estimates.

Lyft/Uber Users and Nonusers

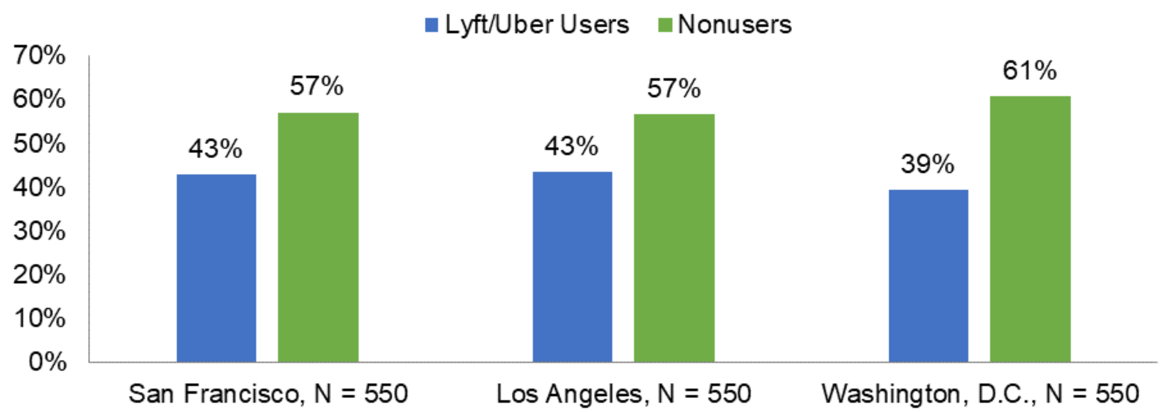
For the control survey analysis, we divided respondents into two groups, as shown in Figure 47:

- Lyft/Uber users: respondents who indicated using Lyft or Uber as a passenger at least once in the prior year to taking the survey, and

- Nonusers: respondents who had not used Lyft or Uber in the prior year to taking the survey, including those who had never used the services.

Across all three markets, a slight majority of control survey respondents were nonusers. Thirty-nine to 43 percent of survey respondents were Lyft or Uber users, depending on the market. These findings were similar to the proportions of TNC users among the general populations of major U.S. metropolitan areas that have been found in previous studies.[9]

Figure 47. Control Survey Lyft/Uber User and Nonuser Distribution



Sociodemographics—Control Survey

Below we present the sociodemographic findings from the control survey, with results broken out by control survey total, control survey Lyft/Uber users, and control survey nonusers. For comparison, findings from these three control survey populations are displayed next to the general population distributions from the ACS 2016.

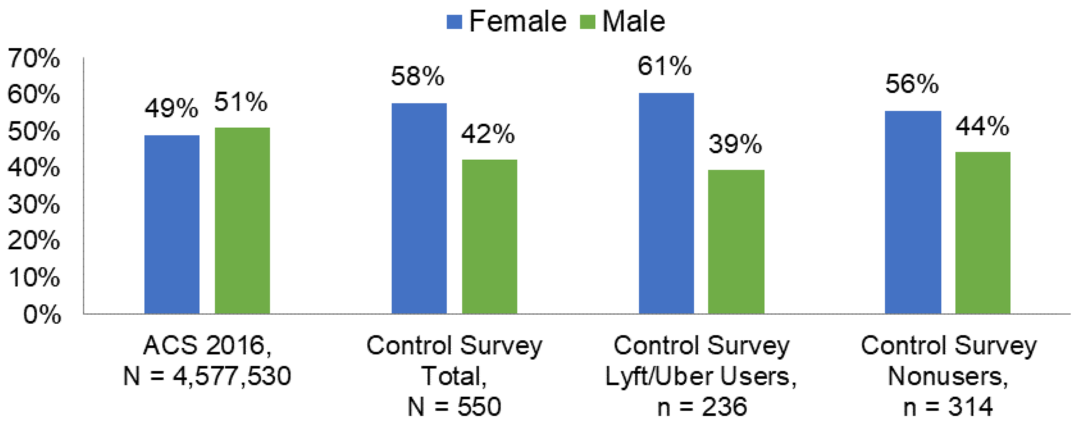
Gender

Across San Francisco, Los Angeles, and Washington, D.C., the control survey population contained a bias toward female respondents relative to the general population (Figure 48). In San Francisco, the share of Lyft and Uber users who were female is slightly higher than in the control survey overall, while in Los Angeles and Washington, D.C. the opposite is true: The proportion of female nonusers was higher than the proportion of females in the overall control survey.

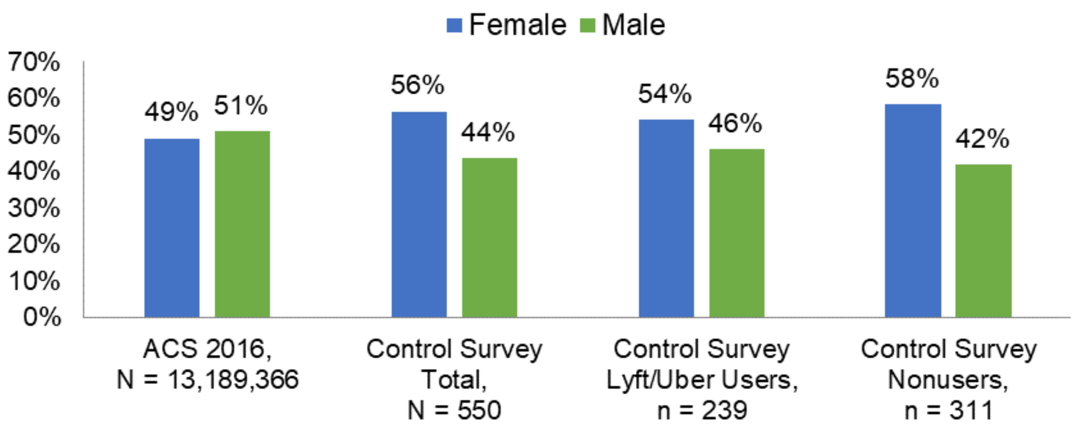
[9] Clewlow and Mishra 2017; Feigon and Murphy 2018

Figure 48. Control Survey Gender Distribution

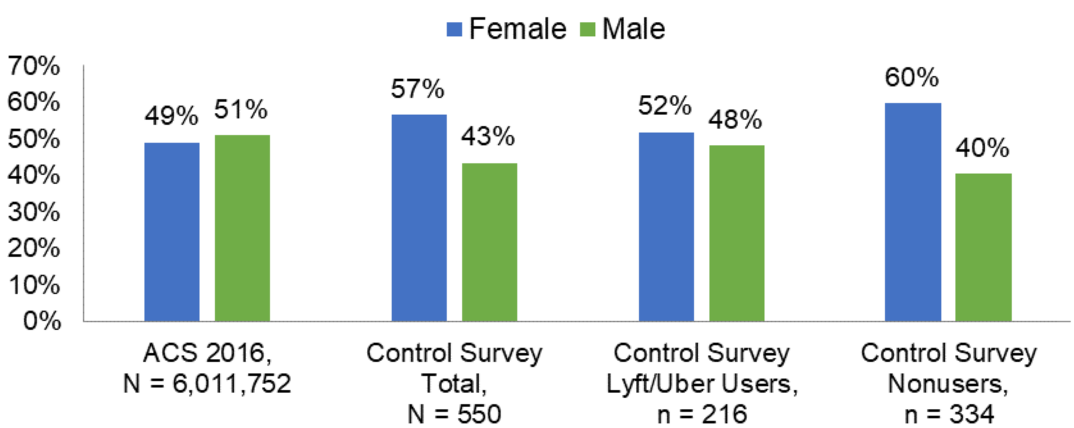
San Francisco



Los Angeles

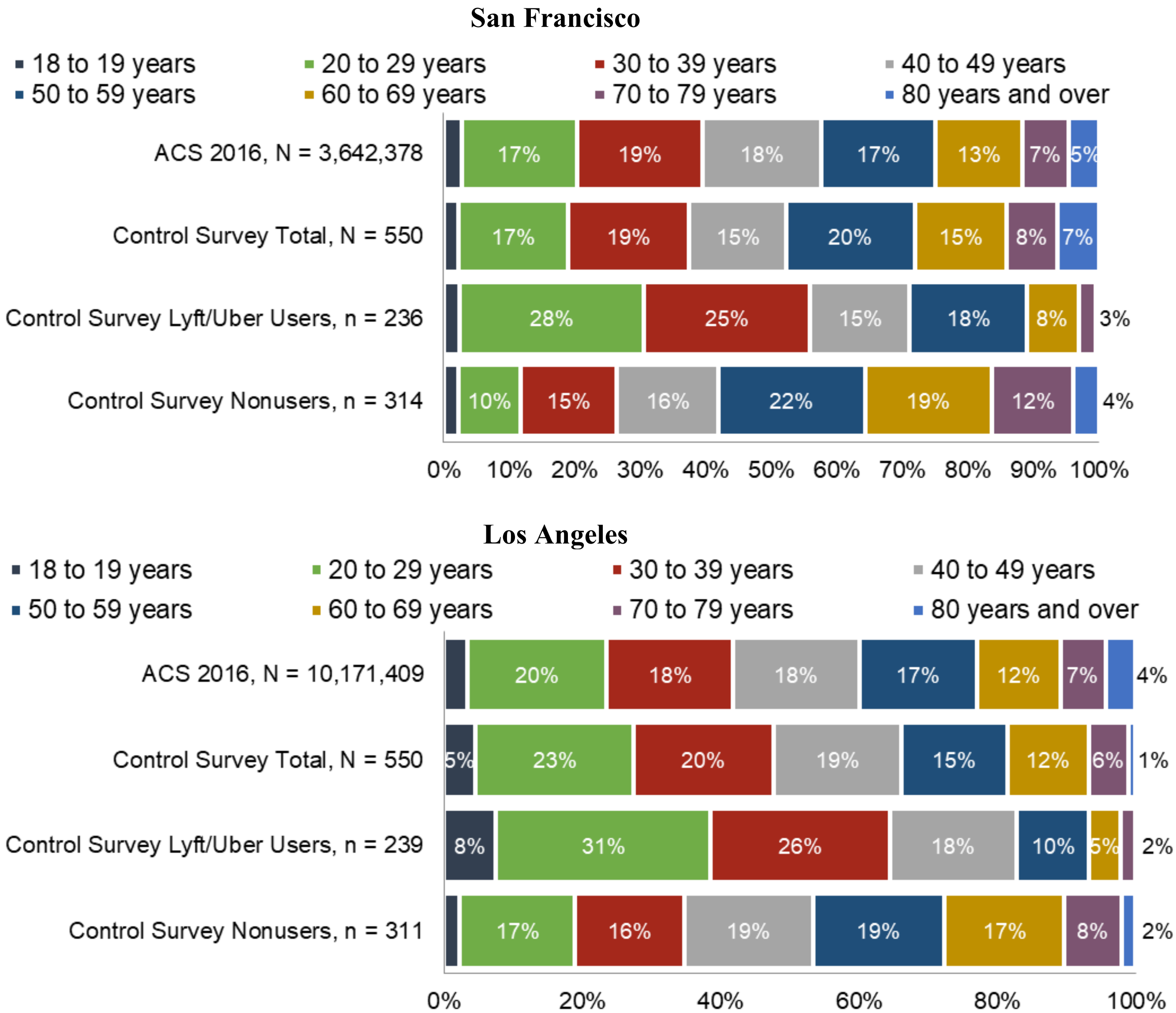


Washington, D.C.



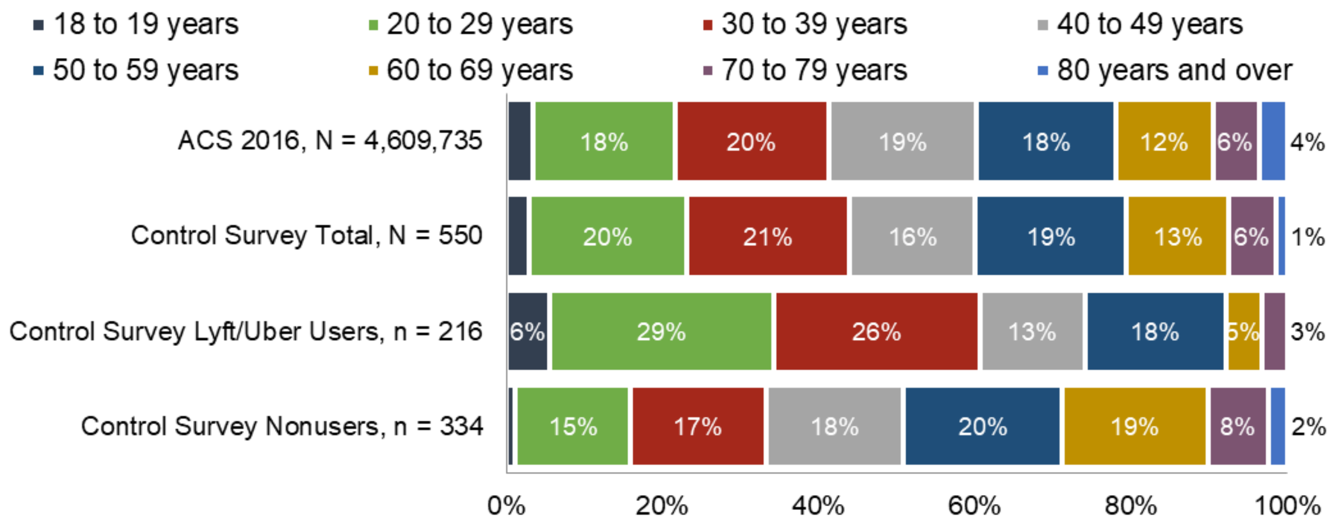
Age
The age distributions of the overall control survey respondents matched up fairly well with the ACS 2016 distributions of the overall CBSA populations. Lyft and Uber users in our control survey skewed younger than nonusers and the general populations of each CBSA (Figure 49).[10] In all three markets, the majority of Lyft and Uber users were under 40 years old, while only about a quarter to a third of nonusers were under 40. Twenty- to 29-year-olds made up the highest proportion of Lyft and Uber users out of any of the age categories, at around 30 percent of control survey TNC users in each market. With that said, a notable portion of older cohorts have used TNC services as well. Among all control survey respondents 60 years and older, 16 percent in San Francisco have used Lyft and/or Uber in the year preceding the survey, 16 percent have in Los Angeles, and 15 percent have in Washington, D.C.

Figure 49. Control Survey Age Distribution



[10] The ACS populations are lower than those presented in Figure 38, as they comprise only those 18 years and older.

Washington, D.C.



Race/Ethnicity

Racial/ethnic distributions in our control survey are shown in Table 54, Table 55, and Table 56. The overall control survey racial/ethnic distributions matched up fairly well with the ACS distributions, with a few exceptions. Across all markets, there were slightly higher proportions of white respondents in the overall control survey populations than in the overall CBSA populations. In addition, the proportion of overall control survey respondents who identified as Hispanic/Latino were lower relative to each general population. For Asians and blacks/African Americans, the control survey and general population proportions were similar.

Comparing Lyft and Uber users with nonusers, our findings show a somewhat more diverse racial/ethnic makeup among the users. Across all three markets in the control survey, there existed a greater proportion of white nonusers than users. In Washington, D.C., black/African American respondents made up 37 percent of Lyft and Uber users, even though they were only 28 percent of the overall control survey sample in this market.

Table 54. San Francisco Control Survey Race/Ethnicity Distribution

San Francisco	ACS 2016, N = 4,577,530	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 236	Control Survey Nonusers, n = 314
White	41%	49%	43%	53%
Black or African American	7%	9%	10%	9%
American Indian or Alaska Native	0%	0%	0%	0%
Asian	24%	26%	28%	25%
Native Hawaiian or Pacific Islander	1%	1%	1%	1%
Hispanic or Latino	22%	14%	17%	12%
Other	5%	0%	0%	0%

Table 55. Los Angeles Control Survey Race/Ethnicity Distribution

Los Angeles	ACS 2016, N = 13,189,366	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 239	Control Survey Nonusers, n = 311
White	30%	36%	33%	39%
Black or African American	6%	8%	8%	8%
American Indian or Alaska Native	0%	0%	0%	0%
Asian	15%	16%	17%	14%
Native Hawaiian or Pacific Islander	0%	0%	0%	0%
Hispanic or Latino	45%	40%	42%	39%
Other	3%	0%	0%	0%

Table 56. Washington, D.C., Control Survey Race/Ethnicity Distribution

Washington, D.C.	ACS 2016, N = 6,011,752	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 216	Control Survey Nonusers, n = 334
White	47%	53%	44%	59%
Black or African American	25%	28%	37%	22%
American Indian or Alaska Native	0%	0%	0%	0%
Asian	10%	10%	10%	10%
Native Hawaiian or Pacific Islander	0%	0%	0%	0%
Hispanic or Latino	15%	9%	9%	9%
Other	3%	0%	0%	0%

Income

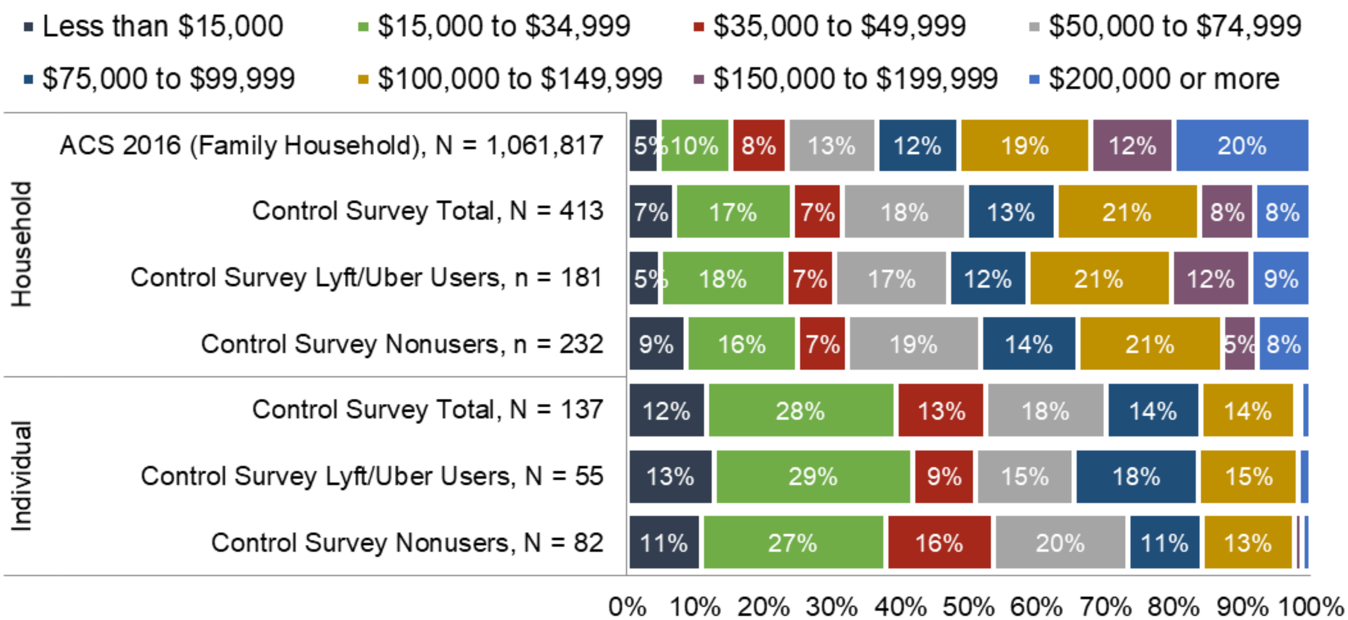
Figure 50 illustrates the distributions of household and individual incomes in each of the three markets among control survey respondents.[11] Similar to the passenger survey income section, we compare these distributions with the ACS family household income distribution in each CBSA. The overall control survey populations contained lower proportions of higher-income households ($150,000 or more) than the respective ACS populations, but otherwise they matched up fairly well with the CBSA distributions. The distributions of household incomes between Lyft and Uber users and nonusers were very similar across all markets, with the exception of higher-income users in San Francisco. Twenty-one percent of household Lyft and Uber users in San Francisco made $150,000 or more per year, while only 13 percent of nonusers made the same amount or more.

Among individuals across all three markets, Lyft and Uber users had slightly greater proportions of higher-income respondents than did nonusers. While there was a greater proportion of TNC users making $75,000 or more per year compared to nonusers, there was also a considerable portion of Lyft and Uber users making under $15,000 per year. This may be due to the generally younger respondents reflected in the individual Lyft and Uber user population, many of whom likely attended school, did not work full time, and/or may not have owned a car.

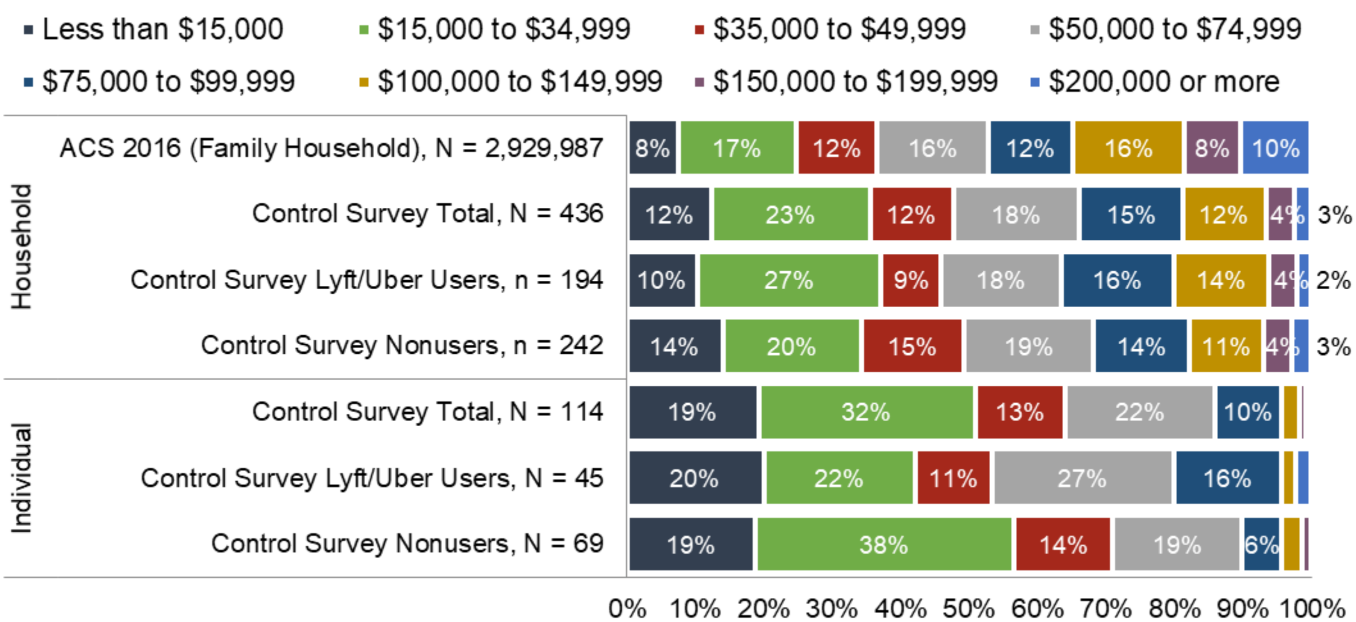
[11] Control survey respondents were asked to indicate their gross 2015 pre-tax income. Respondents identified as households were asked to report their total household income, while those classified as individuals were asked to report their individual income.

Figure 50. Control Survey Income Distributions

San Francisco



Los Angeles



Washington, D.C.

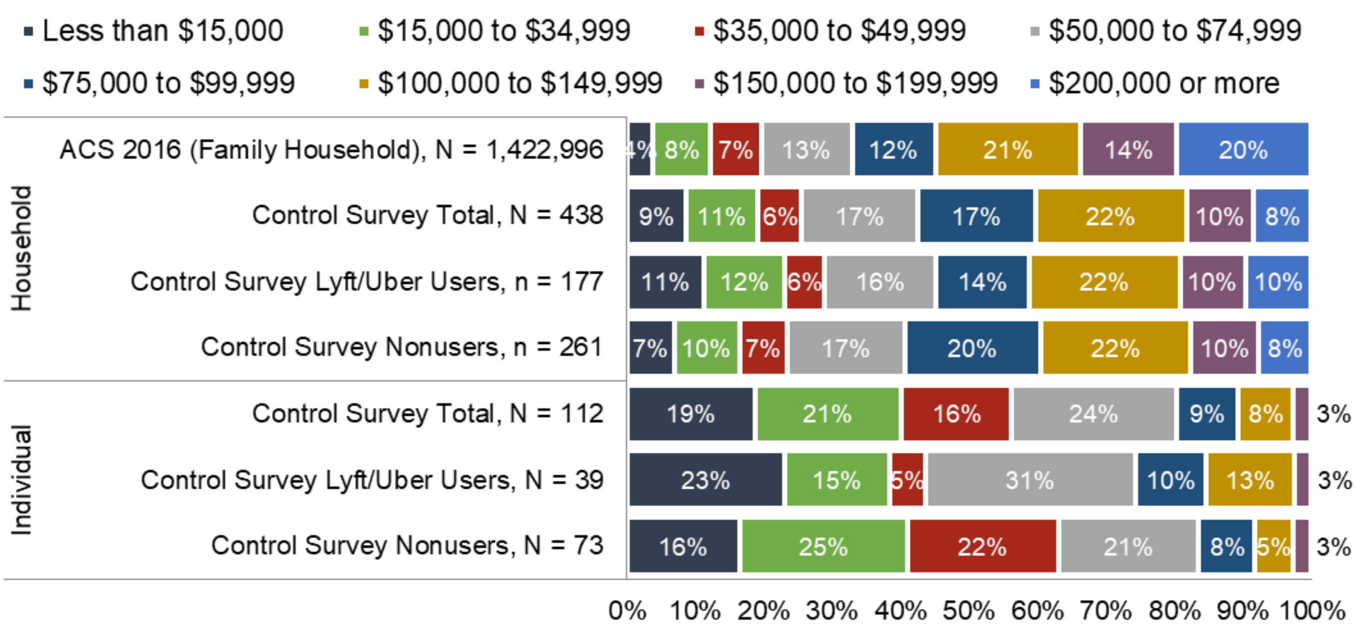


Table 57 below shows the average income per person in the CBSA populations, in the overall control survey, among control Lyft and Uber users, and among control Lyft/Uber nonusers. While the average income per person among our control survey respondents was lower than the CBSA income per capita in each of the three markets, the average income per person actually differed very little between Lyft and Uber users and nonusers.

