The Effects of Ride Hailing Services on Travel and Associated Greenhouse Gas Emissions

April 2018

A White Paper from the National Center for Sustainable Transportation

Caroline Rodier, University of California, Davis

National Center for Sustainable Transportation

ITS UCDAVIS INSTITUTE of TRANSPORTATION STUDIES

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: University of California, Davis; University of California, Riverside; University of Southern California; California State University, Long Beach; Georgia Institute of Technology; and University of Vermont. More information can be found at: ncst.ucdavis.edu.

Disclaimer

Acknowledgments

This study was funded by a grant from the National Center for Sustainable Transportation (NCST), supported by USDOT and Caltrans through the University Transportation Centers program. The authors would like to thank the NCST, USDOT, and Caltrans for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would also like to thank reviewers at the National Association of Regional Councils, American Association of State Highway and Transportation Officials, the Southern California Association of Governments, the Sacramento Area Council of Governments, the California Air Resources Board, the City of Atlanta, and the Vermont Agency of Transportation for providing excellent review comments on preliminary versions of this white paper.

NCST

The Effects of Ride Hailing Services on Travel and Associated Greenhouse Gas Emissions

A National Center for Sustainable Transportation White Paper

April 2018

Caroline Rodier, Institute of Transportation Studies, University of California, Davis

[page left intentionally blank]

TABLE OF CONTENTS

The Effects of Ride Hailing Services on Travel and Associated Greenhouse Gas Emissions

EXECUTIVE SUMMARY

Towards the close of the first decade of the 21st Century, ride-hailing services began to enter the transportation market through smart phone applications that allowed consumers to hail and pay for a ride from drivers using their own vehicle. The information and communication technologies used by these platforms allow for more reliable service, to more locations, with shorter wait times, and at a lower cost than traditional taxi services and, perhaps, public transit. Today, an estimated 15% of adults across the U.S. and 21% in major cities have personally used these services.

The successful entrance of ride-hailing services into the transportation market has raised questions about their effect on the overall transportation system, including congestion, total vehicle miles traveled (VMT), and greenhouse gas emissions (GHGs). Reliable answers are limited, in large part, because of their rapid expansion and the lack of publicly available data from these private ride-sharing companies. However, there is now a small body of research, most conducted in 2016 and 2017, that provides some initial evidence on the impacts of these services. This research includes population representative survey data, targeted ride-hailing user survey data, and measured ride-hailing driver and passenger activity data. In addition, the recent interest in automated vehicles has produced modeling studies that also provide insight into the potential effects of ride-hailing services.

The following framework was developed to identify the range of possible travel effects, both positive and negative, on users of ride-hailing services. This includes the effects of ride-hailing on auto ownership, trip generation, destination choice, mode choice, network vehicle travel, and land use.

Table 1. Summary of the Effect of Ride Hailing Services on Vehicle Miles Traveled and Greenhouse Gas Emissions.

Category	Possible Outcomes	Change Direction
Auto Ownership	Reduce auto ownership because ride-hailing allows users to meet their travel needs at a lower cost.	- VMT/GHG
Trip Generation	Increase auto ride-hailing trips by people who cannot drive due to physical and cognitive limitations, no driver's license, no private vehicle, and alcohol consumption.	+ VMT/GHG
Mode Choice	Increase auto mode share when ride-hailing has an overall lower time and money costs than transit, carpooling, walk, and bike modes.	+ VMT/GHG
	Increase transit mode share when ride-hailing bridges the first and last mile gap to rail and bus transit.	- VMT/GHG
Network Travel	Relocation travel (i.e., ride-hailing vehicle travel without passenger to pick up new passenger).	+ VMT/GHG
Destination Choice and Land Use	If overall travel time and cost for all modes is reduced to central areas relative to outlying, then demand for travel to central areas and residential and employment space in central areas may be greater.	- VMT/GHG
	If overall travel time and cost for all modes is reduced to outlying areas relative to central, then demand for travel to outlying areas and residential and employment space in outlying areas may be greater.	+ VMT/GHG

The available literature, available as of fall of 2017, was synthesized using the above framework. The findings are summarized below.

- **Auto Ownership**: 9% to 10% of respondents in two surveys stated that they gave up a vehicle after joining ridesharing. One of these studies includes a representative sample of the population in seven major U.S. cities and another targeted ride-hailing users in downtown San Francisco. These studies represent initial evidence for some reduction in auto ownership. However, the responses to specific questions in these surveys raise questions about other factors that may contribute to reduced vehicle ownership. More research is needed to verify the cause and effect relationship between reduced auto ownership and use of ride-hailing.
- **Trip Generation**: Available research currently reports a widely varying range of new vehicle trips resulting from the availability of ride-hailing: 8% to 22%. These results are from surveys of a representative sample of U.S. cities (22%), a representative sample of Millennial and Generation Xers in California (8%), and ride-hailing users in San Francisco (8%) and Denver (12%). Available research indicates that reduced physical and legal limits to driving, avoiding drinking and driving, and lack of auto ownership contribute to

new vehicle trips. However, more research is needed to understand the wider range of factors that contribute to variation in induced vehicle trip generation from ride-hailing and their relative importance.