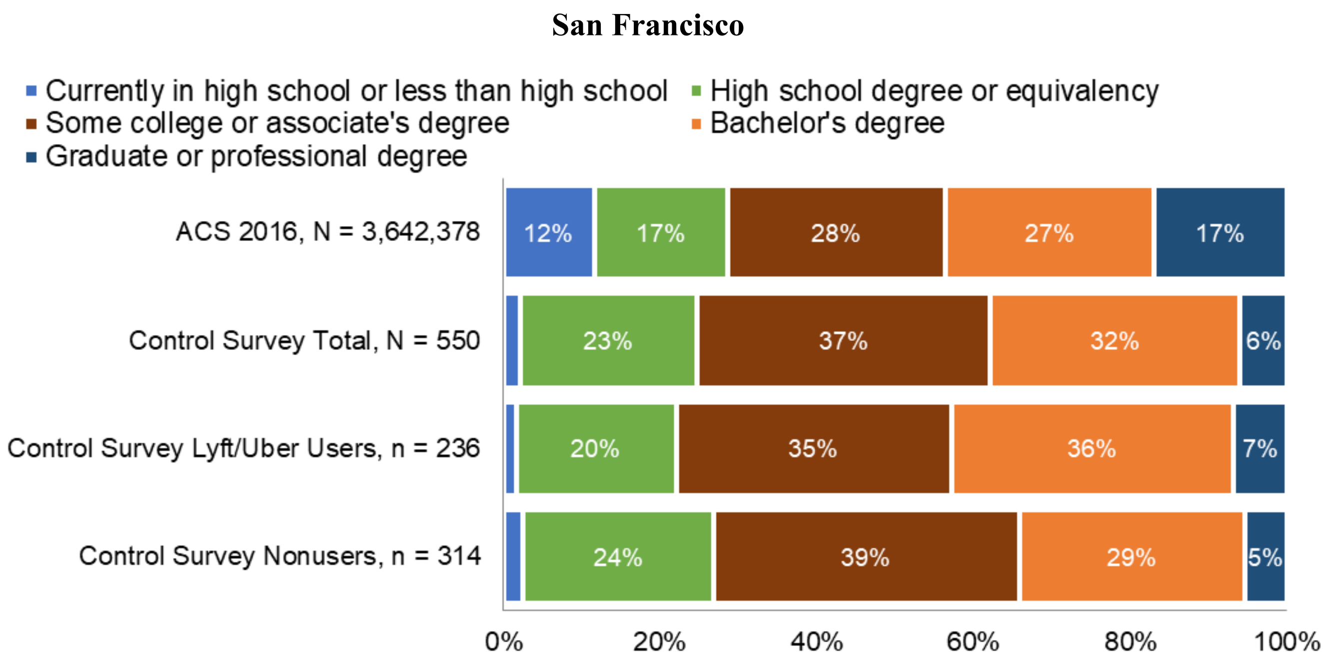
Table 57. Control Survey Income per Person and CBSA Income per Capita

San Francisco	ACS 2016, N = 3,789,906	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 236	Control Survey Lyft/Uber Nonusers, n = 314
Income per Person/Income per Capita	$45,955	$30,682	$30,542	$30,800
Los Angeles	ACS 2016, N = 10,716,690	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 239	Control Survey Lyft/Uber Nonusers, n = 311
Income per Person/Income per Capita	$30,874	$20,591	$19,705	$21,385
Washington, D.C.	ACS 2016, N = 4,838,219	Control Survey Total, N = 550	Control Survey Lyft/Uber Users, n = 216	Control Survey Lyft/Uber Nonusers, n = 334
Income per Person / Income per Capita	$44,958	$31,786	$31,485	$31,988

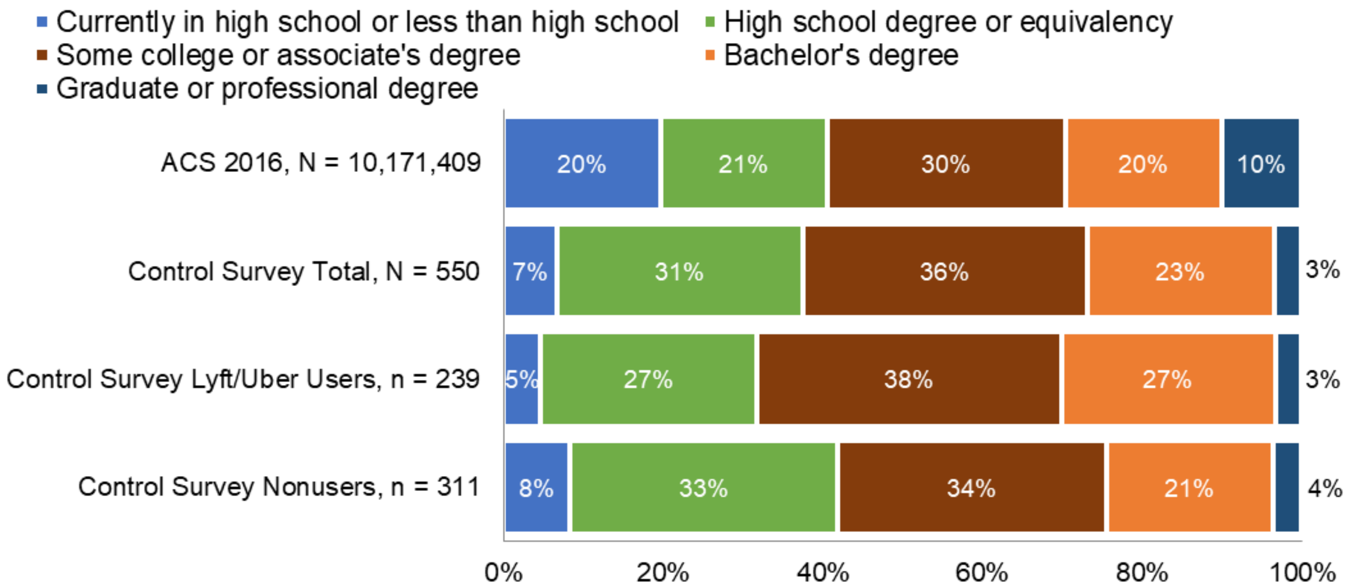
Education
When comparing education levels among respondents across all markets (Figure 51), we found that distributions of educational attainment between Lyft and Uber users and nonusers were fairly similar. However, TNC users had slightly higher proportions of respondents with bachelor's degrees or higher than nonusers, the difference ranging from 2 percentage points to 9 percentage points, depending on the market.

Across all markets, there were greater proportions of those with graduate degrees in the general population than in the overall control survey. Three percent to 6 percent of the control survey populations held graduate degrees, whereas the proportion of graduate degree holders in the CBSAs ranged from 10 percent to 21 percent, depending on the market. In addition, in the control survey there were lower proportions of those without a high school education or currently in high school compared with the rate found in each of the general populations. In the sample selection process for the control survey, we encountered challenges in finding respondents who had less than a high school education. As an alternative, we considered respondents with a high school education or less than a high school education collectively. The totals for the combined categorization matched up fairly well with the general populations. Thus, the combined proportion of less than high school and high school-educated respondents closely matched that found within the general population but leaned toward those with a completed high school education. Overall, the survey reflected the balance of education level within the population fairly well.

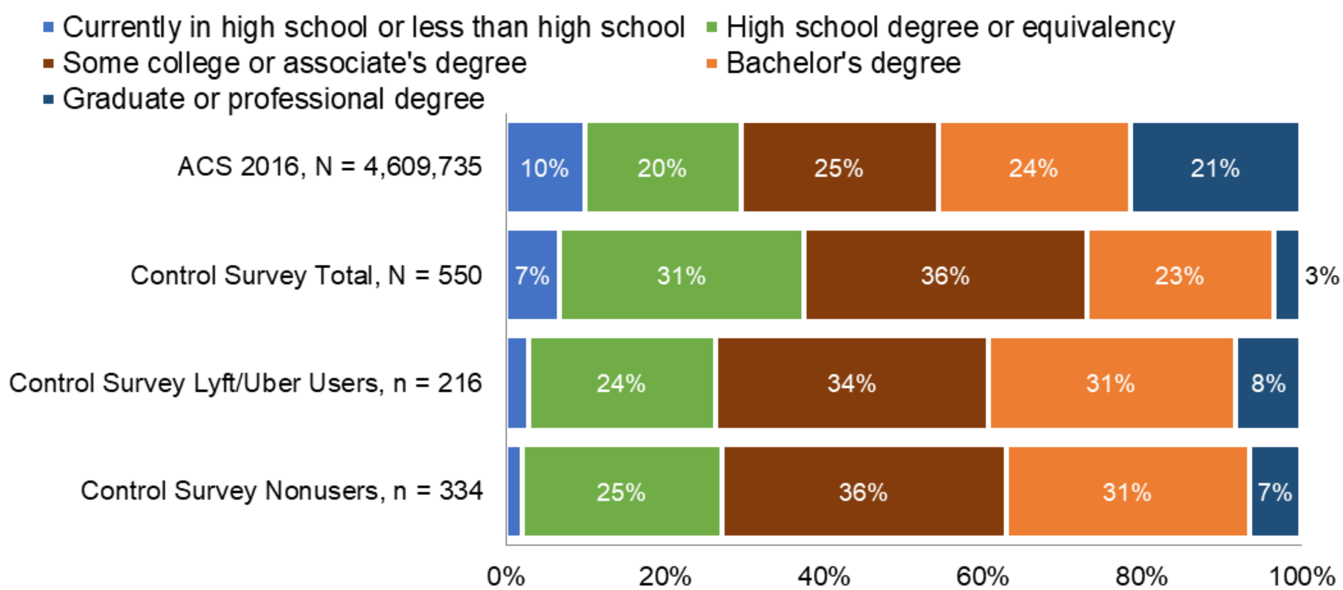
Figure 51. Control Survey Educational Attainment Distribution



Los Angeles



Washington, D.C.



Comparison of Passenger and Control Survey Sociodemographics

While many of the demographic characteristics of Lyft and Uber passengers are similar across our passenger and control surveys, it is important to compare and contrast the compositions of these two distinct populations. Overall, the control survey showed more muted departures from the general population compared with the passenger survey, while still reflecting that those who use TNCs were generally younger, of higher income, and on balance at least moderately more educated than the general population.

The passenger and control survey panels were recruited differently, which in part led to some key demographic distinctions (e.g., racial diversity, income, education). Patterns in the control and passenger survey demographics can help us to better identify attributes that are common among TNC passengers, as well as patterns that may be common to surveys conducted online. Compared with the general populations of each CBSA, both the passenger and control surveys demonstrated a slight gender bias toward female survey respondents, suggesting that females may be more willing to take online surveys than males. In both the passenger and control surveys, the majority of Lyft and Uber passengers were under the age of 40 and younger than the general population (although the proportions of young respondents were higher in the passenger survey), which is consistent with findings in previous studies.

Across all markets in both the control and passenger survey, whites were overrepresented, while Hispanics and Latinos were underrepresented relative to their respective CBSA populations. However, the Lyft and Uber users in the control survey were less white proportionally and slightly more diverse than the corresponding control survey populations overall. These findings suggest that while TNC passengers may be more likely to be white compared with the general CBSA population, the fact that someone has used TNC services is not a strong indicator of any particular racial makeup in our three study markets.

Household income distributions in the passenger and control surveys suggest that TNC passengers tended to have moderately higher incomes compared with the general populations of our three markets. However, the household income distributions in the passenger survey lean in a more pronounced way toward higher income earners than those exhibited among Lyft and Uber users and nonusers in the control survey.

The distribution of educational attainment in the passenger survey was heavily composed of respondents with bachelor's degrees or higher, suggesting that TNC passengers were more highly educated than the general population. But the control survey respondents, by design, reflect distributions of educational attainment much closer to the CBSA populations, and among Lyft and Uber users, they display only marginally higher rates of holding at least a bachelor's degree compared to nonusers. It is likely, however, that the true educational distribution among the TNC passenger population is somewhere between the distributions reflected by the two surveys.

Mode Use and Modal Shift Impacts—Control Survey

To understand whether mode use and modal shift trends among TNC users were actually reflecting broader social trends, respondents to our control survey were asked questions regarding their use of different transportation modes. Respondents who were identified as Lyft/Uber users within the control survey were also asked about the impact that Lyft and Uber had (if any) on their use of these modes. In this section, we display results for all control survey respondents and for Lyft/Uber users and nonusers, as defined in the previous section. This allows an exploration of mode usage patterns among those who did and did not use TNC services. Below are the mode use and modal shift impact findings from the control survey, including commute mode, mode use and frequency of use at the time of the survey, modal shift impacts, and comparison of mode use and modal shift impacts between Lyft/Uber passenger survey and control survey respondents.

<u>Commute Mode</u>

Because commuting is a central component of a household's travel lifestyle, understanding distinctions among modes is an important factor in contrasting commuting behavior across populations. We asked respondents to indicate their main commute mode to work or school and compared their responses with the ACS 2016 five-year estimated commute mode distribution within each CBSA in order to determine how closely our overall control survey matched up with the general population (Table 58, Table 59, and Table 60).

Across all three CBSAs, the ACS and overall control survey commute mode distributions match fairly closely, although it is worth highlighting a few exceptions. Public transit commuters constituted higher proportions of control survey respondents in San Francisco and Los Angeles than their respective general populations. Twenty-five percent of control survey respondents in San Francisco and 13 percent in Los Angeles commuted using public transit, while only 17 percent and 5 percent, respectively, used public transit to travel to work among the general CBSA populations. In San Francisco and Los Angeles, slightly lower proportions of overall respondents commuted by driving compared with those who drove to work in the ACS populations. The overall control survey commute distribution in Washington, D.C., very closely matches the corresponding ACS distribution. Across all three markets there were higher proportions of telecommuters (i.e., those who work from home) among the general population than exist among the overall control survey respondents.

When comparing TNC user versus nonuser commuting behavior, we found that in San Francisco and Washington, D.C., a greater portion of nonusers drove alone to work than did Lyft and Uber users. In San Francisco, 45 percent of Lyft and Uber users drove alone to work versus 61 percent of nonusers. In Washington, D.C., 60 percent of Lyft and Uber users drove alone to work, in contrast to 74 percent of nonusers. In addition, among TNC users in these two CBSAs, there are slightly higher proportions of people who commuted by public transit and active transportation than there were nonusers who do the same. In San Francisco, 40 percent of Lyft and Uber users commuted by bus, rail, biking, or walking, in contrast to 25 percent of the nonuser sample. In Washington, D.C., 24 percent of Lyft and Uber users commuted using public transit or active modes, while 16 percent of nonusers did the same. In Los Angeles, the commute mode distributions between TNC users and nonusers are very similar. More than two-thirds of respondents in each respondent group drove alone to work in Los Angeles.

Table 58. Control Survey Commute Mode to Work in San Francisco CBSA

	ACS 2016, N = 2,237,382	Control Survey Total, n = 345	Control Survey Lyft/Uber Users, n = 179	Control Survey Nonusers, n = 166
Drive alone	59%	52%	45%	61%
Carpool or Vanpool	10%	10%	9%	12%
Public Transit	17%	25%	28%	21%
Bus	n/a	15%	17%	13%
Rail	n/a	10%	11%	8%
Bicycle or Bikesharing	2%	2%	3%	1%
Walk	4%	6%	9%	3%
Telecommute	6%	1%	1%	1%
Other	2%	3%	4%	1%

Table 59. Control Survey Commute Mode to Work in Los Angeles CBSA

	ACS 2016, N = 6,093,213	Control Survey Total, n = 362	Control Survey Lyft/Uber Users, n = 187	Control Survey Nonusers, n = 175
Drive alone	75%	70%	68%	71%
Carpool or Vanpool	10%	9%	9%	9%
Public Transit	5%	13%	14%	13%
Bus	n/a	11%	12%	10%
Rail	n/a	2%	2%	2%
Bicycle or Bikesharing	1%	2%	2%	1%
Walk	3%	4%	3%	5%
Telecommute	5%	0%	0%	0%
Other	1%	2%	4%	1%

Table 60. Control Survey Commute Mode to Work in Washington, D.C. CBSA

	ACS 2016, N = 3,164,716	Control Survey Total, n = 339	Control Survey Lyft/Uber Users, n = 145	Control Survey Nonusers, n = 194
Drive alone	66%	68%	60%	74%
Carpool or Vanpool	10%	10%	12%	8%
Public Transit	14%	15%	17%	13%
Bus	n/a	6%	10%	4%
Rail	n/a	8%	8%	9%
Bicycle or Bikesharing	1%	1%	0%	2%
Walk	3%	4%	6%	2%
Telecommute	5%	1%	1%	1%
Other	1%	2%	3%	1%

Mode Use and Frequency of Use for General Travel Activity

We calculated mode use and modal shift among control survey respondents using the same methodology as in the passenger survey mode use and modal shift section. This approach, outlined in

Figure 9, the Schematic of Mode Shift Questions, ensures that only users of each mode were included in mode use and modal shift questions and results. General travel activity includes all trip purposes.

Mode Use

Similar to the passenger survey, control survey respondents were asked to first indicate which transportation modes they had used in the five years preceding the survey. Table 61 shows the percentage of control survey respondents in the overall sample, in the Lyft and Uber user sample, and in the Lyft and Uber nonuser sample populations who had used each of five common modes (drive alone, public bus, rail or subway, bicycle, and taxi) within the prior five years before the survey.

Table 61. Control Survey Respondent Mode Use in the Prior Five Years

CBSA	Control Survey Population	Drive Alone	Public Bus	Rail or Subway	Bicycle	Taxi
San Francisco	Control Survey Total, N = 550	86%	53%	64%	28%	27%
	Control Survey Lyft/Uber Users, n = 236	85%	66%	78%	38%	37%
	Control Survey Nonusers, n = 314	87%	43%	54%	21%	20%
Los Angeles	Control Survey Total, N = 550	87%	53%	43%	35%	19%
	Control Survey Lyft/Uber Users, n = 239	90%	64%	59%	53%	27%
	Control Survey Nonusers, n = 311	85%	44%	31%	22%	13%
Washington, D.C.	Control Survey Total, N = 550	85%	45%	63%	29%	30%
	Control Survey Lyft/Uber Users, n = 216	82%	61%	80%	44%	46%
	Control Survey Nonusers, n = 334	87%	35%	53%	19%	20%

For general travel activity across all trip purposes, we found further distinctions between Lyft and Uber users and nonusers. The proportion of Lyft and Uber users who had driven alone in the prior five years was slightly lower than the proportion of nonusers who drove alone in San Francisco and Washington, D.C., and slightly higher than nonusers in Los Angeles. For the other four modes (bus, rail, bicycle, and taxi), greater proportions of Lyft and Uber users had used these modes in the prior five years than had nonusers.

This suggests that TNC users in our control survey exhibited more multimodal behavior than nonusers. However, this finding alone does not equate TNC usage to an uptake in other public transit, shared, or active mobility modes like bus, rail, biking, and taxi. Rather, this finding is reflective of various factors. Lyft and Uber users have different demographic profiles (they are younger, on average), TNC passengers generally live within denser areas, and Lyft and Uber users have lower personal vehicle ownership rates, on average, across the control group than among the nonuser population. In the next section, we explore the usage frequency of these five modes within each control survey respondent group.

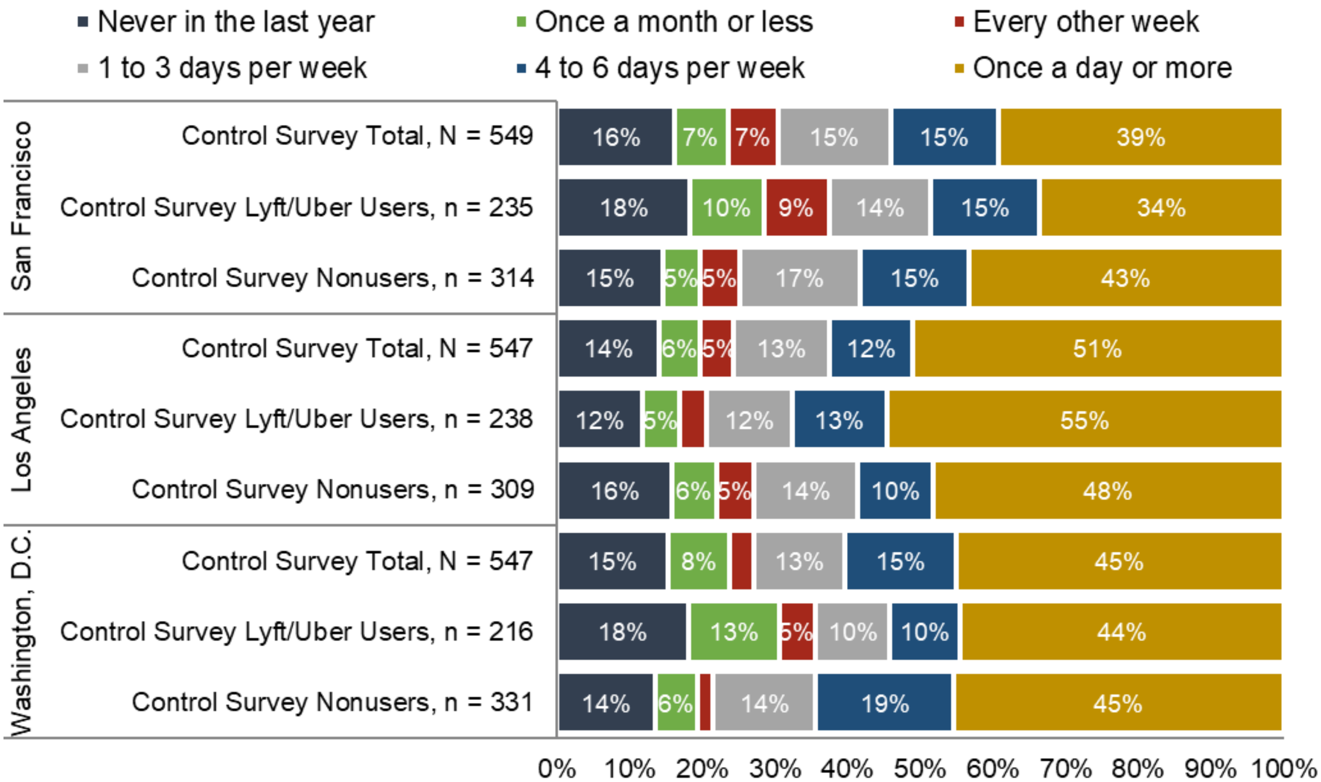
Frequency of Mode Use

Control survey respondents who indicated they had used a particular mode in the five years preceding the survey were then asked to estimate the frequency with which they use each of those modes in the present. Respondents who had not used the mode within the prior year are compiled in the "Never in the last year" category, as shown in Figure 52 through Figure 56.

Drive Alone

Not surprisingly, control survey respondents in Los Angeles drove alone more frequently than did those in the other two CBSAs, with 51 percent of total control survey respondents driving once a day or more. When comparing TNC users and nonusers, we found that nonusers drove alone more frequently than Lyft and Uber users in San Francisco and Washington, D.C., while the opposite was true in Los Angeles. Among nonusers, 58 percent drove four days per week or more often in San Francisco, while only 49 percent of Lyft and Uber users drove alone with the same frequency. In Washington, D.C., 64 percent of nonusers drove alone four days a week or more often compared to 54 percent of TNC users. However, in Los Angeles, 68 percent of Lyft and Uber users drove alone four days per week or more frequently, while only 59 percent of nonusers drove alone this often. These regional differences in driving frequency between TNC users and nonusers suggest that mode-use profiles can vary depending on land-use contexts and demographic profiles.

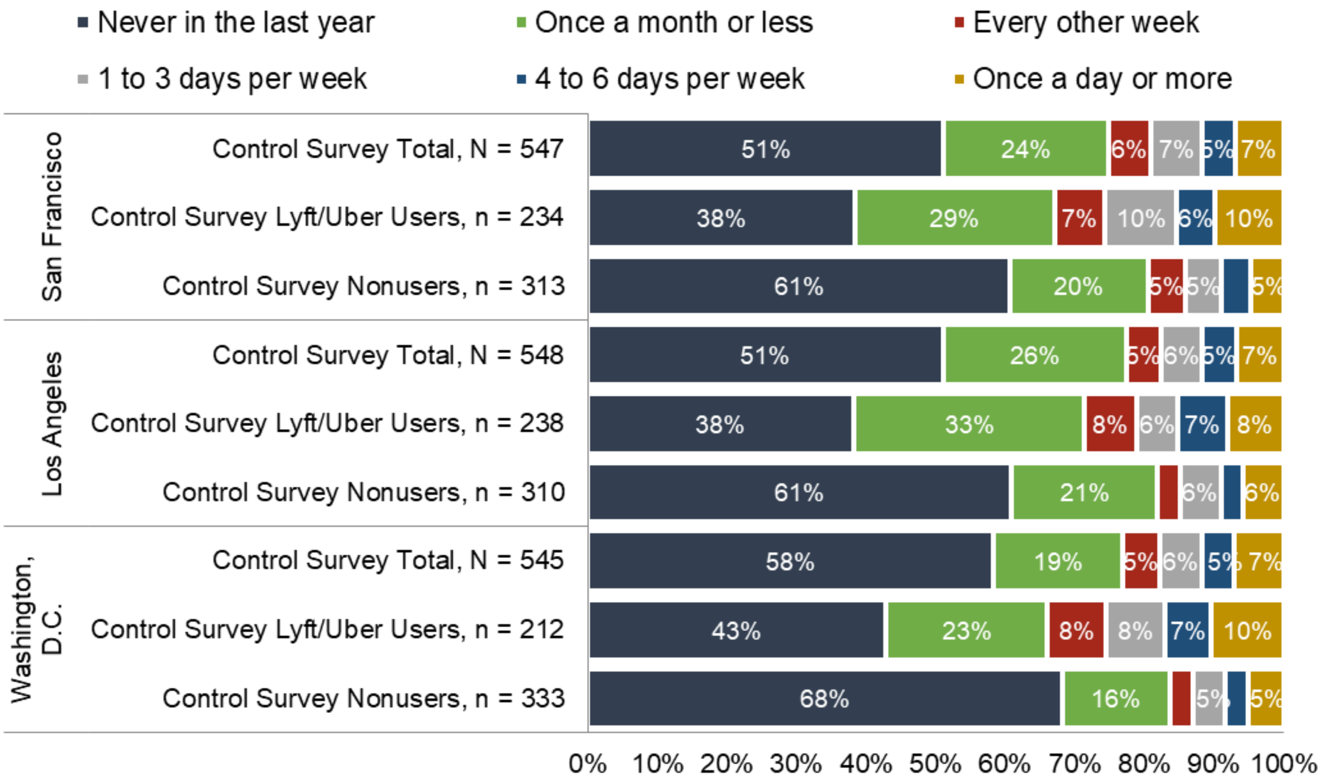
Figure 52. Distribution of Control Survey Drive Alone Use



<u>*Bus*</u>

Control survey Lyft and Uber users rode buses more frequently than did nonusers (Figure 53). However, frequency of bus use was relatively low among control survey respondents in general, with the majority of respondents in each subpopulation and CBSA using buses once a month or less often. In San Francisco and Washington, D.C., around a quarter of TNC users reported taking the bus one day per week or more often, while only 14 percent and 13 percent of nonusers reported taking the bus this frequently in the two CBSAs, respectively. In Los Angeles, 21 percent of Lyft and Uber users rode the bus once per week or more often, while 15 percent of nonusers rode buses this frequently.

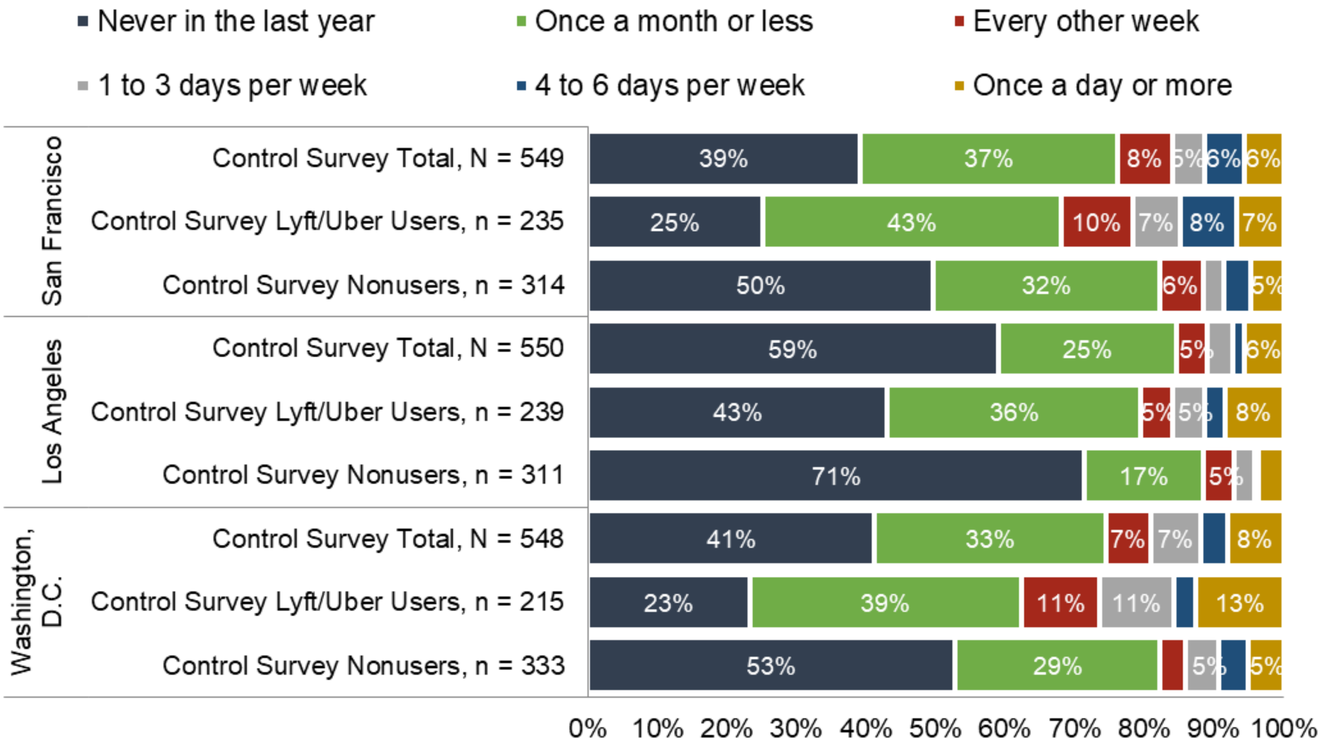
Figure 53. Distribution of Control Survey Public Bus Use



Rail

Similar to bus use among our control survey respondents, Lyft and Uber users more frequently used rail than did nonusers in each of the three CBSAs. Across all three markets, the proportion of TNC users who used rail once per week or more often is approximately double the proportion of Lyft and Uber nonusers who used rail with the same frequency. Among those who did not use TNCs, between 50 percent and 71 percent had not used rail or subway in the year preceding the survey, depending on CBSA, whereas the majority of Lyft and Uber users in each CBSA had used rail at least once in the prior year.

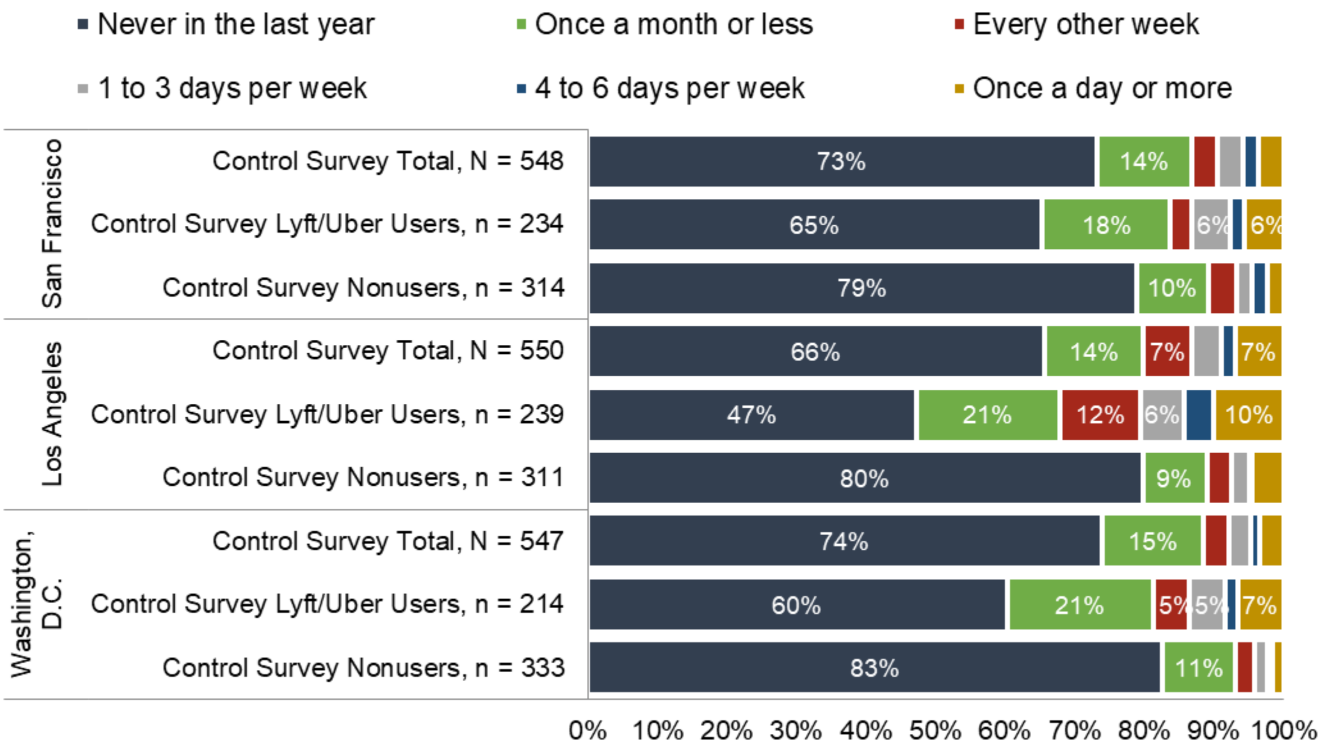
Figure 54. Distribution of Control Survey Rail or Subway Use



Bicycle

While the majority of control survey respondents in each CBSA had not biked within the prior year, TNC users were found to bike more frequently than nonusers, on average (Figure 55). Bicycling was slightly higher among Lyft and Uber users in Los Angeles, where 21 percent of TNC users reported biking one day per week or more often, versus 7 percent who biked with that frequency among nonusers. In San Francisco and Washington, D.C., 13 percent and 14 percent of TNC users biked once per week or more often while only 7 percent and 4 percent of nonusers biked that frequently, respectively.

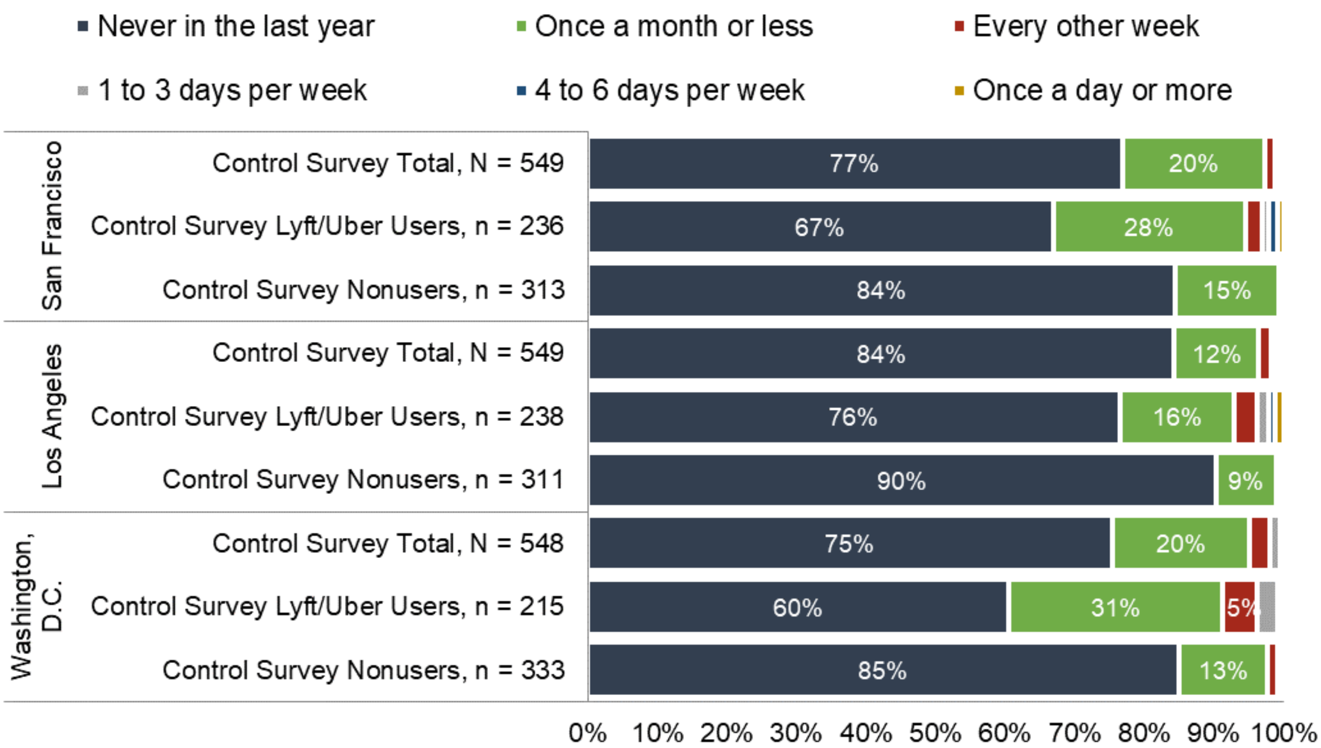
Figure 55. Distribution of Control Survey Bicycle Use



<u>*Taxis*</u>

The vast majority of control survey respondents used taxis only once a month or less often across all of the CBSAs (Figure 56). This included both users and nonusers of Lyft and Uber users. Only 3 percent to 4 percent of Lyft and Uber users took taxi trips once per week or more often across all three CBSAs. Among those who did not use TNCs, 1 percent or less within each market used taxis once per week or more often. In general, the control survey population used taxis fairly infrequently, and taxi use was notably less frequent among nonusers.

Figure 56. Distribution of Control Survey Taxi Use

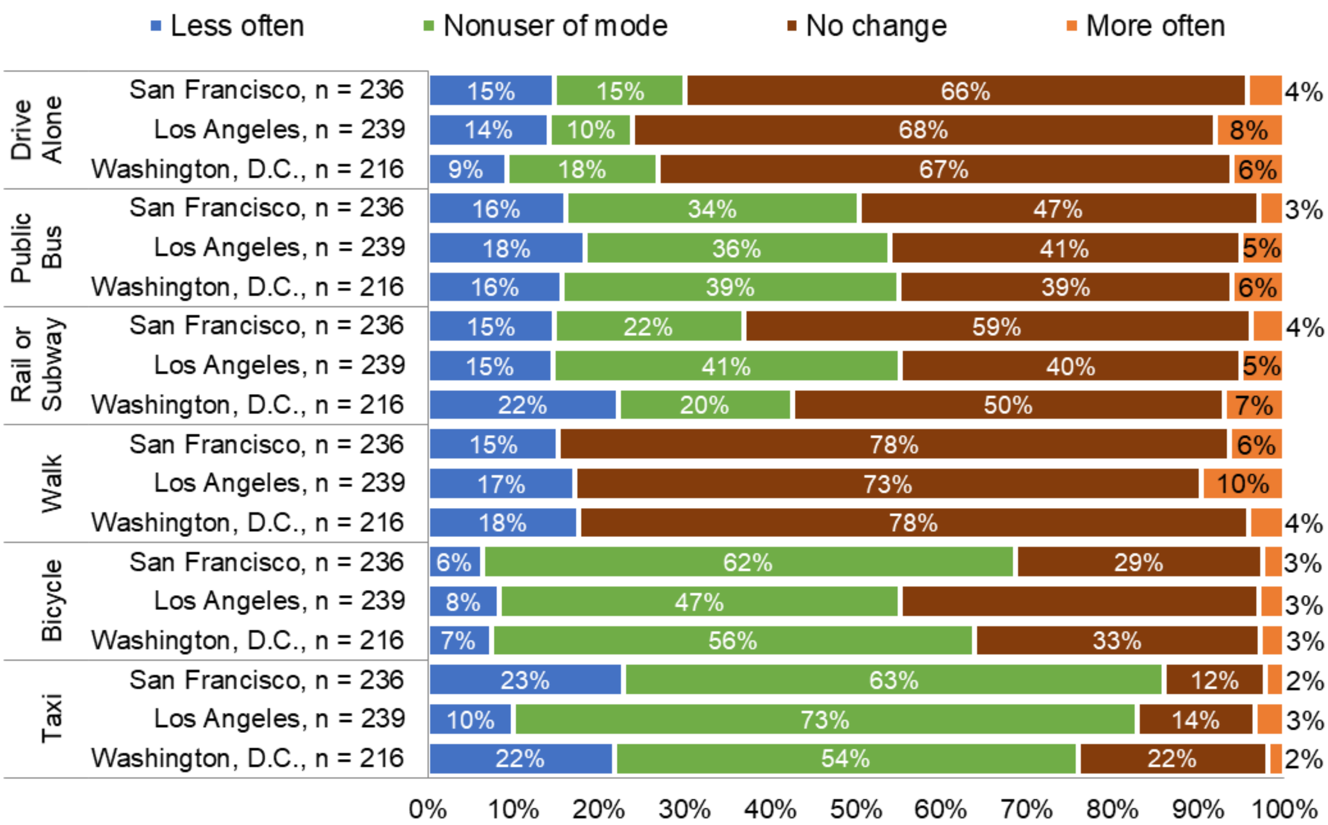


Modal Shift Impacts

As with the passenger survey, Lyft and Uber users in the control survey were asked to consider whether their mode use changed due to the availability of TNCs.[12] If the respondent indicated a change, we then asked Lyft and Uber users to identify whether TNCs had facilitated an increase or a decrease in their use of each mode. Those Lyft and Uber users who had not used the indicated mode in the prior five years are represented in the "Nonuser of mode" group. The results are shown in Figure 57.

[12] The methodology for calculating modal shift impacts due to TNCs in the control survey is the same methodology described in the passenger survey mode use and modal shift sections.

Figure 57. Control Survey Distribution of Modal Shifts (Lyft/Uber Users Only)



Across all six modes in all of the CBSAs, the majority of control survey Lyft and Uber users were either nonusers of the mode or had not changed their use of the mode due to TNC availability. Modal shift results for each of the six modes are discussed below.

<u>*Drive Alone*</u>

The majority of control survey Lyft and Uber users in each CBSA had not changed how often they drive due to TNCs. In each of the three markets, there are slightly greater proportions of those who drove alone less often than those who drove more often due to Lyft and Uber. In San Francisco, 15 percent of control survey Lyft and Uber users drove less often due to TNCs, while 4 percent drove more often. In Los Angeles, 14 percent drove alone less often, while 8 percent drove more often. In Washington, D.C., 9 percent drove alone less often, while 6 percent drove more often.

<u>*Public Transit (Public Bus, Rail, or Subway)*</u>

The majority of control survey Lyft and Uber users either experienced no change in their frequency of public transit use (bus or rail) or were nonusers of public transit. Across the three CBSAs, 16 percent to 18 percent of TNC users took the bus less often due to Lyft and Uber, while only 3 percent to 6 percent took the bus more often. In San Francisco and Los Angeles, 15 percent of Lyft and Uber users took rail less often due to TNCs, while 4 percent and 5 percent, respectively, used rail more often. The most significant shift away from rail occurred in Washington, D.C., where 22 percent of control survey TNC users decreased their frequency of rail use due to Lyft and Uber and 7 percent used rail more often. The magnitude of this shift could have been partially due to the SafeTrack maintenance that significantly reduced rail service in the area during the time of the survey.

Walking

On net, a greater portion of control survey Lyft and Uber users reported walking less often than those who walked more often due to TNCs. Although 15 percent to 18 percent of Lyft and Uber users walked less often due to TNCs, depending on the market, 10 percent in Los Angeles claimed to walk more often due to the availability of Lyft and Uber. This effect may be due to some respondents leaving personal vehicles at home for trips with Lyft or Uber, which could have induced additional walking trips that might have previously been entirely driven in a private vehicle. This effect may be more prominent in Los Angeles relative to the other two markets due to comparatively higher rates of personal vehicle mode substitution.

Bicycle

As seen in the passenger survey, TNCs were not found to either significantly increase or decrease bicycling among control survey respondents. While the vast majority of control survey Lyft and Uber users did not bike or did not change their bicycling frequency due to TNCs, 6 percent to 8 percent reported decreasing how often they bike, while 3 percent reported biking more often due to TNCs.

Taxis

Although the majority of Lyft and Uber users in the control survey did not use taxis, a greater proportion claimed to use taxis less often due to TNCs than those who used them more often. In San Francisco and Washington, D.C., 23 percent and 22 percent of TNC users had decreased their taxi use due to Lyft and Uber, respectively, while only 2 percent in each market had increased their use of taxis. In Los Angeles, the effect was not as pronounced, with 10 percent claiming to use taxis less often and 3 percent using them more often due to TNCs. This result is likely attributable to higher levels of vehicle ownership and lower levels of taxi use in Los Angeles.

Comparison of Passenger and Control Survey Mode Use and Modal Shift Impacts

While mode use and modal shift impact patterns among the passenger survey population and control survey Lyft and Uber user population share similarities, there are also key differences among these two surveyed populations. By comparing mode use and modal shift results across the two survey populations, we can gain deeper insight into the nature of TNC impacts within the three study markets.

In general, the Lyft and Uber users in the control survey used public transit, active modes, and taxis slightly less frequently than those in the passenger survey. Control survey Lyft and Uber users were not found to experience as great an impact on their modal use as were passenger survey respondents, although the modal shift impacts in both surveys across all modes and markets generally moved in the same direction. Both the passenger and control group surveys showed that Lyft and Uber appear to draw from all modes, serving predominantly as a new choice among transportation options.

When comparing commute mode distributions among the passenger survey and control survey Lyft and Uber passenger populations, there is a higher proportion of control survey TNC users who drove alone to work than there is in the passenger survey. In San Francisco, 45 percent of Lyft and Uber users in the control survey drove alone to work, while 26 percent did so among TNC users in the passenger survey. In Los Angeles, driving alone to work was done by 68 percent of Lyft and Uber users in the control survey versus 55 percent in the passenger survey. Finally, in Washington, D.C., we found that 60 percent of the control survey Lyft and Uber users drove alone to work versus 26 percent of passenger survey respondents. There are also slightly higher proportions of passenger survey respondents who commuted using public transit as compared to control survey TNC users. In both the passenger survey and control survey Lyft and Uber passenger populations, there are lower proportions of drive alone commuters than exist in the ACS, strongly suggesting that TNC passengers were slightly less likely to commute to work by car than the general populations within these three CBSAs.

Examining broader mode use and frequency across all travel, we found that control survey Lyft and Uber users drove alone more frequently than do those in the passenger survey population. For example, among passenger survey respondents, only 29 percent in San Francisco and 28 percent in Washington, D.C., drove alone four days per week or more often, compared with 49 percent in San Francisco and 54 percent in Washington, D.C., among control survey Lyft and Uber users. Similarly, while 54 percent of passenger survey respondents in Los Angeles drove alone four times a week or more, 68 percent of control survey TNC users drove alone this frequently.

Conversely, in San Francisco and Washington, D.C., there are slightly more frequent public transit users among the passenger survey populations than among the control survey Lyft and Uber user populations. However, the opposite was found in Los Angeles. Rail use among passenger survey respondents in San Francisco and Washington, D.C., was notably higher than it was found to be among control survey TNC users: 25 percent of passenger survey respondents in San Francisco and 34 percent in Washington, D.C., use rail four days per week or more often, compared with 15 percent and 16 percent of control survey Lyft and Uber users who do the same. Meanwhile, in Los Angeles, control survey TNC users took public transit slightly more frequently than passenger survey respondents.

In order to assess the overall impact on all six modes in the three CBSAs across the control and passenger survey populations, we calculated the comparative net modal shift impacts (Table 62). This calculation involves subtracting the proportion of respondents who used each respective mode more often due to Lyft and Uber from the portion of respondents who used the mode less often due to Lyft and Uber. Overall, we found a net negative impact due to TNCs on all six modes in the three CBSAs among both control survey and passenger survey respondents. However, the degree of negative impact differs across the two survey populations.

Table 62. Net Modal Shift Impacts Due to Lyft/Uber in Control and Passenger Surveys

Mode	**Control Survey Lyft/Uber Passengers**			**Passenger Survey**		
	San Francisco	*Los Angeles*	*Washington, D.C.*	*San Francisco*	*Los Angeles*	*Washington, D.C.*
Drive Alone	–11%	–6%	–3%	–33%	–27%	–26%
Public Bus	–13%	–13%	–10%	–46%	–28%	–37%
Rail or Subway	–11%	–10%	–15%	–35%	–21%	–51%
Walk	–9%	–8%	–13%	–25%	–24%	–27%
Bicycle	–4%	–5%	–5%	–8%	–8%	–6%
Taxi	–21%	–7%	–20%	–49%	–32%	–60%

Note: Units are the portion of respondents who use each respective mode more often due to Lyft and Uber subtracted by the portion of respondents who use the mode less often due to Lyft and Uber

For all modes and in all markets, the net negative impact on mode use due to TNCs was found to be larger among passenger survey respondents than among the control survey Lyft and Uber users. In other words, while the overall direction of modal shift due to TNCs was negative among both the passenger and control survey populations, the magnitudes were greater for the passenger survey respondents. These findings underscore the differences in sampling among the passenger and control survey respondent populations and show that although directional impacts are similar, their magnitudes can vary depending on the makeup of the surveyed population.

Another interesting difference between the control and passenger survey modal shift findings is that a greater proportion of control survey respondents claimed to use certain modes more often due to TNCs, compared with the corresponding portions claiming an increase within the passenger survey. For example, 4 percent to 10 percent of control survey Lyft and Uber users walked more often due to TNCs, depending on the market (Figure 57), while only 3 percent to 4 percent of passenger survey respondents claimed to walk more often (Figure 12). In addition, there are slightly greater proportions of control survey respondents using public transit more often than respondents in the passenger survey. Seven percent of control survey Lyft and Uber users claimed to use rail more often due to TNCs, while this portion was just 2 percent among the passenger survey population. There are a variety of explanations for these differences, including differences in demographics and differences in the spatial distributions of respondent home locations that could be influencing the observed magnitudes of modal shift.

Overall, these comparisons show that the control survey contains slightly more frequent drivers than exist in th passenger survey populations. Conversely, the passenger survey populations contained more frequent public transit (rail and bus) users than did the control survey populations. Last, the net modal shift impacts were found to be negative across both control and passenger surveys, meaning Lyft and Uber passengers took other modes less, on average, due to TNCs. However, the magnitude of these impacts is larger among passenger survey respondents than among control survey Lyft and Uber users, indicating that mode impacts can vary based on the sampling methodology and population sampled.

Driver Survey—Results and Discussion

We developed a short survey of about 20 questions that was sent to Lyft and Uber drivers who had provided at least one ride over the three months leading up to October 1, 2016, within one of the three study CBSAs. The survey asked drivers about their driving frequency and behavior, their home location and usual passenger pickup market locations (hereafter referred to as the “primary passenger market”), the distance they traveled to this primary passenger market, and details regarding their vehicle ownership. Even though drivers received the survey from one platform or the other, respondents were asked to consider their driving on both platforms (Lyft and Uber combined) when answering questions. The survey efforts yielded 1,300 completed driver surveys in the San Francisco CBSA, 2,568 in the Los Angeles CBSA, and 1,166 in the Washington, D.C., CBSA.

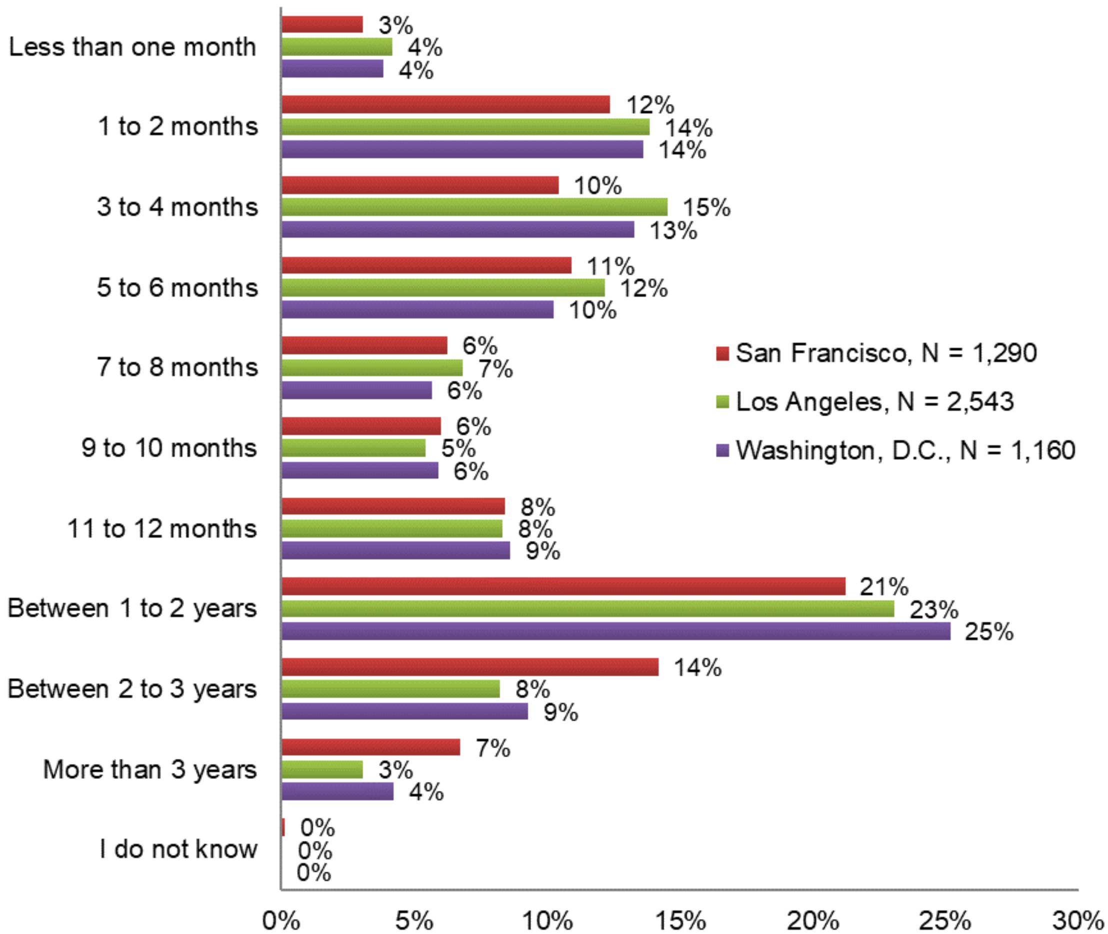
Driver Tenure and Driving Behavior

The survey asked respondents about their tenure as a driver with Lyft and/or Uber and their driving behavior over the 12 months prior to the survey, including how many months they were active, how many days they drove in an average month, and miles driven in an average month. This section presents the results.

Driver Tenure

We asked drivers how long they had been driving with Lyft or Uber. Almost half of the respondents had driven with Lyft or Uber for one year or more: 42 percent of respondents in San Francisco, 34 percent in Los Angeles, and 39 percent in Washington, D.C. Conversely, nearly equal proportions of respondents had driven for only six months or less at the time of our survey: 37 percent of respondents in San Francisco, 45 percent in Los Angeles, and 41 percent in Washington, D.C. This fairly high proportion of new drivers echoes other studies that suggest there are high turnover rates among TNC drivers (Mishel 2018). However, we note that driver respondents in this study reflect a survey sample and do not necessarily reflect the tenure distribution of all active drivers on the Lyft and Uber platforms in the three CBSAs. In addition, driver tenure distributions may change over time as TNCs mature in a given area.

Figure 58. Tenure of Driving with Lyft or Uber

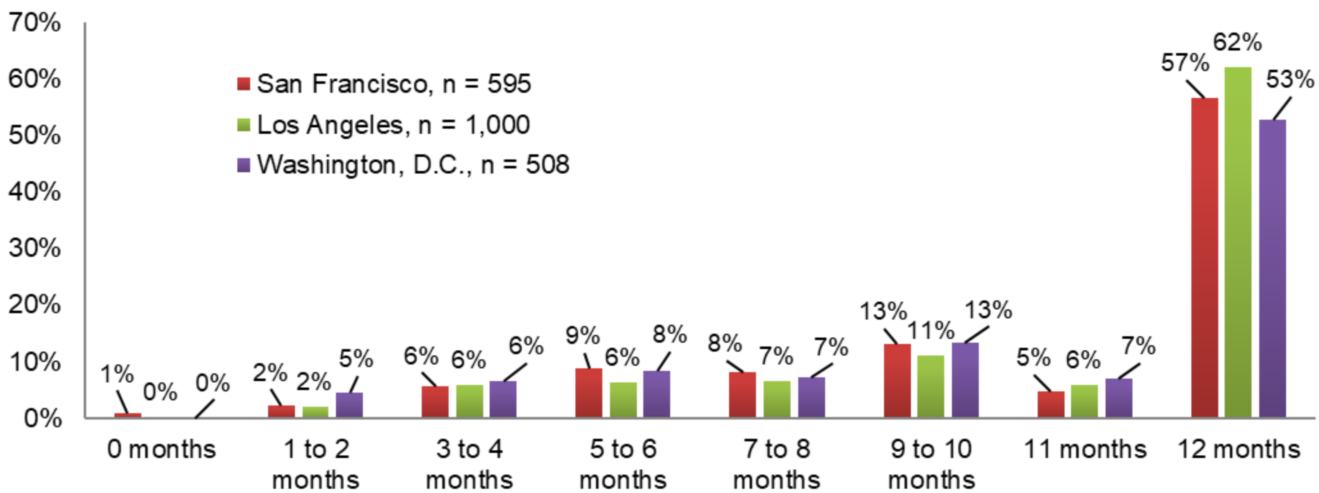


Months Driven in the Past Year

We asked driver respondents how many months they had driven with Lyft and/or Uber during the past year. Figure 59 shows the number of months driven in the past year among respondents who had been driving with Lyft or Uber for a year or longer. Of these drivers, more than half in each market had driven every month in the past year. About three-quarters of all driver respondents in each CBSA had driven nine or more months over the past year. For the respondents who had been driving with Lyft or

Uber for less than a full year, about three-quarters had driven every month since starting. Overall, these findings show that the driver survey respondents were fairly active drivers with Lyft and Uber.

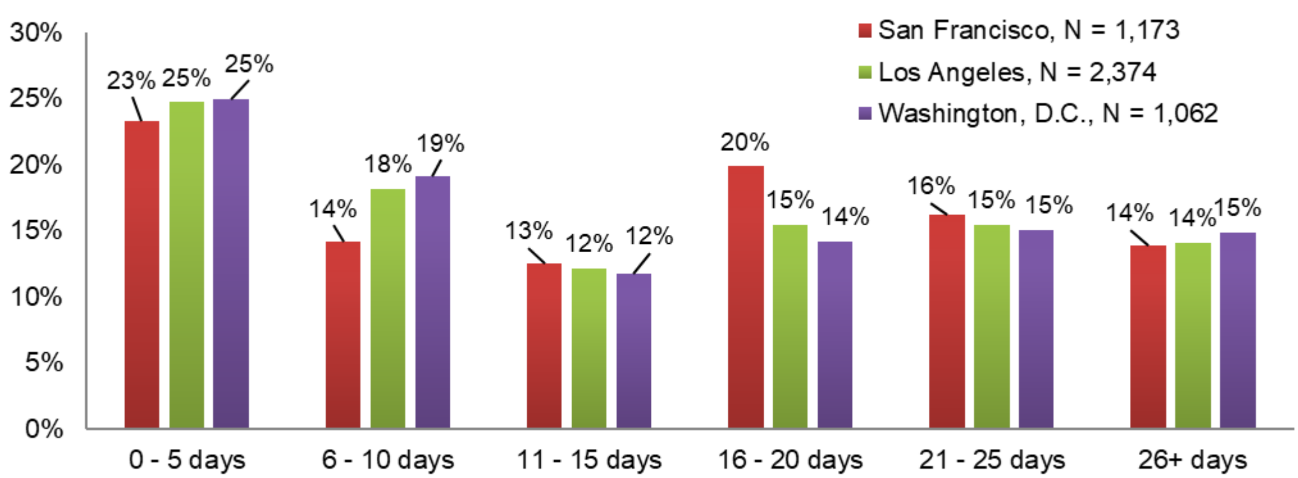
Figure 59. Months Driven With Lyft and/or Uber During the Past Year (Drivers Active for 1+ Years Only)



Days Driven in an Average Month

Figure 60 displays the distribution of the number of days driven during an average month with Lyft and/or Uber, as reported by respondents. About a quarter of respondents in each market drove five days or fewer during an average month. A larger proportion drove more than half of the days during an average month: 50 percent of respondents in San Francisco, 45 percent in Los Angeles, and 44 percent in Washington, D.C. Thirty percent of driver respondents in each market drove 21 days or more during an average month, which effectively equates to a typical five-day work week. Although our survey did not assess hours driven, these findings emphasize that a notable portion of respondents reported being very active drivers with Lyft and/or Uber.

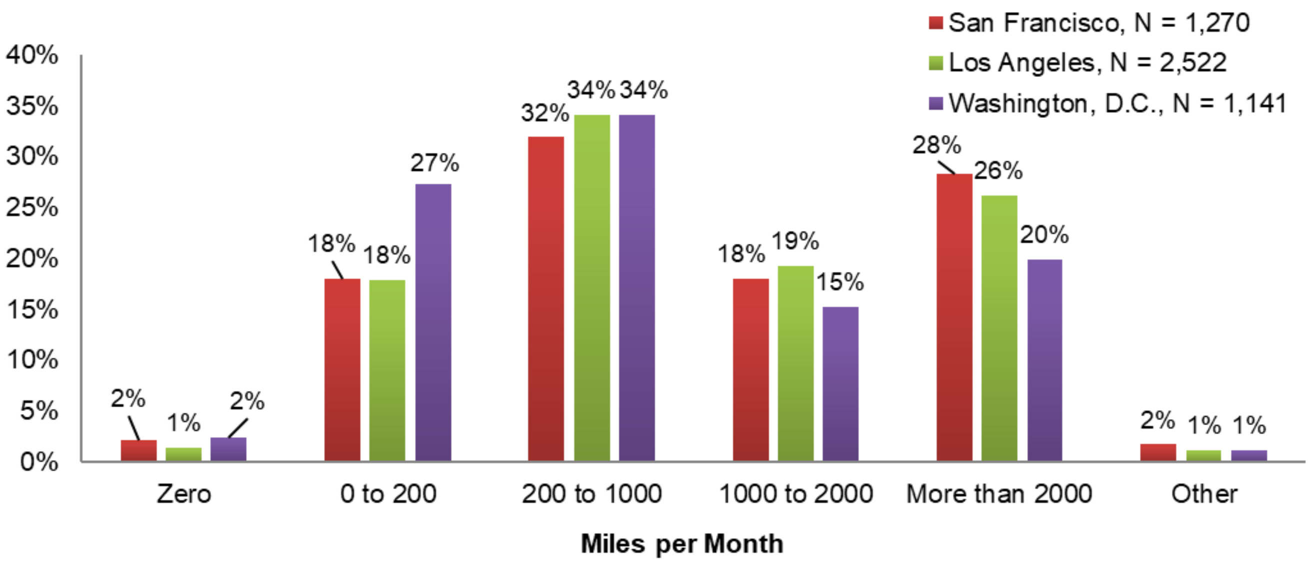
Figure 60. Average Days Driven per Active Month



Miles Driven in an Average Month

We asked driver survey respondents to estimate how many miles they drove with Lyft and Uber (combined) during the average month over their prior 12 months of driving. There exists a wide distribution of average miles driven per month among the responses, as shown in Figure 61. Twenty percent of driver respondents in San Francisco, 19 percent in Los Angeles, and 30 percent in Washington, D.C. drove no more than 200 miles per month, on average. Approximately half of the driver respondents in all three markets drove between 200 and 2,000 miles per month, on average. A surprisingly high proportion of respondents selected the maximum answer option, "More than 2,000 miles per month," with 28 percent in San Francisco, 26 percent in Los Angeles, and 20 percent in Washington, D.C. reported driving this many miles in an average month. Again, this suggests that a notable portion of the driver survey respondents have been very active TNC drivers.

Figure 61. Average Miles Driven per Active Month



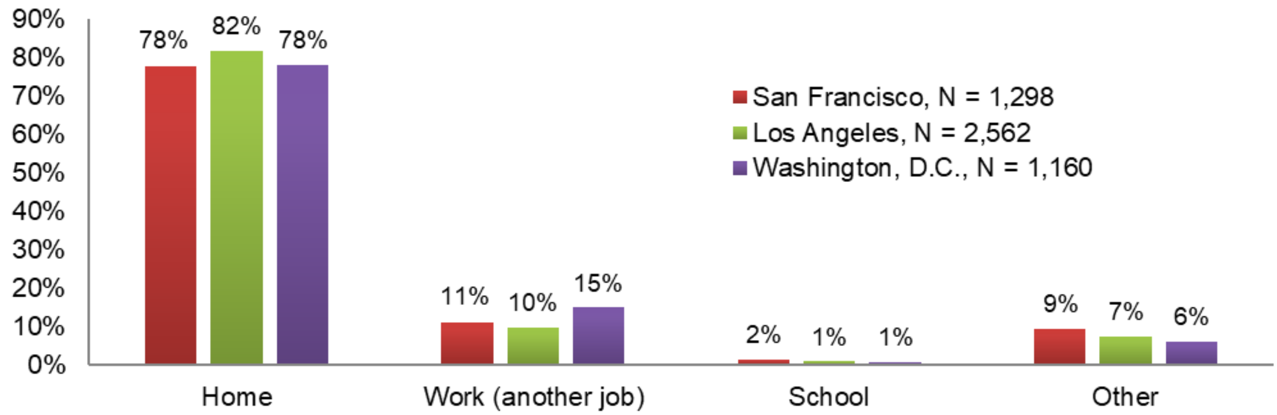
Accessing the Primary Passenger Market

We asked driver respondents about their travel patterns before starting a driving session with Lyft and/or Uber. Their answers offered insights into driving that is not recorded by the TNCs themselves because it occurs while the drivers' apps are not activated. Results presented in this section include typical departure location, distance driven with Lyft and Uber apps off (distance driven to the passenger market), and distance from origin to primary passenger market.

Typical Departure Location

Figure 62, below, shows that most driver respondents departed from their home before beginning a driving session with Lyft or Uber. More than three-quarters of respondents in each market said they normally depart from home, while 10 percent to 15 percent of respondents across the three CBSAs would leave from a workplace before logging in to the Lyft or Uber driver app. A small portion of driver respondents (2 percent or less across the three markets) would leave from school before starting a driving session, and another 6 percent to 9 percent claimed they typically left from another type of location, such as a gas station or coffee shop, before beginning to drive.

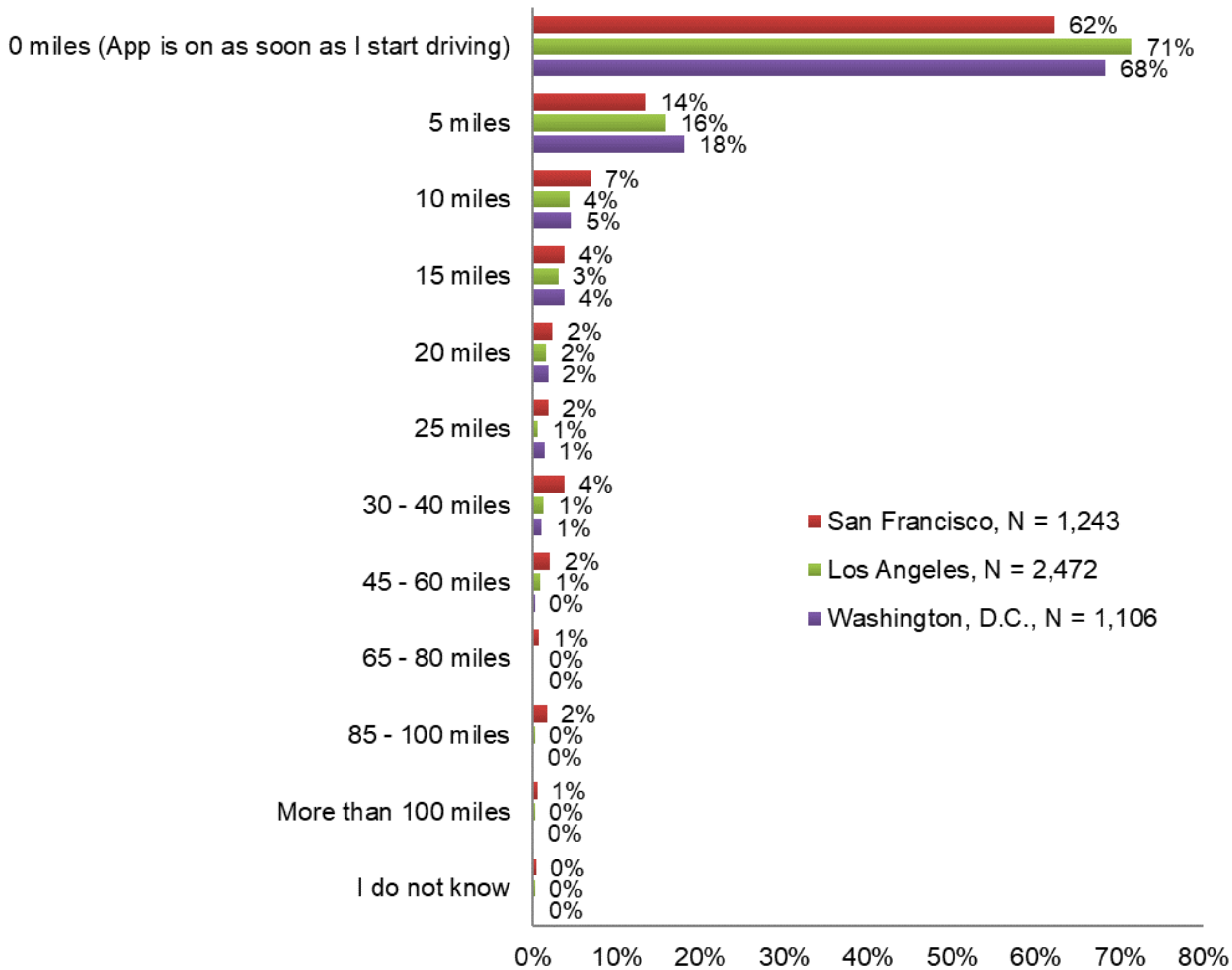
Figure 62. Typical Departure Place Before Driving With Lyft and/or Uber



<u>Distance Driven with App Off</u>

The mileage traveled by TNC drivers after leaving their departure location but before turning on their Lyft or Uber app is important to measure, as it estimates a component deadheading mileage produced by drivers while they are unavailable to passengers. Figure 63 shows the distribution of respondents' typical miles driven before logging in to the driver app. The majority of driver respondents turn their Lyft or Uber app on right away when beginning a drive, with 62 percent in San Francisco, 71 percent in Los Angeles, and 68 percent in Washington, D.C. reporting that they do so. In addition, more than 85 percent of driver respondents in each market turn on their app right away or within 10 miles of their origin. San Francisco has the highest proportion of respondents, 17 percent, who typically drive 15 miles or more before turning on their Lyft or Uber app; only 8 percent of respondents in Los Angeles and 9 percent in Washington, D.C., normally do so. Overall, these results show that the majority of TNC drivers activated their Lyft or Uber app immediately upon leaving their departure location or very shortly thereafter. However, there is a small portion of drivers who reported typically driving longer distances before turning on their app, with this behavior being more common in San Francisco than in Los Angeles or Washington, D.C.

Figure 63. Miles From Origin Before Logging In to App

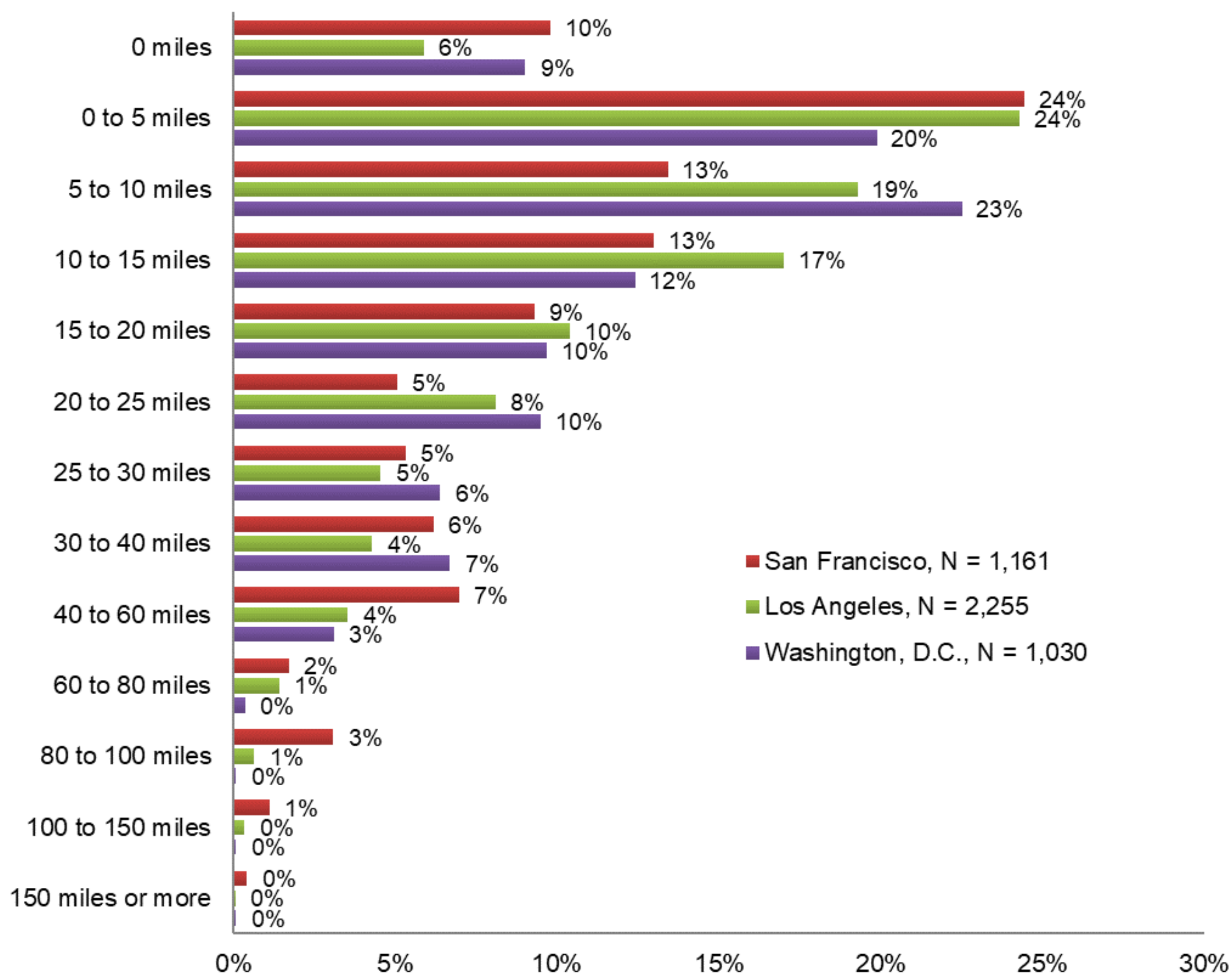


Distance From Origin to Primary Passenger Market

The driver survey asked respondents to indicate their home location and primary passenger pickup city to gain a better understanding of where TNC drivers lived and where they most often drove with Lyft and Uber. The responses to these questions in the survey instrument were recorded as zip codes for home locations and as cities for non-home origin locations and for the primary pickup market. We used the Google Maps API to geocode the mileage between each driver respondent's origin location and primary city for picking up passengers. After cleaning responses for city and zip code entry errors, we were left with 1,161 valid respondents in San Francisco, 2,255 in Los Angeles, and 1,030 in Washington, D.C. We note that these distances represent the mileage traveled between a driver's typical origin location and what the driver considers to be his or her primary passenger market. In reality, since most drivers turn their Lyft or Uber app on very shortly after departing from their origin location, they may not always travel to their primary passenger market every time they drive. However, these results provide a general understanding of driver distance from the stated passenger market.

Figure 64, below, shows the mileage distributions from origin to primary passenger market among driver respondents. The average distance from respondents' origins to their primary passenger markets is 19 miles in San Francisco and 14 miles in both Los Angeles and Washington, D.C. San Francisco's higher average was spurred by a higher concentration of drivers who traveled longer distances to their passenger market. The picture looks a little different when the median distances are considered. The median distance from origin to primary passenger market among driver respondents was just 11 miles in San Francisco and 10 miles in Los Angeles and Washington, D.C. The fact that the median distances were lower than the average distances suggests that there were a small minority of respondents driving exceptionally long distances to their passenger markets. The majority of respondents across the three CBSAs traveled 15 miles or less from their typical origin to their primary passenger market: 61 percent of respondents in San Francisco, 67 percent in Los Angeles, and 64 percent in Washington, D.C. However, San Francisco contained a greater proportion of long access distances than the other two markets. Twenty percent of driver respondents in San Francisco traveled 30 miles or more between their typical origin and primary passenger market, compared with just 10 percent each in Los Angeles and Washington, D.C. These slight differences in access distances by CBSA are likely due to land-use and housing cost factors across the study CBSAs. Nonetheless, these average distances are not exceptionally long when compared to the average U.S. commute distance of approximately 12 miles (NHTS 2017).

Figure 64. Distance From Origin to Primary Passenger Market



Driver Home and Primary Passenger Market Locations and Distance From Passenger Market

As mentioned above, the driver survey asked respondents to indicate their home zip code and primary passenger pickup city. In this section, we display the distributions of driver respondent home and primary passenger market locations in each of the three CBSAs. We also show average distances from origin to passenger market disaggregated by home and passenger market locations. We use county subdivision designations for home and passenger pickup market mapping, since this classification is generally an easily identifiable designation of cities or areas within each CBSA. Distances between departure location and primary passenger market were calculated using the Google Maps API. Note these results reflect the driver respondents only and do not necessarily represent the home and passenger market breakdown among all TNC drivers within the three CBSAs.

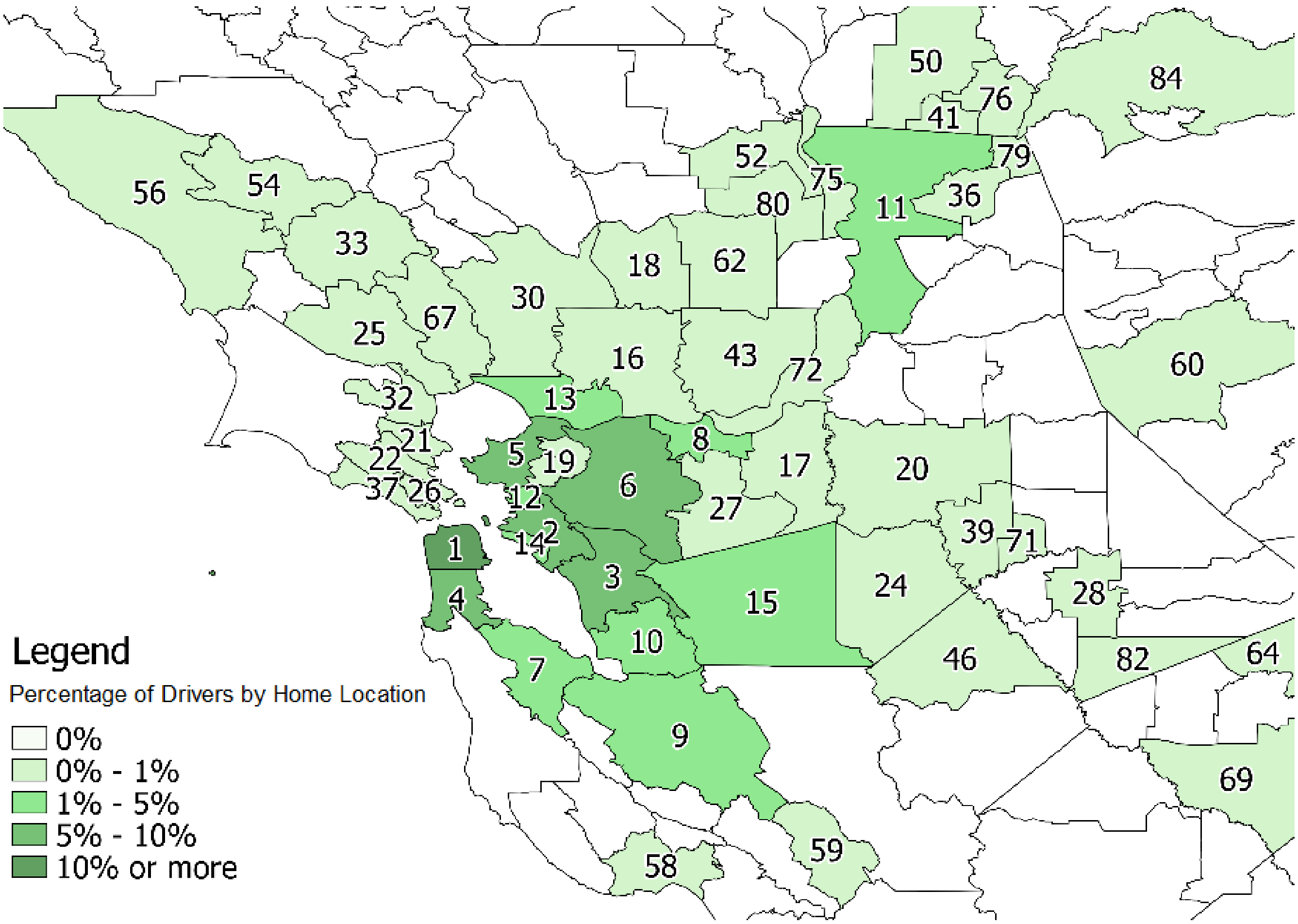
<u>San Francisco Bay Area—Home Location and Average Distance to Passenger Market</u>
First, we display driver respondent home location and average distance to passenger market attributes in the San Francisco Bay Area. The number displayed inside the county subdivision is the rank ordering of the subdivision in terms of respondent concentration by home location. We distributed the survey to drivers who had completed at least one ride within Alameda, Contra Costa, Marin, San Francisco, or San Mateo County in the three months prior to survey distribution.

As shown in Figure 65 and Table 63, the reported home location of driver respondents is dispersed across the greater Bay Area and other locations in northern California. By county subdivision, San Francisco has the highest proportion of respondents, at about 17 percent. Many driver respondents also live in the East Bay Area or on the Peninsula. Drivers from Alameda County make up 27 percent of the driver population, and those from San Mateo County constitute about 13 percent of respondents. Around 12 percent of the driver respondents reside outside of the nine-county Bay Area, with about 3 percent from Sacramento County and 3 percent from the San Joaquin Valley. The remaining 31 percent of drivers reside throughout the other six Bay Area counties: Contra Costa, Marin, Napa, Santa Clara, Solano, and Sonoma.

We also obtained a public data set of the business locations of registered TNC drivers for the city of San Francisco. Although these data reflect registered business locations and not necessarily home locations of drivers, we expect that many TNC drivers registered using their home address. By comparing the home location distribution of driver survey respondents with findings from the public data set, we were able to compare and contrast the two to generate a more complete understanding of where San Francisco Bay Area TNC drivers live.

Similar to the proportion found in the driver survey (12 percent), these registration data show that 10 percent of drivers were registered in a location outside of the nine-county Bay Area. In contrast, 30 percent of drivers in the public data set were registered within the city of San Francisco, while just 17 percent of driver survey respondents reside in San Francisco. Additionally, just 21 percent of drivers in the registration data set were listed in Alameda County and 12 percent are registered in Contra Costa County, in contrast to 27 percent and 19 percent of driver survey respondents who live in these counties, respectively. Overall, this comparison suggest that while the majority of TNC drivers reside within the nine-county Bay Area, the proportion of drivers living within specific counties fluctuates depending on the data source used and the time at which the sample was taken.

Figure 65. San Francisco Driver Respondent Home Location Ranked by Number of Respondents



The average distance from typical origin to primary passenger market varies by respondent home location, as seen in Table 63. Unsurprisingly, respondents who resided in San Francisco travel the shortest distances to the pickup market, at 4 miles on average. Those who lived farther away from San Francisco and the Bay Area displayed higher average distances from their primary passenger market. For example, drivers who lived in Sacramento were 76 miles away from their primary passenger market, on average. Drivers residing in the San Jose area also experienced a higher access distance, at 36 miles on average. However, these drivers make up smaller portions of our respondent population, at 2.9 percent in the Sacramento county subdivision and 3.5 percent in San Jose. Note, however, we did not sample from drivers who had given rides in Sacramento and San Jose, two other major markets, which may explain the lower proportion and higher average distances associated with drivers who reside in these areas.

Table 63. San Francisco Driver Respondent Home Location and Average Distance to Passenger Market

Label	Home County Subdivision	Percentage of Respondents	Average Mileage to Passenger Market Grouped by Home Location
1	San Francisco	17.2	4
2	Oakland	10.0	8
3	Hayward	8.7	15
4	South San Francisco	8.3	10
5	West Contra Costa	7.4	13
6	Central Contra Costa	5.3	23
7	San Mateo	4.9	14
8	Antioch-Pittsburg	3.7	25
9	San Jose	3.5	36
10	Fremont	3.1	25
11	Sacramento	2.9	76
12	Berkeley	2.4	7

San Francisco Bay Area—Primary Passenger Market and Average Distance by Market

Figure 66 displays the primary passenger market of the San Francisco CBSA driver respondents. The majority of respondents, about 58 percent, indicated the City of San Francisco as their primary passenger market (Table 64). Around 20 percent of respondents indicated that either Oakland or Berkeley was their primary passenger market. Outside of these three cities, other county subdivisions in the Bay Area have much smaller proportions of respondents who consider these areas to be their primary passenger market. The number inside each county subdivision is the same rank ordering of driver home locations as outlined above. In some unique cases, certain county subdivisions (such as the Half Moon Bay County subdivision, labeled as 89 below), serve as primary passenger markets, but they have no driver respondents living within them.

Figure 66. San Francisco Driver Respondent Primary Passenger Market

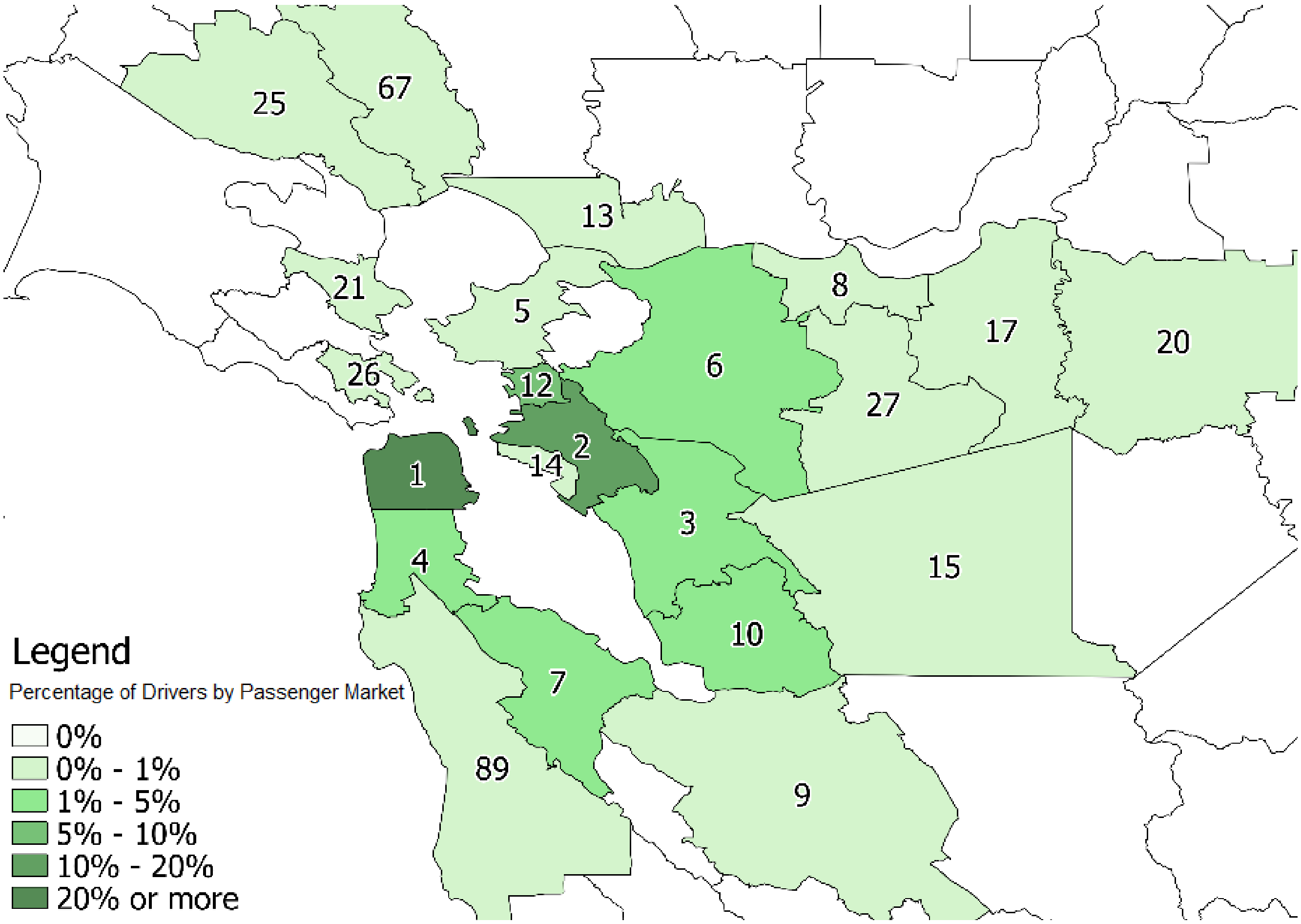


Table 64 shows the average distance driven from home or another origin location, disaggregated by respondents' primary passenger market. Interestingly, the San Francisco passenger market has one of the highest average distances by market location, at 23 miles on average. That is, San Francisco was the market that drivers travel the longest to reach, on average. This is driven by a minority of respondents traveling significant distances to reach the market. Both Oakland and Berkeley, the next most popular passenger markets, have average access distances of 15 miles. More suburban county subdivisions, like San Mateo, Fremont, and Hayward, all exhibit lower distances traveled to market, on average. These associations are likely due to the larger and more dispersed population of drivers who consider San Francisco and more urban East Bay locations, like Oakland and Berkeley, as their primary passenger market, leading to relatively higher average distances traveled to access these markets. Conversely, the lower respondent percentages and average access distances among suburban county subdivision markets suggest that drivers serving these regions were more likely to be serving their home city or area as their primary passenger market.

Table 64. San Francisco Driver Respondent Primary Passenger Market and Average Distance to Passenger Market

Label	Market County Subdivision	Percentage of Respondents	Average Distance to Passenger Market Grouped by Market Location
1	San Francisco	58.3	23
2	Oakland	12.8	15
12	Berkeley	7.6	15
6	Central Contra Costa	2.3	11
7	San Mateo	2	4
4	South San Francisco	1.5	16
10	Fremont	1.3	8
3	Hayward	1.1	8
9	San Jose	0.8	19

<u>Los Angeles and Orange Counties—Home Location and Average Distance to Passenger Market</u>

Next, we examine the spatial distribution of driver activity in both Los Angeles and Orange County. The home locations of driver respondents in the Los Angeles and Orange County areas are dispersed throughout the greater Southern California region, as shown in Figure 67 and Table 65. Analogous to Figure 65, the shading in Figure 67 shows the concentration of respondents, while the number within the region displays the rank ordering of respondent home locations within the county subdivision. The home county subdivisions with the greatest proportions of driver respondents were in the Los Angeles subdivision at around 21 percent, in the San Fernando Valley at about 17 percent, and in Anaheim–Santa Ana–Garden Grove, at nearly 9 percent of respondents. That is, nearly half of all respondent home locations were concentrated in these three county subdivisions. The remaining driver respondents resided in other cities within Los Angeles County or external regions of the metropolitan area. Overall, the majority of driver respondents resided within Los Angeles County, at 72 percent, while about 15 percent lived in Orange County. The remaining 13 percent were outside of Los Angeles and Orange Counties. Almost 9 percent of respondents live in San Bernardino or Riverside County.

Figure 67. Los Angeles Driver Respondent Home Location Ranked by Number of Respondents

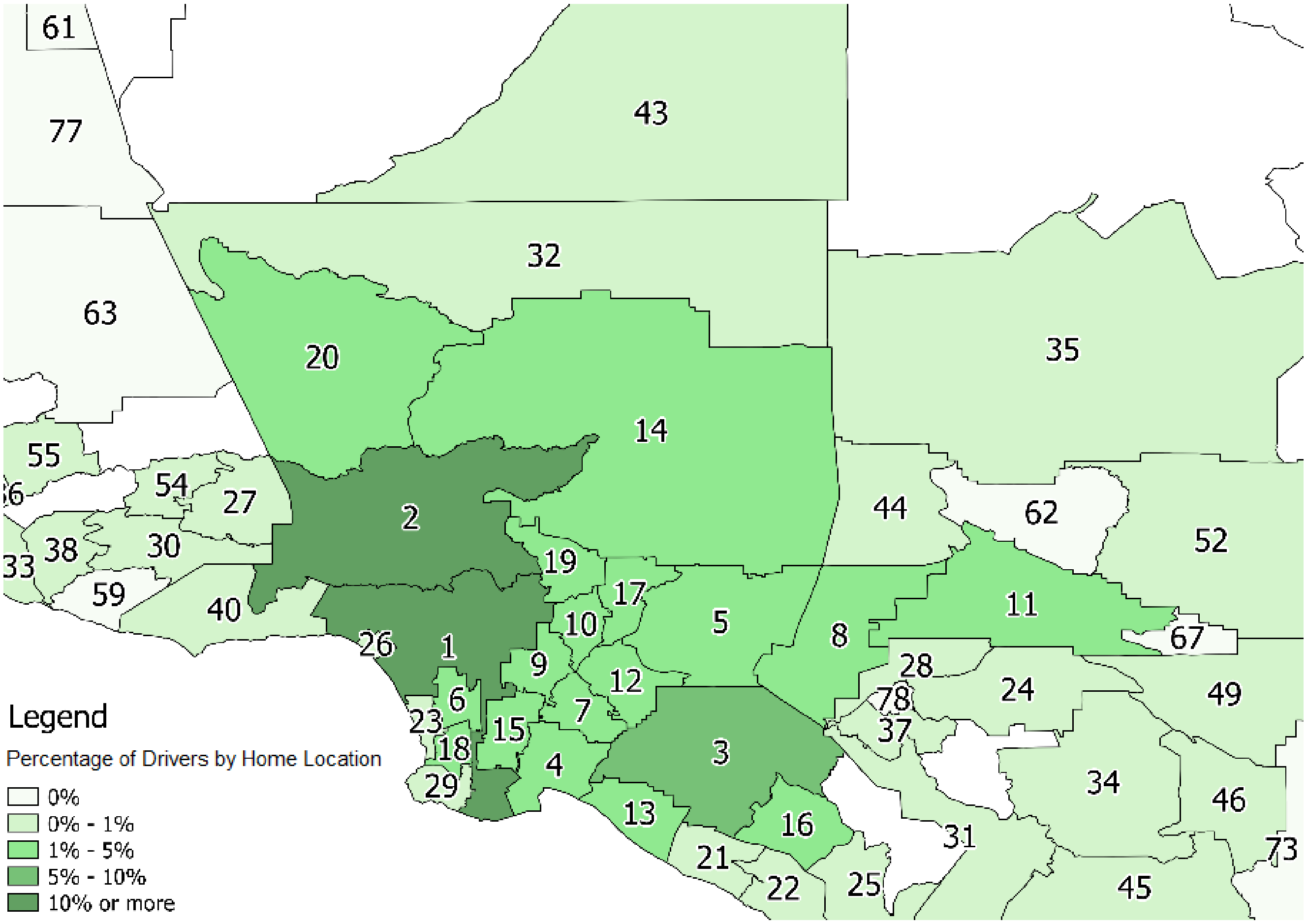


Table 65 displays the percentage of respondents residing in each home county subdivision, as well as the average distances to passenger markets by home location for the Los Angeles CBSA. Driver respondents residing in the Los Angeles County subdivision had an origin that is 8 miles away, on average, from their primary pickup market. Those residing in the San Fernando Valley had a slightly longer average access distance to their passenger markets, at 14 miles on average. Respondents residing in the more distant regions of San Bernardino and South Antelope Valley (which includes Palmdale) traveled some of the longest distances to their primary passenger market, at 32 miles and 29 miles on average, respectively.

Table 65. Los Angeles Driver Respondent Home Location and Average Distance to Passenger Market

Label	Home County Subdivision	Percentage of Respondents	Average Distance to Passenger Market Grouped by Home Location
1	Los Angeles	21.2	8
2	San Fernando Valley	16.9	14
3	Anaheim–Santa Ana–Garden Grove	8.6	10
4	Long Beach–Lakewood	4.6	14
5	East San Gabriel Valley	4.2	17
6	Inglewood	4.2	11
7	Downey–Norwalk	2.8	13
8	Ontario	2.6	22
9	South Gate–East Los Angeles	2.4	8
10	Southwest San Gabriel Valley	2.2	9
11	San Bernardino	2.1	32
12	Whittier	2.1	13
13	North Coast	2.0	11
14	South Antelope Valley	1.9	29
15	Compton	1.7	12
16	Irvine–Lake Forest	1.3	15
17	Upper San Gabriel Valley	1.3	12
18	Torrance	1.3	7
19	Pasadena	1.2	13
20	Newhall	1.1	22
21	Central Coast	1.0	8
22	South Coast	1.0	15

Los Angeles and Orange Counties—Primary Passenger Market and Average Distance by Market

As shown in Figure 68 and Table 66, about half of the driver respondents in Los Angeles and Orange Counties indicated somewhere within the Los Angeles County subdivision as their primary passenger market. Anaheim–Santa Ana–Garden Grove, the San Fernando Valley, Santa Monica, and Long Beach–Lakewood each represent 3 percent to 7 percent of driver respondents' passenger markets. Los Angeles County accounts for about 72 percent of respondents' primary passenger markets, Orange County represents 14 percent, and areas outside of these two counties compose the remainder. This passenger market proportion in Los Angeles and Orange Counties is comparable to the proportion of driver respondent home locations across the two counties. Although all of the three core cities in this study (San Francisco, Los Angeles, and Washington, D.C.) account for more than half of driver respondents' primary passenger market locations, the core county subdivision of Los Angeles had the lowest proportion out of the three, at just slightly over half of the respondents indicating it as their primary market.

Figure 68. Los Angeles Driver Respondent Primary Passenger Market

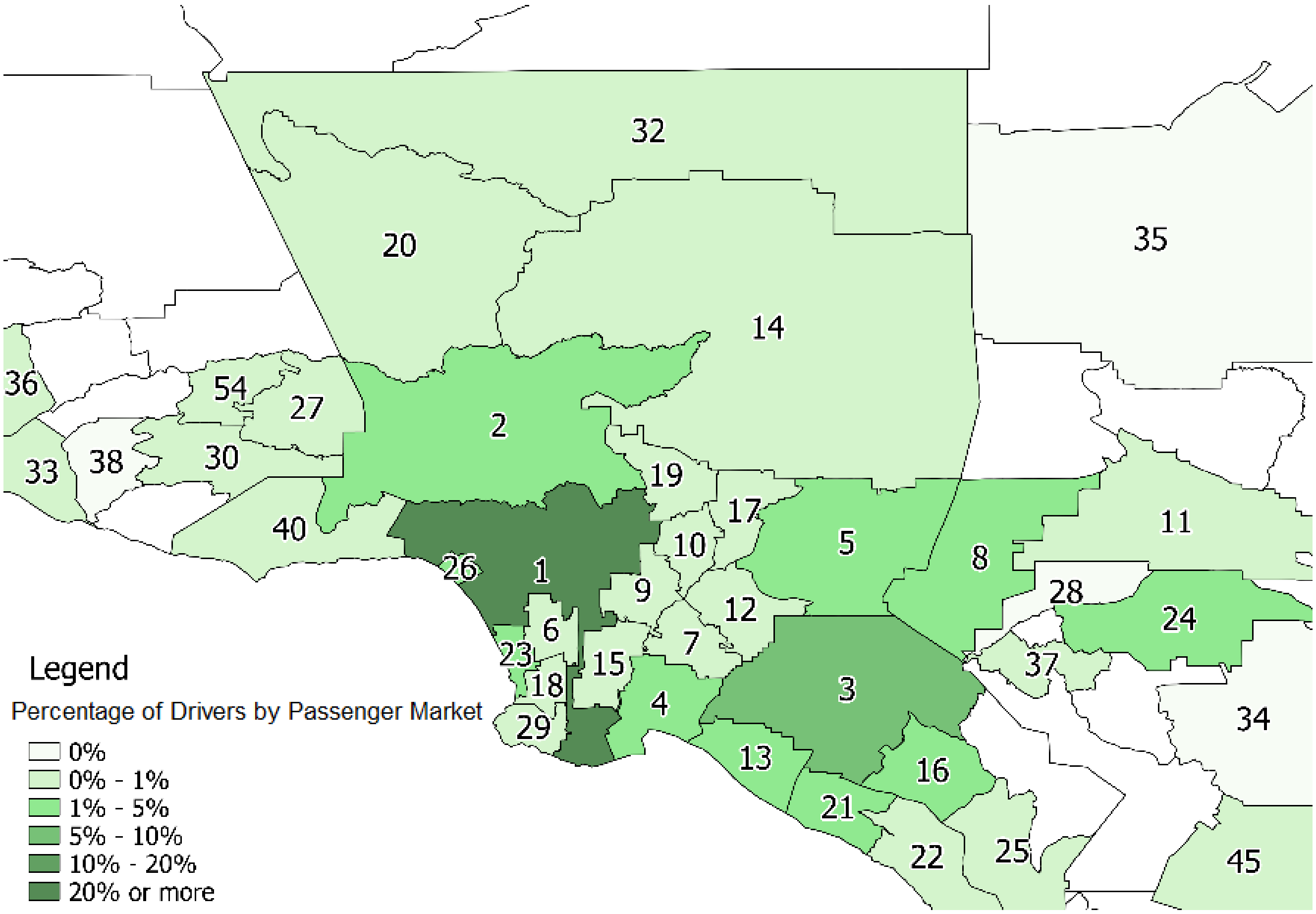


Table 66 shows the proportion of respondents and average distance to passenger market, disaggregated by passenger market as defined by market county subdivision locations. Driver respondents whose primary market was the Los Angeles County subdivision had an access to passenger market distance of 17 miles, on average. Respondents indicating Anaheim–Santa Ana–Garden Grove and the San Fernando Valley as their primary market had slightly lower access distances, at 11 and 7 miles on average, respectively. The Santa Monica market had one of the highest average distances by market location, at 19 miles on average. The primary passenger market and average distance distributions exhibited in the Los Angeles CBSA had patterns similar to those seen in the San Francisco CBSA. The most common core passenger market county subdivision, which is Los Angeles, had relatively higher average access distances among respondents, while the next most popular and less dense areas, like the San Fernando Valley and Anaheim–Santa Ana–Garden Grove, had relatively lower average access distances. This again suggests that more drivers would travel into the core Los Angeles area relative to those who served more suburban markets. Those who served suburban markets were more likely to be local or nearby residents.

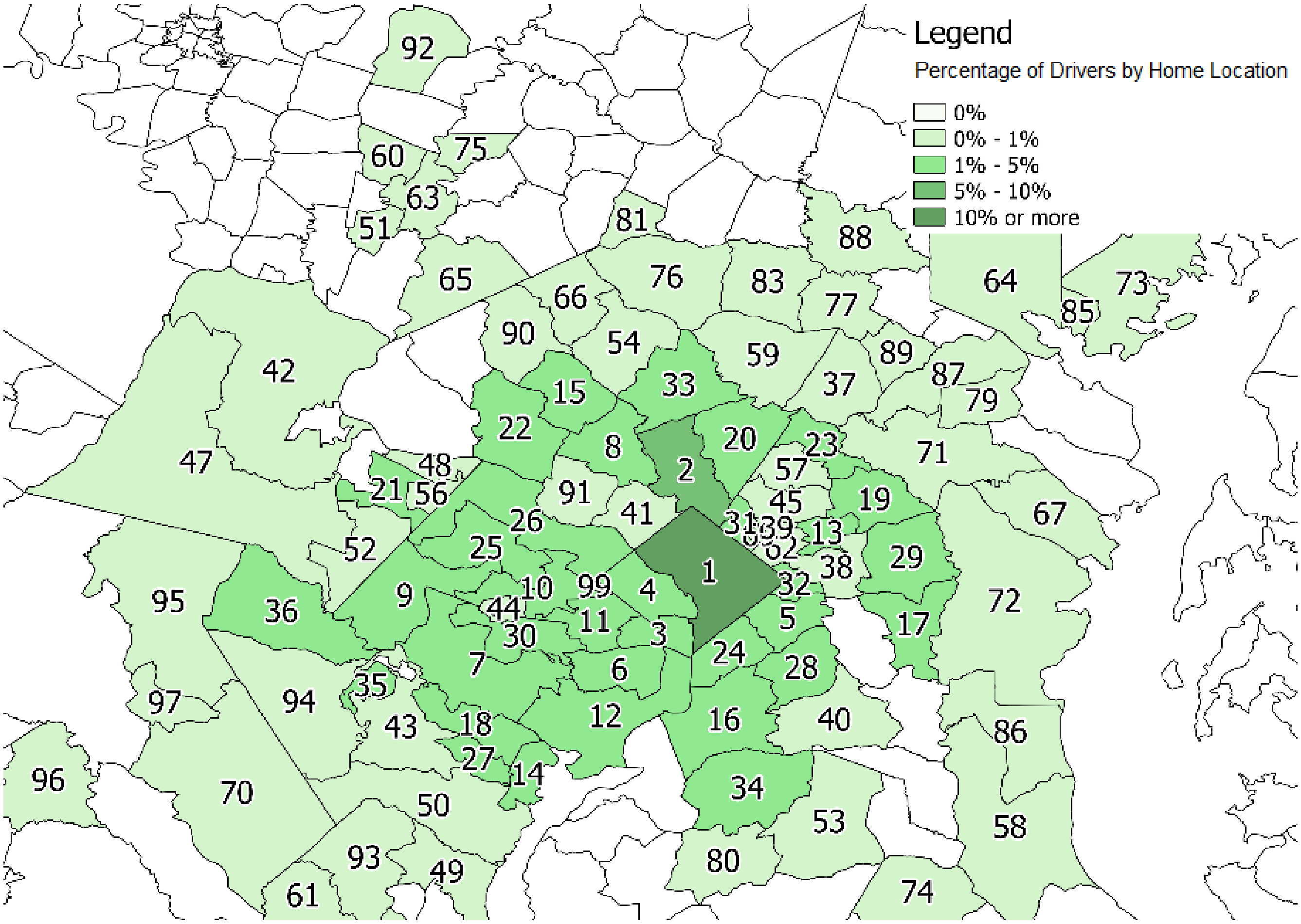
Table 66. Los Angeles Driver Respondent Primary Passenger Market and Average Distance to Passenger Market

Label	Market County Subdivision	Percentage of Respondents	Average Distance to Passenger Market Grouped by Market Location
1	Los Angeles	50.7	17
3	Anaheim–Santa Ana–Garden Grove	6.8	11
2	San Fernando Valley	4.7	7
26	Santa Monica	3.8	19
4	Long Beach–Lakewood	3.6	10
21	Central Coast	2.8	18
16	Irvine–Lake Forest	2.4	15
23	South Bay Cities	1.9	8
8	Ontario	1.8	10
13	North Coast	1.3	8
5	East San Gabriel Valley	1.3	5
24	Riverside	1.1	15

Washington, D.C. CBSA—Home Location and Average Distance to Passenger Market

Finally, we discuss driver respondent spatial findings in the Washington, D.C., CBSA. As shown in Figure 69 and Table 67 below, the driver respondent home locations were dispersed across the Washington, D.C., area. The highest proportion of respondents by county subdivision lived in the District itself, at 14 percent of respondents. About 43 percent of driver respondents resided in Virginia, and another 43 percent lived in Maryland. Nearly all of the drivers resided within the Washington-Arlington-Alexandria CBSA.

Figure 69. Washington, D.C., Driver Respondent Home Location Ranked by Number of Respondents



As expected, driver respondents who lived closer to Washington, D.C., tended to travel shorter average distances, as displayed in Table 67. The average access distance of those residing in Washington, D.C., and Arlington, Virginia, is 5 miles, and it is 7 miles on average for those residing in the nearby county subdivisions of Montgomery County, District 13 (Silver Spring, Maryland, and surrounding area), and Alexandria, Virginia. Driver respondents who live in Montgomery County, District 9 (Gaithersburg, Maryland, and surrounding area), and the Broad Run, Virginia, area drove some of the longest distances to their primary pickup market, at 23 miles on average.

Table 67. Washington, D.C., Driver Respondent Home Location and Average Distance to Passenger Market

Label	Home County Subdivision	Percentage of Respondents	Average Distance to Passenger Market Grouped by Home Location
1	Washington	14.0	5
2	Montgomery County, District 13	5.5	7
3	Alexandria	4.7	7
4	Arlington	3.6	5
5	Spauldings	3.5	12
6	Lee	3.5	13
7	Springfield	2.8	16
8	Montgomery County, District 4	2.6	13
9	Sully	2.5	17
10	Providence	2.5	10
11	Mason	2.4	8
12	Mount Vernon	2.4	15
13	Lanham	2.1	11
14	Woodbridge	2.0	19
15	Montgomery County, District 9	1.9	23
16	Piscataway	1.9	11
17	Marlboro	1.8	19
18	Occoquan	1.8	19
19	Bowie	1.7	11
20	Montgomery County, District 5	1.7	13
21	Broad Run	1.7	23
22	Montgomery County, District 6	1.5	18

Washington, D.C. CBSA—Primary Passenger Market and Average Distance by Market

Figure 70 shows the spatial distribution of passenger markets among driver respondents in the Washington, D.C. CBSA. Shown in Table 68, about 72 percent of respondents indicated a location within the District of Columbia as their primary passenger market. Nearly 8 percent of driver respondents considered Arlington or Alexandria their primary passenger market. About 6 percent of respondents chose somewhere in Montgomery County, Maryland, as their primary passenger market, with the remainder serving primary markets elsewhere. Out of the three study cities, Washington, D.C., proper had the highest proportion of driver respondents in the region who considered the city core to be their primary passenger market. This proportion is less than 60 percent in both the San Francisco and Los Angeles areas, but it is more than 70 percent in the Washington, D.C., area.

Figure 70. Washington, D.C., Driver Respondent Primary Passenger Market

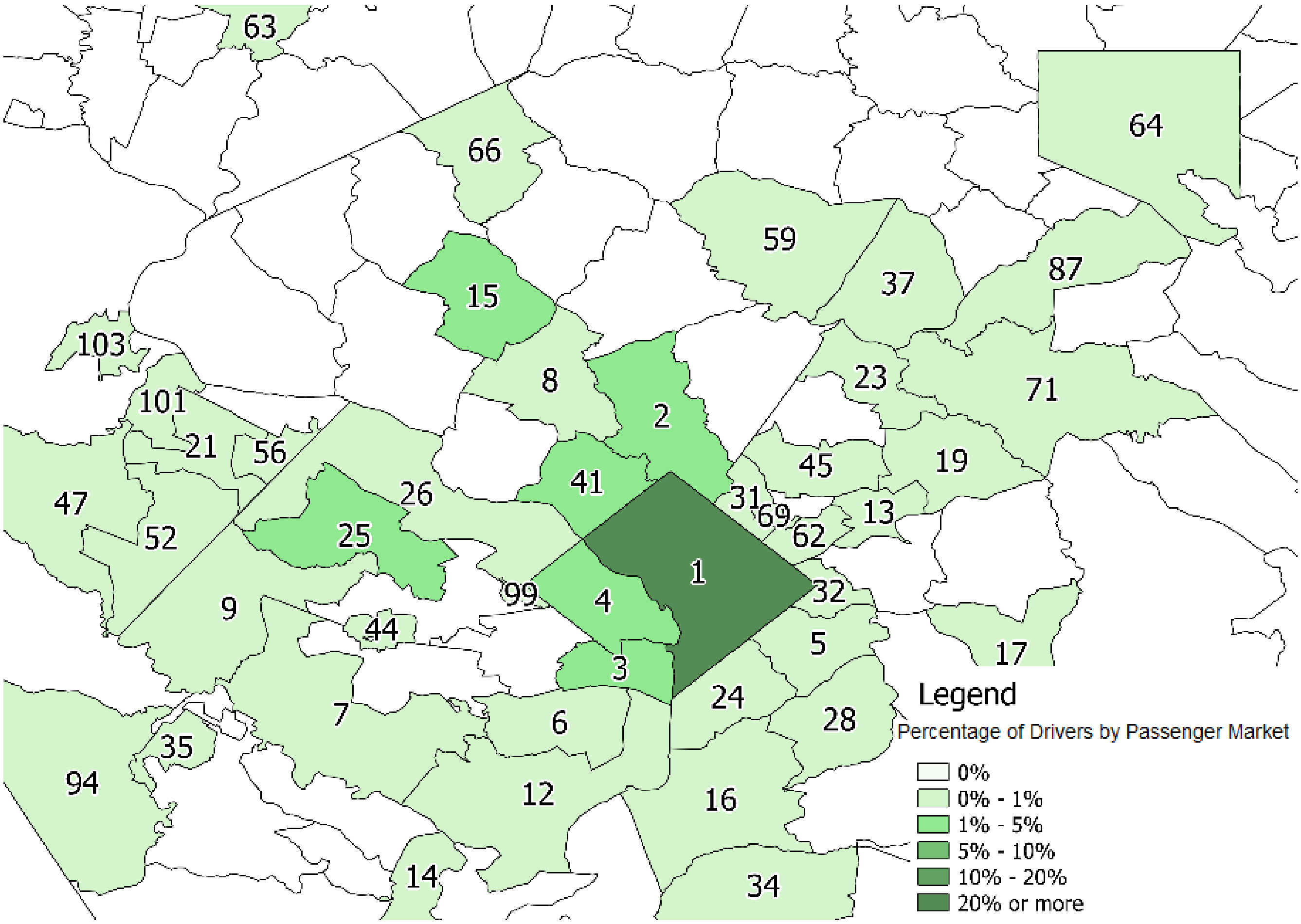


Table 68 shows the average access to market distance of driver respondents in the Washington, D.C., CBSA by passenger market, as well as the percentage of respondents considering the subdivision to be their primary passenger market. Only those subdivisions with 1 percent or more of respondents reporting it as a primary market are shown. This accounts for 86 percent of respondents; the remaining 14 percent are distributed among a collection of smaller markets. Driver respondents whose primary market was Washington, D.C., had an access distance of 16 miles, on average. This suggests that a fair number of drivers access the market from homes located outside the district. Out of the three study CBSAs, the Washington, D.C., area had the lowest proportion of driver respondents that lived within the core city, at just 14 percent. Respondents indicating Arlington or Alexandria as their primary market had slightly lower access distances at 12 miles for Arlington and 9 miles for Alexandria, on average.

Table 68. Washington, D.C., Driver Respondent Primary Passenger Market and Average Distance to Passenger Market

Label	Market County Subdivision	Percent of Respondents	Average Distance to Passenger Market Grouped by Market Location
1	Washington	71.9	16
4	Arlington	4.7	12
3	Alexandria	3.0	9
2	Montgomery County, District 13	1.8	10
15	Montgomery County, District 9	1.4	7
41	Montgomery County, District 7	1.3	12
25	Hunter Mill	1.2	8
14	Woodbridge	1.0	5

<u>Summary—Home and Primary Passenger Market Locations and Distance from Passenger Market</u>
Examining the home location, the primary passenger market, and the average distance to market data, we found that less than one-quarter of driver respondents across the San Francisco and Washington, D.C. CBSAs lived within the jurisdictional boundaries of San Francisco and Washington, D.C. Similarly, less than one-quarter of respondents in the Los Angeles CBSA resided within the core county subdivision of Los Angeles. Conversely, more than half of all respondents indicated the core city subdivision of each market as their primary passenger pickup market, with the highest proportion at almost 72 percent in Washington, D.C. Although many driver respondents did not live in the core city, most of the driver survey respondents resided within areas of immediate proximity. Only a small portion of our respondents lived in areas far outside of their respective CBSA, as discussed within this section. For example, only 12 percent of respondents in the San Francisco CBSA lived outside of the nine-county Bay Area, and just 13 percent of Los Angeles CBSA drivers resided in counties other than Los Angeles or Orange.

Naturally, those who live within the core study cities themselves have a shorter average distance to travel to their primary market, which is usually in the core city. These core city markets also reflect a higher average distance of travel to them because a large share of respondents in each CBSA travel to them from outside jurisdictions. However, the average distances are not exceptionally long commutes. In San Francisco, the average distance to market was 23 miles (Table 64), in the Los Angeles county subdivision it was 17 miles (Table 66), and in Washington, D.C., it was 16 miles (Table 68).

Comparatively, respondents who considered an area other than the core city to be their primary pickup market exhibited somewhat lower average access to market distances, likely because they lived closer to their stated passenger markets. Finally, we note that the findings in this section reflect our particular driver survey sample during late 2016. These spatial patterns may change over time, and the distributions of the contemporary driver populations may be different from those found in this driver survey. Nonetheless, these results offer insights into the dynamics of the geographic distribution of home and passenger market locations among TNC drivers across these three CBSAs.

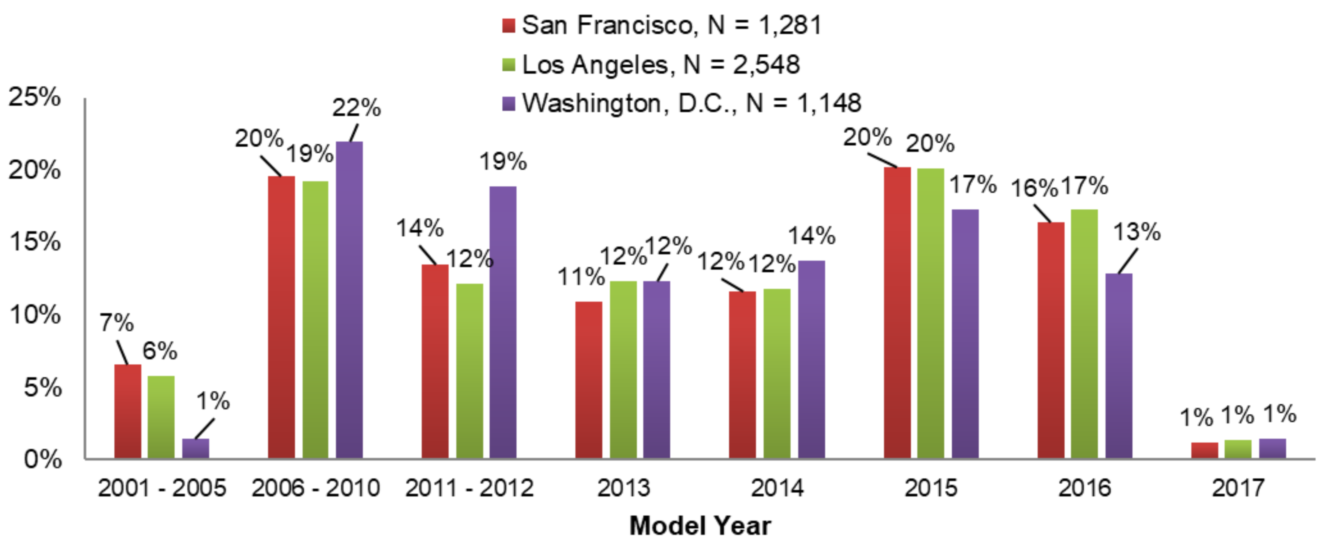
Vehicle Characteristics

We asked driver respondents questions regarding the vehicle they used for driving with Lyft and/or Uber, as well as whether that vehicle was purchased, at least in part, due to their driving with Lyft and Uber. This section presents results about driver respondents' vehicles, including the model year, vehicle type, and vehicle drivetrain, and about their vehicle purchases due to Lyft and Uber.

<u>Model Year</u>

We asked respondents to indicate the model year of the vehicle they use to drive with Lyft and/or Uber; their answers are displayed in Figure 71. Driver respondents had relatively new vehicles, in general. Both operators have vehicle age requirements that vary by city. More than half of our respondents in each of the three markets had a vehicle from model year 2013 or newer. The average vehicle in each of the three markets was approximately 4.5 years old at the time of the survey. This is much lower than the average age of 11.6 years for a typical car in the United States (IHS Markit 2016). Vehicles with a model year of 2005 or older are not very common, making up only 1 percent to 7 percent of respondents' vehicles, depending on the market.

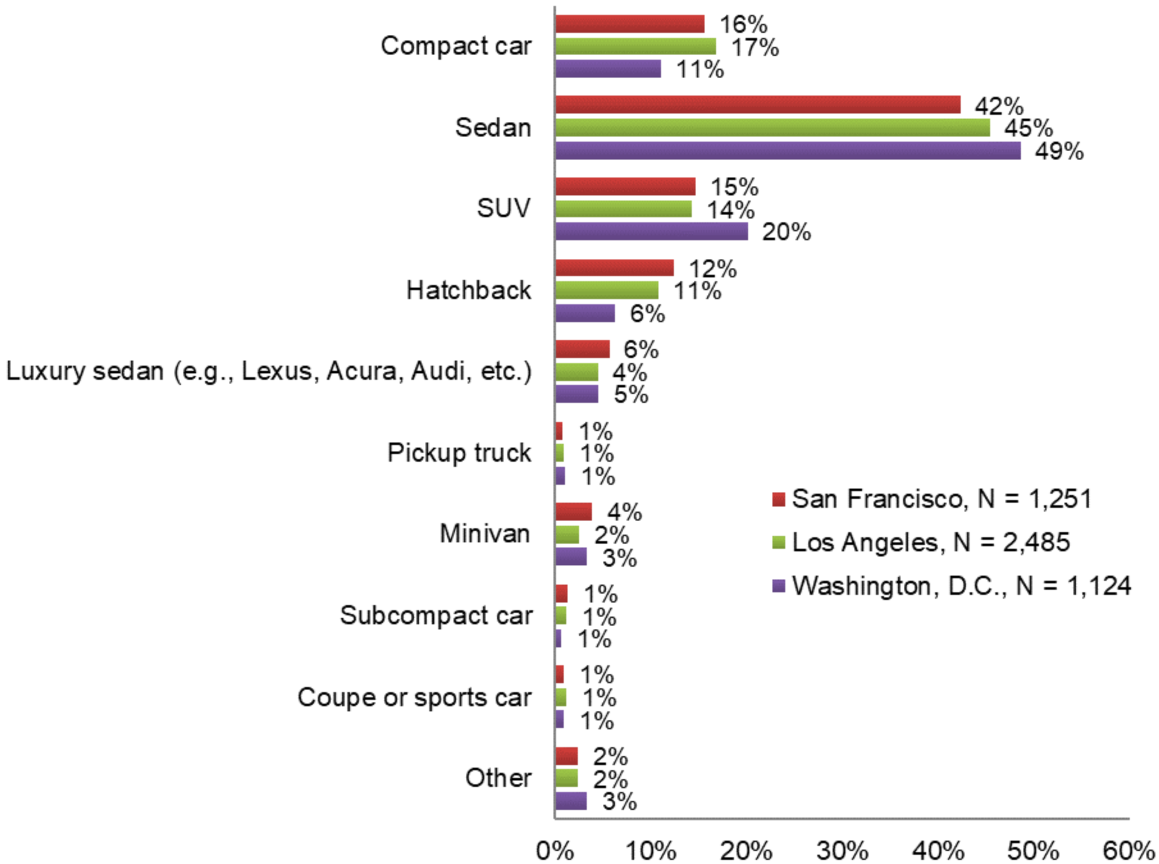
Figure 71. Vehicle Model Year



<u>Vehicle Type</u>

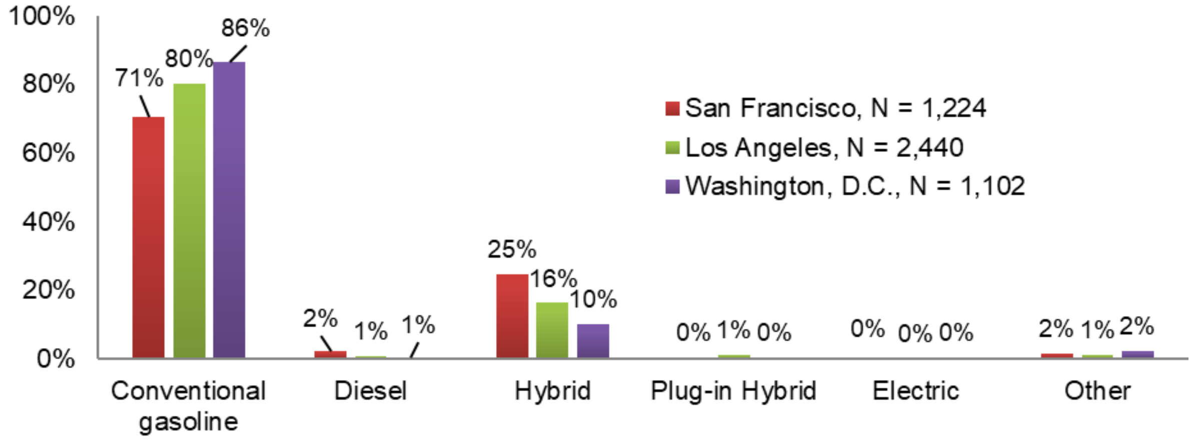
We asked respondents about the general type of vehicle they use to drive with Lyft and/or Uber, their responses are shown in Figure 72. Regular sedans were the most common vehicle type among driver respondents, with nearly half in each CBSA driving this vehicle type. In San Francisco and Los Angeles, sedans were followed by compacts, SUVs, and hatchbacks as the next most common vehicle types. In Washington, D.C., SUVs were the second most common vehicle type, with 20 percent of driver respondents owning these. A small portion of respondents drove luxury sedans (4 percent to 6 percent, depending on the market) as well as minivans (2 percent to 4 percent).

Figure 72. Vehicle Type



<u>Vehicle Drivetrain</u>
The survey also asked driver respondents about their vehicle drivetrain. As shown in Figure 73, Conventional gasoline vehicles were the most common among driver respondents, with 71 percent in San Francisco, 80 percent in Los Angeles, and 86 percent in Washington, D.C., owning this type of car. Hybrids were the next most common, making up 25 percent of respondents' vehicles in San Francisco, 16 percent in Los Angeles, and 10 percent in Washington, D.C. These proportions were much higher than the overall share of hybrid vehicles in the United States at the time of the survey, which was only about 2 percent in 2016 (U.S. EIA 2018). Since fuel costs are among the largest expenses of TNC drivers, it follows that many opt to drive more fuel-efficient vehicles, like hybrids. Small portions of driver respondents reported having a diesel, plug-in hybrid, electric, or other vehicle drivetrain in this survey. It is likely that the share of all-electric vehicle is higher that it was at the time of the survey.

Figure 73. Vehicle Drivetrain



<u>Vehicle Purchasing Due to Lyft and Uber</u>

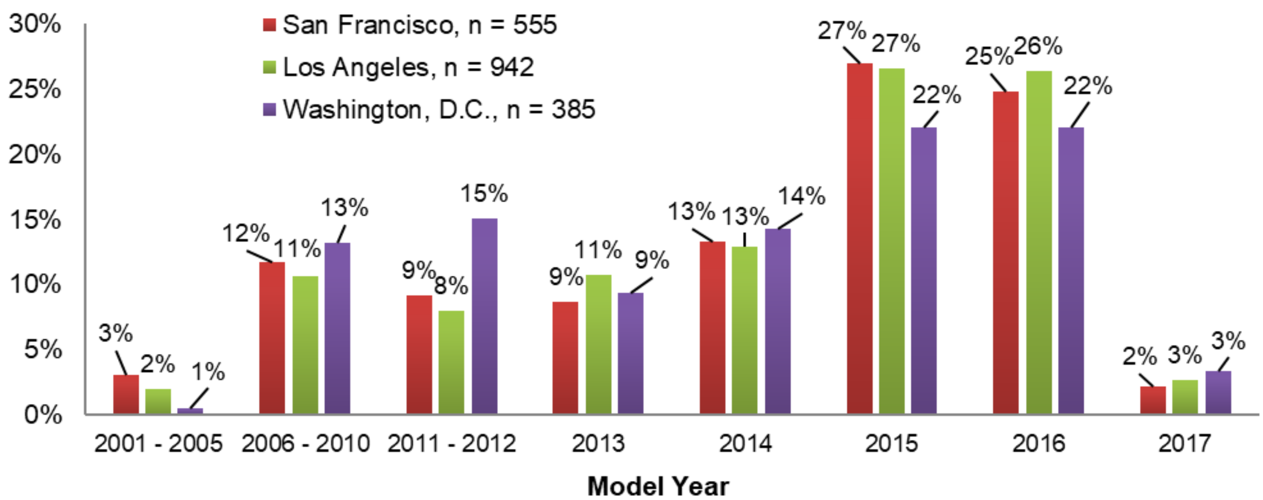
We asked driver survey respondents whether they purchased their vehicle specifically to drive with Lyft and Uber. As shown in Table 69, below, although the majority of driver respondents in each CBSA had their vehicle prior to driving with Lyft or Uber, a notable portion claimed to have purchased a vehicle either partially or primarily due to TNCs. Forty-three percent of respondents in San Francisco, 37 percent in Los Angeles, and 34 percent in Washington, D.C., reported that they bought or leased a vehicle either primarily or partially due to driving with Lyft and Uber. Although these rates likely vary across driver samples and may change over time, it shows that a significant portion of vehicle purchases were attributable to Lyft and Uber among TNC driver respondents. Interestingly, a greater proportion of respondents across all three markets said they acquired a vehicle *primarily* due to driving with Lyft or Uber than reported doing so only *partially* due to TNCs.

Table 69. Vehicle Purchase Caused (or Not) by Lyft and Uber

Did you purchase your vehicle specifically to drive with Uber and/or Lyft?	**San Francisco, N = 1293**	**Los Angeles, N = 2541**	**Washington, D.C., N = 1139**
No, I had this vehicle prior to driving with Uber and/or Lyft.	51%	58%	62%
No, I purchased/leased this vehicle after starting to drive with Uber and/or Lyft, but they did not significantly influence my decision to purchase/lease a vehicle.	6%	5%	4%
Yes, I purchased/leased this vehicle *partially* due to my driving with Uber and/or Lyft.	16%	15%	12%
Yes, I purchased/leased this vehicle *primarily* due to my driving with Uber and/or Lyft.	27%	22%	22%

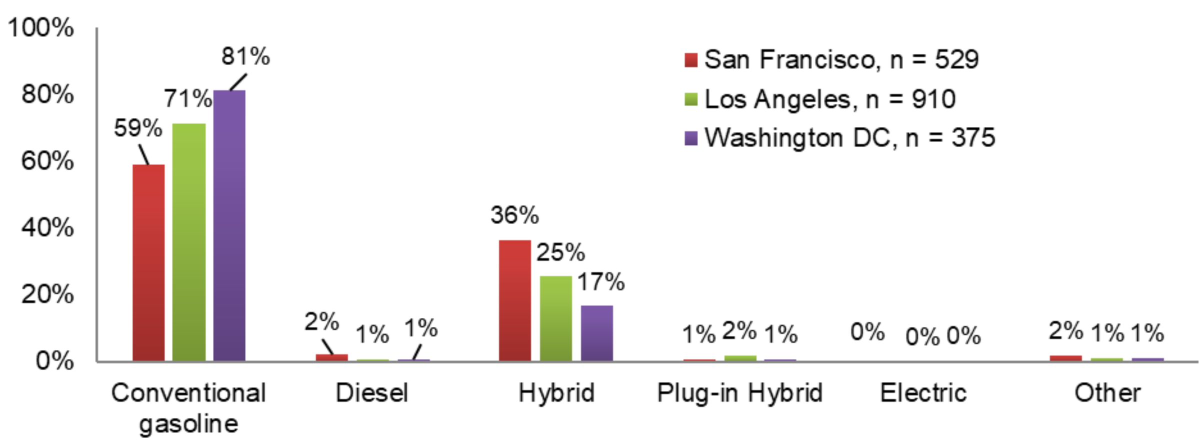
Model Year and Drivetrain of Acquired Vehicles
Those who bought or leased a vehicle at least partially due to their driving with Lyft and/or Uber numbered 560 respondents in San Francisco, 946 in Los Angeles, and 387 in Washington, D.C. The vehicles that were acquired by this subpopulation tended to be newer than those owned by the broader population of driver survey respondents. Figure 74 shows that at least 70 percent of vehicles acquired due to Lyft and Uber across all three markets were model year 2013 or newer. The average age of these vehicles was about 3.5 years.

Figure 74. Model Year of Vehicles Acquired by Drivers Due to Lyft or Uber



In addition, hybrid drivetrains constituted a sizable portion of driver respondent vehicles purchased or leased due to TNCs, as displayed in Figure 75. Thirty-six percent of these vehicles in San Francisco were hybrids, as were 25 percent in Los Angeles and 17 percent in Washington, D.C. These were greater shares of hybrids, by 7 to 11 percentage points, than existed in the overall surveyed driver populations, depending on the CBSA. These findings suggest that drivers who acquired a vehicle at least in part due to driving with Lyft and/or Uber were more likely to get a hybrid vehicle than the average TNC driver.

Figure 75. Drivetrain of Vehicle Acquired Due to Lyft or Uber



Summary—Vehicle Characteristics
The vehicle characteristics questions in our driver survey provide insight into vehicles used by those driving with Lyft and Uber as well as vehicles that were acquired due to TNC activity. We found that TNC vehicles were typically much newer than the average car in the United States, as our driver respondents' average vehicle age was 4.5 years as compared to the average U.S. vehicle that was more than 11 years old at the time of the survey (IHS Markit 2016). The average age of U.S. vehicles has generally been over decade for a number of years. The most common general vehicle types among driver respondents were sedans, while other common types included compacts and SUVs. The majority of driver survey respondents owned a conventional gasoline vehicle. However, a sizable portion owned a hybrid vehicle, most notably in San Francisco, where 25 percent of driver respondents owned a hybrid. Although the majority of drivers in our survey owned their vehicle prior to driving with Lyft or Uber, about 43 percent in San Francisco, 37 percent in Los Angeles, and 34 percent in Washington, D.C., purchased a vehicle either partially or primarily due to TNCs. These vehicles tended to be newer (3.5 years old, on average) and included a higher share of hybrids than existed in the overall driver respondent population.

Population-Level Vehicle Registrations and Estimated Changes due to TNCs

As a notable portion of the population within the three study CBSAs use TNCs, the analysis explored whether vehicle ownership impacts were visible at the population level using available data. This was done using vehicle registration data across the three CBSAs. The data for this purpose is imperfect. There are many factors beyond just TNCs that contribute to fluctuations in vehicle registrations, including economic factors, population growth, gasoline prices, among others. In addition (as will be shown in Washington D.C.), large registration events by a government or industry can cause anomalies in the data that can confound broader observations. Nonetheless we investigated whether estimated vehicle impacts due to TNCs would have been realistic within the context of yearly changes in total vehicle registrations. To assess this, we estimated the total population of Lyft or Uber passengers that were represented by the passenger survey sample. Then, with factors derived from the survey, we estimated the vehicles removed from the population within each CBSA. We compared those estimates with trends in vehicles registered within each CBSA and the core city of each market.

Trends in Total Vehicles Registered by CBSA
We first present longitudinal vehicle registration data within the three CBSAs. For the San Francisco and Los Angeles CBSAs, we used data received from the California Department of Motor Vehicles (DMV) on estimated vehicle registrations by county (California DMV, 2020). The data divide registrations by general vehicle type. We included the 'Auto' and 'Truck' (which includes pickup trucks) vehicle types to produce estimates of registered passenger vehicles. For the Washington, D.C. CBSA, we used data from a variety of sources since the CBSA includes areas spanning two states and the District of Columbia. For the District of Columbia, we used motor vehicle registration data from the District of Columbia DMV (DC DMV, 2020). For the state of Virginia, we used vehicle registration statistics by jurisdiction provided by the Virginia DMV (Virginia DMV 2020). Finally, for Maryland, we used vehicle registrations by county from the Maryland Motor Vehicle Administration (MVA 2020). We included passenger vehicle and light-duty truck vehicle types for the Virginia counties, private and commercial automobiles and trucks for Washington, D.C., and total vehicle registrations (which were not reported by vehicle type) for the Maryland counties due to data definition differences. We chose to use 2010 as the starting year because it is a couple of years prior to the emergence of TNC services (like Lyft and uberX) in 2012 and has some distance from start of the

Great Recession. The series ends in 2019 and thus all results here reflect trends and events preceding the global disruptions of the pandemic.

Since vehicle ownership rates are influenced by population and its growth rate, we also display the population sizes in each CBSA of those 18 years and older over the corresponding time period and used these data to calculate vehicle registrations per capita (+18). We applied the American Community Survey one-year estimates for the San Francisco and Los Angeles CBSAs, and five-year estimates for the Washington, D.C. CBSA. This higher level of time aggregation is due to the lack of one-year estimates for many of the smaller jurisdictions within the Washington D.C. CBSA (U.S. Census ACS 2016). The vehicle registration and population data within the three CBSAs are shown in Table 70 through Table 72 along with derivative calculations below.

Table 70. Vehicle Registration and Population Changes in San Francisco CBSA

Year	Vehicle Registrations	Year-Over-Year Change in Registrations	CBSA Population (18 and older)	Vehicle Registrations per Capita over 18
2010	3,258,670	-	3,423,935	0.95
2011	3,244,268	-14,402	3,467,619	0.94
2012	3,294,122	49,854	3,527,655	0.93
2013	3,392,693	98,571	3,585,124	0.95
2014	3,465,136	72,443	3,657,752	0.95
2015	3,552,756	87,620	3,716,734	0.96
2016	3,640,807	88,051	3,739,464	0.97
2017	3,659,545	18,738	3,789,565	0.97
2018	3,682,093	22,548	3,798,163	0.97
2019	3,746,967	64,874	3,807,683	0.98

Table 71. Vehicle Registration and Population Changes in Los Angeles CBSA

Year	Vehicle Registrations	Year-Over-Year Change in Registrations	CBSA Population (18 and older)	Vehicle Registrations per Capita over 18
2010	9,258,508	-	9,709,067	0.95
2011	9,229,002	-29,506	9,829,315	0.94
2012	9,352,475	123,473	9,958,037	0.94
2013	9,599,512	247,037	10,081,702	0.95
2014	9,800,815	201,303	10,236,630	0.96
2015	10,018,399	217,584	10,344,073	0.97
2016	10,301,941	283,542	10,344,691	1.00
2017	10,313,471	11,530	10,423,003	0.99
2018	10,330,891	17,420	10,403,807	0.99
2019	10,474,419	143,528	10,380,574	1.01

Table 72. Vehicle Registration and Population Changes in Washington, D.C. CBSA

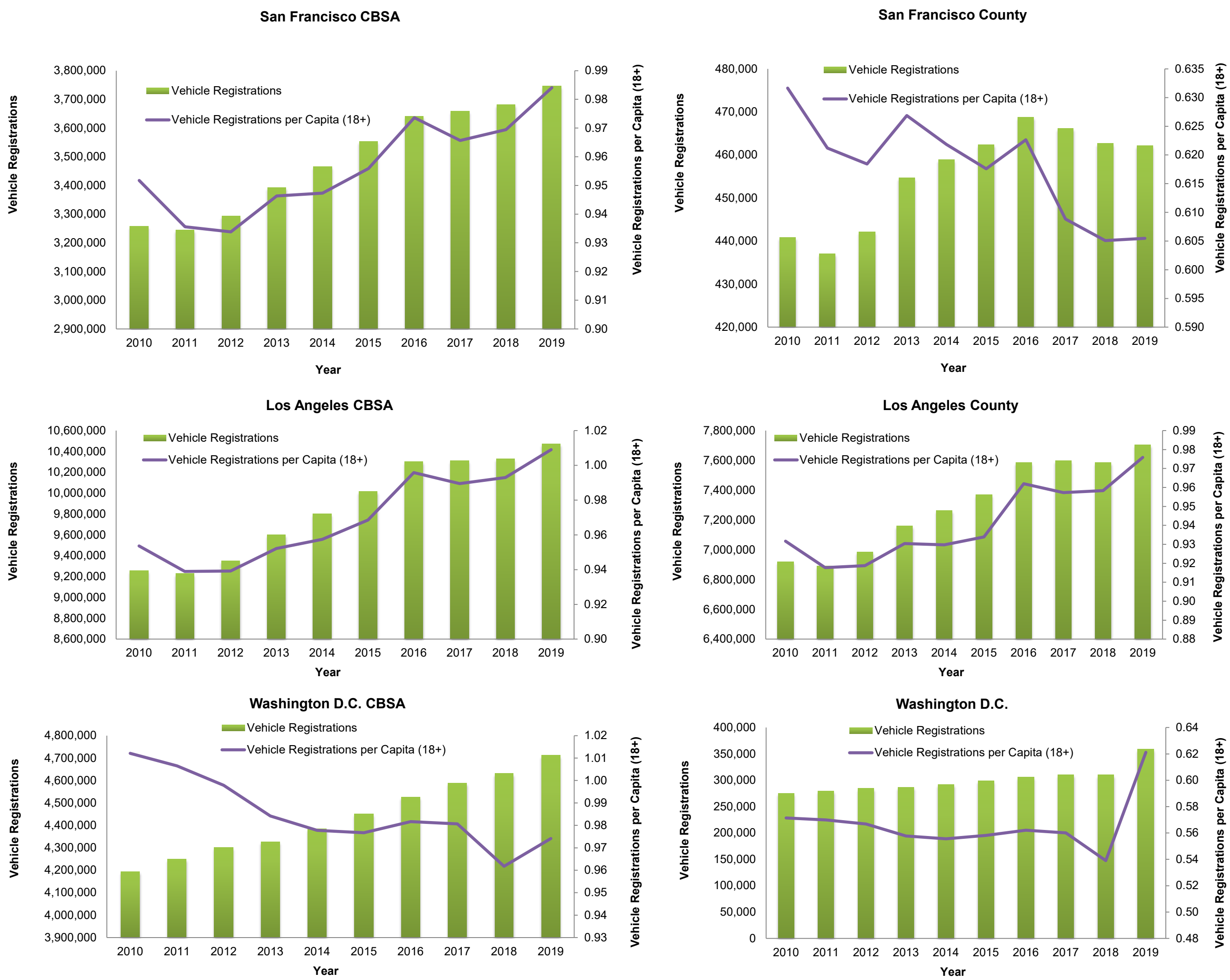
Year	Vehicle Registrations	Year-Over-Year Change in Registrations	CBSA Population (18 and older)	Vehicle Registrations per Capita over 18
2010	4,194,047	-	4,143,888	1.01
2011	4,249,533	55,486	4,222,059	1.01
2012	4,302,152	52,619	4,311,464	1.00
2013	4,327,046	24,894	4,396,638	0.98
2014	4,385,479	58,433	4,485,144	0.98
2015	4,452,028	66,549	4,558,185	0.98
2016	4,525,383	73,355	4,609,735	0.98
2017	4,588,383	63,000	4,678,886	0.98
2018	4,630,906	42,523	4,815,061	0.96
2019	4,711,912	81,006	4,837,112	0.97

In the two California CBSAs, total vehicle registrations have grown each year since 2012, likely due to both the economic recovery and population growth after the years following the Great Recession. Registrations in these two CBSAs grew steadily from 2012 to 2016 at an annualized rate of 2.53% in San Francisco and 2.45% in Los Angeles. From 2016 to 2019, the registration growth rate dropped substantively to an annualized rate of 0.96% in San Francisco and 0.55% in Los Angeles. Similarly, vehicle registrations per capita (+18) grew at an annualized rate of 1.05% in the San Francisco CBSA and 1.48% in Los Angeles CBSA from 2012 to 2016. From 2016 to 2019, registrations per capita grew slower at an annualized rate of 0.36% in San Francisco and 0.44% in Los Angeles.

The registration trends in the Washington D.C. CBSA show somewhat linear growth from year to year. Overall, registration growth rates were lower. The average annualized growth rate from 2012 to 2016 is 1.27%. From 2016 to 2019, the annualized growth rate rose slightly to 1.36%. For registrations per capita, there was a decline at an annualized rate of 0.41% from 2012 to 2016. From 2016 to 2019, registrations per capita declined at annualized rate of 0.26%.

Analysis of the core cities within each CBSA shows similarities in trends, but there are also some distinctions specific to the urbanization present within San Francisco, Los Angeles, and Washington D.C. Registration and vehicle per capita (+18) trends are shown for these core jurisdictions alongside their broader CBSAs in Figure 76 below. A review of this figure will show the 2019 observation in Washington D.C. is a notable one for being significantly out of trend. According to the District of Columbia DMV, this out of trend data point was the result of 1) a moderate increase in personal/private class vehicle purchases, 2) a significant replacement of government fleets and taxi cabs, and less significantly 3) 500 Motor Driven Cycles (MDC) that were approved by the DDOT and were registered and placed on the streets of the District of Columbia. Besides the small number of MDC registrations, the impacts from these events could not be disentangled. The resulting increase is so large that it represents a one-year growth of 15.8% in registrations within the district. This contrasts with an average annualized growth rate of 1.5% from 2010 to 2018.

Figure 76. Registration Trends in CBSAs versus Core City Jurisdictions



The figures on the left replot the registrations and vehicle registrations per capita (18+) that are presented in Table 70, Table 71, and Table 72. The figures on the right show the analogous data exclusively for the core CBSA jurisdiction, i.e., San Francisco County, Los Angeles County, and Washington D.C. As with the CBSA, the trends in San Francisco show a rise in registrations during the middle of the decade. But this peaks in 2016, and it exhibits a decline from 2017 through 2019. The San Francisco trend in registrations per capita (18+) shows a slight but steady decline through 2018 before leveling off at 0.61 registrations per capita (18+) in 2019. Growth in Los Angeles CBSA and county registrations is visible from 2012 to 2016. It starts to level off from 2016 to 2018, and increases again in 2019. Registrations per capita (18+) also exhibit a dip during 2017 to 2018 before rising again in 2019. Finally, the comparison between the Washington D.C. CBSA and the core D.C. district show trends similar to each other. The larger CBSA shows vehicle registration growth but an overall decline in registrations per capita (18+). The core district also shows registration growth from 2010 to 2018 (1.5% annual average as noted above). As noted earlier, there is an out-of-trend 15% increase in registrations in 2019 strictly within the district that is due to reasons largely outside of growth in personal vehicles (see above for details). This final observation causes the trend within Washington D.C. (lower right) to depart significantly from the declines in registrations per capita (18+) through 2018. The trend through 2018 suggests a gradual decline in registrations per capita (18+), but the true observation is unknown because the effect of these confounding events cannot be disentangled with available data. As for the broader Washington D.C. CBSA, the effect is present but not as large. The CBSA witnessed a trend of general decline in registrations per capita (18+) through 2019, sharing the experience of the City of San Francisco.

Registrations are influenced by a number of exogenous trends, including economic and population growth. Commercial activity also influences vehicle registrations and such agency data cannot easily disentangle vehicles dedicated for commercial use. While many factors impact registration changes, it is possible that some impact on registration trends would be visible given the size and scale of Lyft and Uber operations before the pandemic. This may come in the form of vehicle registration declines or through the reduction of growth that would otherwise occur. Trends in vehicle registrations and registrations per capita (18+) show some departure from the growth observed before Lyft and Uber achieved significant scale (e.g., around 2016). Furthermore, these departures have occurred during periods in which economic growth has been robust and otherwise undisturbed by economic major events. These observations do not prove that the changes are directly caused by the presence of Lyft and Uber, but such changes would be consistent with the findings of this study when extended to a larger population.

Population of Lyft or Uber Passengers represented by Survey Sample

In evaluating vehicle registration trends, and the changes seen within recent years, there arise questions as to the potential order of magnitude that vehicle shedding and suppression could have on regional registrations respectively. To advance the evaluation of these questions, we estimate the number of vehicles that may be removed due to TNCs in each of the three CBSAs. First, we estimate the total size of passenger survey population Lyft and Uber passengers in each of the CBSAs. Using the control survey and citing a national survey sample collected by the Pew Research Center (Jiang 2019), we estimate the portion of active TNC passengers in each of the three CBSAs. Next, we generate estimates for the total number of Lyft and Uber passengers in each CBSA that matches our passenger survey population as shown in Table 73.

In the passenger survey, we defined the passenger survey population as those who had used Lyft or Uber services (combined) at least seven times during the study year. As an overall population estimate, the Pew dataset found that 36% of U.S. adults used TNC services (in 2018). Of that population, 10% used them weekly, 22% monthly, and 67% used the services less than once a month.

Those using Lyft and Uber weekly and monthly unequivocally fall within the definitions of our passenger survey population. It is the third category that presents some uncertainty. Less than once a month equates to 11 times a year or less. If this frequency was uniformly distributed, then about 45% of this category would fall within seven uses or above. In reality, it is probably a little lower than that, since the distribution likely skews towards zero, with a balance of respondents within the category using the service less frequently. We can evaluate this through an exercise of approximation. If we assume 40% of this 67% that use the services less than once a month per year employ them at least seven times per year, then taken together with the broader population more frequently using TNCs as defined above, we derive an estimate of about 21% of the overall U.S. population using TNCs at least seven times per year. We can generate a similar estimate from the control survey, where we asked respondents to estimate how many times they had used Lyft and Uber (combined) over the past year. The percentage of total respondents that had used TNCs five times or more in the past year was 29% in San Francisco and Los Angeles and 24% in Washington, D.C. Taking the midpoint of these estimates from the Pew study and our control survey, we estimate the percentage of the general population that would fall within the passenger survey population. These data are shown in Table 73 below.

Table 73. Estimated TNC Passenger Survey Population by CBSA

CBSA	2016 CBSA Population (18 and older)	Estimated % of General Population in Lyft/Uber Passenger Survey Population			Lyft/Uber Passenger Survey Population Estimate
		Generated from Pew Study	Generated from Control Survey	Midpoint Estimate	
San Francisco	3,739,464	21%	29%	25%	930,481
Los Angeles	10,344,691	21%	29%	25%	2,574,041
Washington, D.C.	4,609,735	21%	24%	23%	1,050,467

Not surprisingly, we find the Los Angeles CBSA has the largest number of estimated TNC passengers, at approximately 2.57 million, followed by the Washington, D.C. CBSA at 1.05 million and the San Francisco CBSA at 0.93 million. Recall that our population in this table is defined as an estimate of those who had used TNC services at least seven times during the study year.

Estimate of Vehicles Removed from the Population

Next, we apply the net personal vehicle change per respondent percentages from this study to this population to estimate the total vehicles removed due to TNCs in each CBSA. Results are displayed in Table 74 below.

Table 74. Total Estimated Personal Vehicles Removed due to TNCs by CBSA

CBSA	Estimated Lyft and Uber Passenger Survey Population	Net Personal Vehicle Change per Respondent	Total Vehicles Reduced due to Lyft/Uber
San Francisco	930,481	-10.5%	97,700
Los Angeles	2,574,041	-10.9%	280,570
Washington, D.C.	1,050,467	-7.4%	77,735

Total estimated personal vehicles removed due to TNCs range from about 78,000 in Washington, D.C. to about 281,000 in Los Angeles. It is important to note that these numbers should be thought of as static with the population. That is, while VMT and GHG impacts are annual in nature, recurring each year that eliminated vehicles are not driven, vehicle suppression and sale impacts remain fixed year to year, but they can change should the impacted population grow or shrink or the rates of suppression, shedding, and acquisition change significantly within the population. For example, someone who reports shedding a vehicle due to Lyft and Uber may have done so several years prior. The driving impacts are annual, while only a single vehicle remains removed. Similarly, a respondent who suppresses a personal vehicle purchase due to TNCs may sustain this suppression effect across multiple years, while Lyft and Uber (and possibly other modes) provide the necessary mobility. Any annual change in vehicles removed due to Lyft and Uber is the change in vehicles shed and suppressed by new members of the population who employ TNCs in substitution of personal vehicle ownership, as well as the net impact of existing members who may even shift their impacts over time. For example, Lyft and Uber may suppress the need of a personal vehicle for a passenger for a while (e.g., a number of years). But eventually, that passenger's needs might change, and with those changes Lyft and Uber may no longer serve as a personal vehicle substitute, even if they continue to use TNCs with some frequency. Passengers within the population may pass in and out of this and other states of vehicle impact during their course of use. The important measure is the balance of these impacts over time within the population. Collectively, these estimates reflect the total personal vehicles removed due to TNCs rather than a rate of vehicle removal.

When we apply the impact percentages to the population of the core cities of the CBSAs, we can estimate the magnitude of vehicle impacts within these jurisdictions. Naturally, it is unlikely that the population within the core CBSA jurisdiction and the broader CBSA are impacted at uniform rates. However, the estimation of core city impacts can reveal the order of magnitude of estimated impact values relative to vehicle registration trends within plots on the right side of Figure 76 above. The estimated impacts for the core jurisdictions are shown in Table 75 below.

Table 75. Total Estimated Personal Vehicles Removed due to TNCs by Core City

County or District	Estimated Lyft and Uber Passenger Survey Population	Net Personal Vehicle Change per Respondent	Total Vehicles Reduced due to Lyft/Uber
San Francisco	187,345	-10.5%	19,671
Los Angeles	1,961,953	-10.9%	213,853
Washington, D.C.	126,321	-7.4%	9,348

The results shown in Table 74 and Table 75 provide context as to what the survey results imply for vehicle impacts given the estimated size of the total population represented in the passenger survey. For clarity, we again note that these estimated population sizes were produced using external information that was not supplied by the operators. In that way, they do not directly connect with other calculations of the study, but rather serve as a calculation exercise of assessing the plausible order of magnitude of vehicle impacts. The estimated population includes users of both operators.

The vehicle removal is manifested in the form of reduced registrations by the population as well as reduced registration growth. In other words, growth that would have happened in the absence of TNCs does not happen. Both of these effects are likely at play in several of the plots shown in Figure 76 above. In all cases, the estimated TNC vehicle impact would comprise a relatively small percentage of total registrations. In the CBSAs, the percent of estimated vehicles removed would constitute between 1.7% and 2.7% of registrations in 2016. In the core jurisdictions, where slightly more pronounced changes in trend are noted, estimated reductions in vehicles comprise 3.1% to 4.2% of all registrations in 2016.

Changes in the growth rates of vehicle registrations and/or registrations per capita also occurred during this period, with some changes larger than others. Both the San Francisco and Los Angeles CBSAs follow similar patterns of significant growth in vehicle registrations from 2012 to 2016, followed abruptly by much more modest growth from 2016 to 2019 and stagnations in vehicles registered per capita during this time as well. The core jurisdictions show either similar or more pronounced changes in vehicle registrations and registrations per capita (+18) trends. These variations and trend changes are very likely due to factors beyond the presence of TNCs. But the timing of reduced growth in vehicle registrations does not coincide with any other major shocks to the economy that would have obviously dampened vehicle demand (such as reduced economic growth or higher fuel prices). It does align with a period in which TNC use was rising considerably in the U.S. The Pew Research Center found that the share of Americans who have used TNCs has more than doubled since 2015, from 15% in 2015 up to 36% in 2018 (Jiang 2019).

Ultimately, using derivatives of the survey analysis and exogenous data on vehicle registration trends, we find the estimated magnitudes of net personal vehicle changes that could have been due to TNCs in the three CBSAs are in line with plausible changes observed in magnitudes and growth rates within the context of population-level vehicle registrations and registrations per capita (+18).

Conclusion and Policy Recommendations

TNC services have grown rapidly across the world since they launched in San Francisco in August 2012. Lyft, Uber, and their global counterparts, which continue to evolve, provide on-demand mobility services that are altering travel choices and behavior. While there are clear benefits to these services for passengers, the broader societal impacts of TNCs before the pandemic are the focus of many studies. The pandemic of COVID-19 caused an abrupt halt to TNC growth and use through a disruption that has reverberated across the transportation industry.

Our analysis examines the pre-pandemic impacts of TNCs and pooled services on travel behavior, vehicle miles traveled, and greenhouse gas emissions in three U.S. markets. On balance, we found that in two of the three markets evaluated, San Francisco and Los Angeles, TNCs were net contributors to VMT and GHG emissions. However, in the third market, Washington, D.C., we found that Lyft and Uber may have been enabling a small reduction in VMT and GHG emissions. One of the primary distinctions of this market is that Lyft and Uber were delivering services with considerably less driving per passenger relative to the California markets. However, another key reason for this result was that the travel and vehicle ownership impacts of Lyft and Uber were producing a reduction in VMT and GHG emissions among its user population. When Lyft and Uber are used instead of personal vehicle driving and other vehicle modes, such as taxis and rental cars, such substitution does not reduce VMT or GHG, but it also does not significantly add to it. The primary drivers of VMT and GHG change were the impacts on vehicle ownership. Vehicle shedding was, in two of the three markets, the second-largest component of impact. The largest component was personal vehicle suppression: the prevention of car ownership. For a minority of the population, Lyft and Uber enabled users to own fewer cars than they would have otherwise. Given the lasting VMT implications derived from personal vehicle ownership, this impact can be sizeable. In the California markets, this impact was not enough to overcome the considerable VMT that Lyft and Uber vehicles are estimated to drive in combination. But in the Washington, D.C., market, when combined with other contributing impacts, it was found to be large enough. We found through a sensitivity analysis that suppression rates would have to be considerably more powerful in the California markets, without substantive changes in the overall VMT per person, to yield a net reduction in VMT and GHG emissions. Still, through mode substitution and impacts on vehicle ownership, Lyft and Uber are offsetting a fair amount of the driving that they conduct to deliver their services. Finally, an analysis of vehicle registration trends within the three markets and their core jurisdictions show changes in growth that suggest the presence of TNCs is influencing vehicle ownership within the population. We find that these changes would align with the order of magnitude of impacts that we would have expected to have seen occur at the population level given findings in the passenger survey and estimates of the passenger survey population. There are, of course, many factors that influence vehicle registration trends, but we note that the observed declines in registration growth and registrations per capita (18+) are occurring during an otherwise healthy economic period.

Not surprisingly, there are many remaining questions surrounding TNC impacts. More research is needed to better understand these impacts and how they change over time. This is particularly in light of the fact that TNC systems, and their use by passengers, may have some fundamental differences in a post-pandemic future. In addition, the dynamics of the system services could be such that seemingly contradictory findings can legitimately coexist. As one example, congestion and changes in VMT are related, but also distinctly different impacts. Congestion is time- and space-dependent VMT, whereas aggregate VMT-change can more broadly occur anywhere. We did not find that Lyft and Uber reduce VMT in San Francisco, where previous research has suggested that they increase congestion. But even if, in the future, Lyft and Uber were to reduce VMT and GHG more broadly, they could continue to contribute to congestion in high traffic areas. In less dense neighborhoods, the added mobility benefits of TNCs may be able to outweigh drawbacks related to congestion and emissions. However, more research is needed to investigate TNC impacts across various land-use contexts. A number of innovations may enable a convergence to this future, where Lyft, Uber, and related services provide automobility that is cost effective and efficient enough to facilitate less reliance on personal vehicles and usher in larger reductions in VMT and GHG emissions from transportation. Among those innovations are advances in vehicle automation that are integrated into shared fleets, as well as advances in vehicle electrification, pooling (upon its return to practice), pricing, data sharing, and other mechanisms within the public and private infrastructure. Based on our analysis and other TNC studies, we make several recommendations aimed at improving TNC benefits while mitigating their costs within a post-pandemic future.

Mitigate Negative Effects and Encourage Positive TNC Impacts via Pricing

TNC services have been one of many factors discussed in the context of road charging (RC). RC is the concept of pricing transportation infrastructure to achieve a desired outcome, to collect fees, or both. The use of TNCs (especially without pooling) has been found to produce additional traffic congestion in downtown areas, more miles driven, and greater emissions. These effects could worsen if the services are not fueled using cleaner energy sources and appropriately priced along with other transportation modes including personal vehicles and public transit. Pricing mechanisms can include:

- Trip-based fees;
- Mileage-based pricing;
- Spatiotemporal pricing (cordon pricing, express lanes, curb pricing);
- Mode or occupancy-based fees; and
- Access to high occupancy vehicle lanes or express lanes.

Some U.S. cities have explored the pricing of TNC services to achieve policy outcomes such as increased revenues or congestion reduction. The city of Chicago opted to use a portion of its per-trip TNC tax to fund specific rail improvement projects (Greenfield 2018). New York City added a $2.75 per-trip fee for TNC trips that begin, end, or pass through most of Manhattan, including a discounted per-passenger fee of $0.75 for pooled rides (Hu 2019). In San Francisco, Supervisor Aaron Peskin proposed a proposition to enact a 3.25% tax for single-passenger trips and a 1.5% tax on shared rides (Kukura 2019). An expert task force in Chicago had recommended reforming tax policy to incentivize "multi-passenger rides." If pooling returns to TNCs in the future, policy mechanisms like these could be used in more cities to incentivize pooling through a tiered structure of taxation that encourages shared rides and higher vehicle occupancy.

However, a future implementation of RC and occupancy-based pricing should apply to all forms of transportation, not just TNCs. Pricing single-occupancy vehicles (SOVs) in a way that appropriately reflects their emissions and congestion impacts, whether the SOVs are privately driven or driven as part of a TNC fleet, is a strategy that could improve the environment and the performance of the transportation system overall. Crafting policies that tax both private SOVs and TNC vehicles should be sure to account for the complications that arise when comparing private vehicle and TNC vehicle occupancies. Since TNCs of the present day always include a driver inside the vehicle, any future SOV pricing that is considered should be applied to single-*passenger* TNC trips in a fashion similar to how they are applied to private SOV trips.

TNC taxes also could be used to reduce the costs of TNCs and public transit to low-income travelers. These structures could even be implemented like a "feebate" for vehicle occupancy, where single-occupancy trips would be charged a fee and pooled trips would be given a rebate (or discount) that is based on income, further lowering passenger cost. These and similar structures may be considered for pricing TNC activity by time of day and location (e.g., city core at peak hours) but also by vehicle occupancy and traveler income.

Future policy should also seek to maximize the positive impacts of TNCs. For instance, TNCs can reduce the demand for personal vehicle ownership in households, by enabling households to shed vehicles while suppressing the need for others to buy them. As a result, parking demand in dense urban areas could decrease (or not increase as quickly with a growing population), freeing up valuable space for other uses such as housing, parks, or commercial development. This study and others show that TNCs can have an impact on personal vehicle ownership. Approximately 8 percent to 12 percent of the passengers we surveyed shed or suppressed a vehicle, depending on the city. It is naturally unclear whether such an impact has or will sustain itself at similar magnitudes within a post-pandemic future. But if it does, it could prove to be an opportunity for public transit agencies, which could have a larger pool of potential riders using public transit and TNCs together. While TNCs and other shared modes compete with public transit under some circumstances, informed policies will be vital to ensuring that the positive impacts of TNCs are leveraged and negative impacts are mitigated in the future. In March 2018, the city of Paris began to offer subsidies for residents who get rid of a personal vehicle and for those who buy an electric bicycle (Bevilacqua 2018). Similar policies that encourage the selling of personal vehicles in favor of more sustainable modes like public transit, active transportation, and shared modes, should be explored in the United States.

Encourage Pooling and Higher Vehicle Occupancies When Again Safe to Do So

Prior to the pandemic, TNCs demonstrated that the distribution of passenger demand and routing algorithms could combine trips at a large scale and pool trips of different passengers together. The demonstration of TNCs and pooled services, which are enabled by dynamic routing applications, presents an opportunity for real-time pooling. The pandemic made pooling a safety hazard and the option presently remains unavailable in many cities. Should pooling options return to most cities, the impacts found from such practices could also return as well. Increased pooling can reduce private TNC VMT that might otherwise occur. It could also lead to a reduced reliance on personal vehicles and their associated emissions and costs. With the potential benefits, however, our study demonstrated that TNCs and pooled services were taking a significant portion of passengers from public transit in each of the three study cities.

Even successful pooled TNC services could increase congestion in denser urban areas, if people shift from rail, bus, and active transportation. As shown in this study, pooled services were more competitive with public transit than regular TNCs because of the similar price point of pooled rides. In more suburban and rural areas, where there is higher single-occupancy vehicle use and lower public transit modal share, pooled TNCs may have different and even more beneficial impacts. However, there may also be a higher proportion of deadheading miles in these areas due to less dense built environments and lower overlapping travel demand. Further research is needed on the impacts of TNCs in less dense areas and in different built environments.

More broadly, the impact of pooling was highly dependent on the match rate that was achieved. This is relevant not only for future policy but for future measurement. Pooled trips that are never matched are effectively private TNC trips, so it will be important to understand the matching that occurs to assess the pooling impact. One challenge, however, is that match rates may remain a sensitive subject to TNC operators for competitive reasons. Another consideration related to competition is that matching becomes technically more challenging with increased competition in the TNC industry. TNC services effectively functioned as duopoly in most U.S. markets during the previous decade. Even with just two operators, there is a challenge with matching in that a passenger looking to pool with Lyft may miss a more efficient real-time opportunity to pool with Uber. As other entities potentially enter the market, the technical capability to match may decline considerably. This potential problem suggests that future operators and policymakers should consider establishing mechanisms for sharing passengers who seek pooled rides across platforms in real time. Such a mechanism would encounter considerable technical and institutional hurdles, but it could permit better matching at a regional level.

When it is again safe to share rides within TNCs, policies that encourage pooled rides by filling empty seats should be prioritized to decrease traffic congestion and emissions. As discussed earlier, occupancy-based taxation paired with rights-of-way access policies (roadway and curb) could be an effective tool for policymakers to help cultivate higher vehicle occupancies, regardless of transportation mode. In addition, pooling incentives and priority curb access at airports, office parks, college campuses, events, and other special locations could be an effective strategy for managing demand and potentially reducing VMT and GHG emissions. More research is needed on this topic.

Advance Data Sharing and Standardize Impact Assessment Methodologies

To make both short- and long-term decisions, public transit agencies need data about regional travel behavior. Prior to the pandemic, TNCs made up a notable portion of travel in major U.S. cities. As discussed in the background section, TNCs were found to make up 15 percent of vehicle trips within San Francisco (SFCTA 2017) and 7 percent of total VMT in New York City (Schaller 2017a) in studies using data from 2016. At present, there are limited agreements for TNC companies to report performance data to public entities in the United States. A handful of public agencies do receive some activity data from TNC companies. For example, the New York City Taxi and Limousine Commission (TLC) receives and is able to disclose some information about origins and destinations of TNC trips at a granularity higher than zip code (block and lot level), but this information varies by operator. The city of Chicago releases data quarterly on registered TNC vehicles, drivers, and trip data including origin and destinations aggregated by census tract, start and end times rounded to the nearest 15 minutes, and fares rounded to the nearest $2.50 (Freund 2019). Regardless of how TNC and related services evolve in a post-pandemic future, public stakeholders should have sufficient information to make informed decisions about funding allocation and infrastructure improvements. However, challenges to this can arise, as TNC companies often have competitive and privacy concerns regarding their proprietary technology and the personal information of users. While there are data-sharing approaches and privacy protection architectures, continued discussion is regularly needed among the private, public, and academic sectors to determine appropriate structures for data exchange under specific circumstances.

There is also a lack of consistency in the assessment methodologies among TNC studies, at present. At some level, there is necessary for healthy scientific inquiry that looks at the same issue in different ways. Different measurement approaches that are accurate and valid should generally concur on their findings. At the same time, methods that do not appropriately cover relevant populations or ineffectively measure key impacts can skew public understanding and create confusion. It is important for public entities to understand the methodologies applied and to leverage that understanding to develop standards of data collection and analytical approaches for evaluating TNC impacts. Such standardization does not mean that methods cannot evolve or improve, but the establishment of methodological benchmarks could permit better comparisons across studies and improve analysis. Broadly, it would allow researchers to better compare impacts across locations and over time so that policy decisions can be made using a more consistent framework.

Promote Public-Private Partnerships with Public Transit Operators, Leading to Socially Beneficial TNC Use Cases

Public-private partnerships and pilot projects with TNC companies can be implemented to achieve desired public goals. Public agencies are conducting pilot projects with TNC companies for various use cases including first and last mile to public transit, supporting existing public transit or paratransit services, providing mobility for low-income populations, late-night or special-event services, and others. Public entities should continue to experiment with pilots and procurement processes, learning best practices, and enacting flexible terms so that modifications can be made quickly, if needed to adapt the project. Projects that are demonstrating benefits may turn into more permanent fixtures of public transportation systems. It could be that the future of public transportation is a mix of conventional and shared mobility modes. Low-density environments may find that coordinated shared mobility services can deliver similar or better mobility at lower cost than conventional fixed-route transit. TNCs could be one of the scalable tools for public transit agencies to consider deploying to supplement mobility in areas where operations are expensive and ridership is low. Several projects within the FTA's MOD Sandbox Program have demonstrated such collaborations aimed at meeting a variety of these objectives. Further research and policies are needed to help remove barriers to public-private partnerships that can advance pilots and experimentation. Pilots can provide key understanding of partnership trade-offs and help to evolve our transportation systems to deliver widespread and equitable mobility more efficiently and effectively across a range of land use and built environments.

TNCs and Equity Considerations

This report and others find that TNC passengers tend to be younger, more highly educated, and on balance more white than the general public. The demographic trends found in this study are similar to those found for other shared mobility services like carsharing and bikesharing. These results suggest that certain portions of the population may not be gaining the mobility benefits of TNCs. The public sector and private operators should take measures to ensure that these services are available to disadvantaged groups. Using a framework to transportation equity called STEPS (spatial, temporal, economic, physiological, and social barriers), we suggest the following policy approaches to increase equity using TNC services (Shaheen et al. 2017):

- Spatial: Policies that address spatial barriers can improve mobility. These include encouraging first- and last-mile programs and curb-to-curb service in areas poorly serviced by taxis and public transit.
- Temporal: Employers and public agencies can partner with TNCs to offer late-night services when traditional public transit is not operating.
- Economic: Public entities can offer subsidies for low-income users to improve mobility. In addition, multiple payment options can allow use among those who are unbanked.
- Physiological: In order to ensure high-quality mobility for those with physical or cognitive difficulties, services for older adults and persons with disabilities should be encouraged. These services can include paratransit or partnerships with medical providers.
- Social: Relevant stakeholders should work together to minimize sociodemographic profiling by TNC drivers. Offering multiple in-app language options and targeted outreach to low-income and minority communities could expand the mobility benefits of TNCs to more diverse groups of users.

These policy considerations could increase transportation equity in communities if properly and thoughtfully implemented.

TNCs and Vehicle Electrification

This study showed that while a notable portion of TNC drivers own hybrid vehicles, far fewer owned plug-in hybrid electric vehicles (PHEVs) or electric vehicles (EVs). Since the data of this study was collected, electric vehicles have expanded and proliferated within TNC fleets. Still, they represent a minority of the overall fleet. There are a number of barriers to EV ownership among TNC drivers. EVs made up about 1 percent of new vehicle sales in this country in the first half of 2017 (Klippenstein 2018). A major barrier to EV adoption is lack of available charging infrastructure, particularly in public areas where TNCs may need to charge regularly. The broader EV industry in many instances is facing a 'chicken and egg' problem, where the public sector and private property owners are hesitant to build out more EV charging infrastructure due to perceived lack of demand, yet those interested in purchasing an EV may be reluctant to do so because of the lack of charging infrastructure. This introduces logistical problems for TNC drivers, who may have to cancel a ride if their range is low and a passenger requests a destination with limited charging infrastructure along the way. Policies could help encourage TNC drivers to purchase EVs and PHEVs by providing vehicle purchase and home charging subsidies, funding strategically placed charging infrastructure, or offering dedicated charging points to TNC drivers. However, because TNC vehicles are privately owned, mandating EVs under the current model of vehicle ownership would be difficult. Shared automated vehicles could change this dynamic and make it easier for public entities to pass ordinances regarding vehicle propulsion within shared fleets. It is important to note that California's SB 1014 (California Clean Miles Standard and Incentive Program), signed into law in 2018, has mandated emission reductions from TNCs, like Uber and Lyft, through fleet electrification (California Legislative Information, 2018). Starting in 2023, SB 1014 requires annual targets and goals for GHG emission reductions per passenger-mile driven on behalf of a TNC and requires TNCs to develop a GHG emission reduction plan that includes proposals detailing how each company will meet their targets. The policy measures the number and proportion of passenger miles traveled by zero-emission modes, including ZEVs, bikes, and scooters. Operators have taken some steps toward encouraging EV use on their platform. Lyft launched a 'Green Mode' ride request option that allows passengers to request a hybrid or EV (Lyft 2019). The company also connects drivers to renting cars for TNC service, including EVs, has also declared a commitment to having 100% electric vehicles on its platform by 2030. Uber similarly launched the 'Green Future' program to connect drivers with incentives to drive EVs within the platform and has also declared a virtually identical commitment to becoming a zero-emission platform by 2030. These and other developments are encouraging, and if seen through may advance the de-carbonization of transportation more rapidly than an exclusive approach of policy applications.

Today, the transportation industry is at somewhat of an inflection point given the disruptions of the global pandemic. The ultimate direction of this inflection remains to be seen and a return to the previous norms of mobility are very possible. The pandemic raised barriers to many of the core mechanisms and principals that shared mobility has relied upon to execute its services. Despite these developments, the industry has endured and may emerge stronger. The results of this study showed that TNCs are effective at influencing traveler behavior in ways that reduce emissions. At the same time, it also showed that much work needs to be done to deliver those benefits with greater efficiency. This research builds on the work that precedes it, and will hopefully contribute to the studies, policies, and operations that follow it to advance those broader objectives.

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