- **Mode Choice**: One of the more controversial issues surrounding ride-hailing is whether these services support transit use by increasing first and last mile access to transit or undermine transit by a providing a faster and cheaper travel alternative. The research as of the fall of 2017 suggests that the substitution effect is stronger than the complementary effect. In response to the question, “What mode(s) would you have used if ride-hailing were not available?” in four surveys, 16% to 33% of respondents indicated that they would have taken transit if ride-hailing was not available. These results are from surveys of a representative sample of U.S. cities (17%), a representative sample of Millennial and Generation Xers in California (16%), and ride-hailing users in San Francisco (33%) and Denver (22%). These studies also show some use of ride-hailing for access and egress purposes (3%, 9%, 5%, and 6%, respectively), but this is more than offset by reductions in transit travel. These studies show reductions in carpool, walk, and bike travel, and one study suggests that ride-hailing may also reduce carsharing. Research is needed to more carefully measure the transit ridership effects of ride-hailing and the potential to increase the use of ride-hailing as a first and last mile transit access mode.
- **Network Vehicle Travel without Passengers**: Research available as of the fall of 2017 suggests that empty vehicle travel can range from about 10% to 20% in high density downtown urban areas where the supply of ride-hailing vehicles is relatively high and about 45% to 60% in lower density suburban areas where the supply of ride-hailing vehicles is relatively low. These results are based on three studies that use ride-hailing driver activity data and two modeling studies. The studies reviewed in this report are limited due to lack of access to ride-hailing activity data. More studies that use ride-hailing driver activity data are needed, particularly in suburban areas.
- **Destination Choice and Land Use.** No studies have been conducted on the destination and land use effects of ride-hailing.

In sum, the results of our analysis indicate that ride-hailing will tend to produce modest reductions in auto ownership and increase vehicle trip generation, vehicle mode share, and network vehicle travel necessary to pick up new passengers. Overall, these effects would tend to increase VMT and associated GHG emissions. However, there are no studies that examine the impact of all these factors on VMT.

The effect of vehicle travel without passengers on total systemwide VMT is estimated for the City of San Francisco in a study that uses ride-hailing vehicle activity data and in several modeling studies in Austin (Texas). The San Francisco study shows an overall increase in VMT of 6.5% on a typical weekday and of 10% on the weekend and, in Austin, the increase ranges from 8% to 11% for a typical weekday.

Several studies attempt to estimate change in VMT and represent mode choice and vehicle travel without passengers. One study combines ride-hailing vehicle activity data and passenger survey data and finds an average 85% increase in VMT for each ride-hailing trip. Modeling studies in Austin and Lisbon show increases on the order of 20% to 50%.

Note, however, there are numerous uncertainties associated with all these studies, as is detailed in the full white paper. Better understanding of the full impacts of ride-hailing can be improved with greater access to driver and passenger activity data across a wider range of geographic and socio-demographic contexts. However, the available research as of 2017 suggests that ride-hailing, as currently used in U.S. cities, is contributing to a net increase in VMT and associated GHG emissions; however, the total magnitude of that increase is uncertain. Future research should provide more certainty about the total magnitude of the problem.

As a result, policy makers may want to evaluate policies that support the use of ride-hailing services for first and last mile service to transit and for disadvantaged populations (low income, disabled, and without vehicles) to access basic services and opportunities, for example, through subsidized fares. Outside of dense city areas, policy makers may want to explore restrictions on ride-hailing services or distance-based pricing policies to minimize empty vehicle travel and support transit use. Inside dense city areas, curb-based pricing policies for pick-up and drop-off access may offset lost parking revenues and continued use of transit. Policies should also be considered that encourage ride-hailing drivers to use electric vehicles.

Introduction

Towards the close of the first decade of the 21st Century, ride-hailing services began to enter the transportation market through smart phone applications that allowed consumers to hail and pay for a ride from drivers using their own vehicle. The information and communication technologies used by these platforms allow for more reliable service, to more locations, with shorter wait times, and at a lower cost than traditional taxi services and, perhaps, public transit. Today, an estimated 15% of adults across the U.S. (Smith, 2016) and 21% in major cities (Clewlow and Mishra, 2017) have personally used these services. Estimates of regular users (at least once per week) are lower, however: 3% nationally (Smith, 2016). Research consistently finds that today's ride-hailing users are relatively young, well-educated, and wealthy adults who live in urban areas (Smith, 2016; Alemi et al., 2017a; Dias et al., 2017; Clewlow and Mishra, 2017).

The successful entrance of ride-hailing services into the transportation market raises questions about their effect on the overall transportation systems, including congestion, total vehicle miles traveled (VMT), and greenhouse gas emissions (GHGs). Reliable answers are limited in large part because of their rapid expansion and the lack of publicly available data from these private ride-sharing companies. However, there is now a small body of research, most conducted in 2016 and 2017, that provides some initial evidence on the impacts of these services. This research includes population representative survey data, targeted ride-hailing user survey data, and measured ride-hailing driver and passenger activity data. In addition, the recent interest in automated vehicles has produced modeling studies that also provide insight into the potential effects of ride-hailing services.

The objective of this white paper is twofold. First, to provide a framework that identifies the range of possible travel effects, both positive and negative, of ride-hailing services. Second, to synthesize the existing literature on ride-hailing services through the application of this framework. This review focuses on the GHG effects of ride-hailing that are associated with increased VMT and it includes available literature as of the fall of 2017. To date, there is no evidence that links ride-hailing to use of more fuel-efficient vehicles.

Framework for Understanding the Travel and Greenhouse Gas Effects of Ride-Hailing

Table 2 articulates a framework for understanding the mechanisms by which ride-hailing may change use travel behavior and associated GHGs. Seven categories of change are summarized in Table 2 and are described in more detail in the following text.

- Auto Ownership: Ride-hailing services may meet the travel needs of some individuals more affordably than personally owned vehicles. When this is the case, individuals may decide not to purchase a vehicle, or they may give up a vehicle that they currently own. The variable cost of ride-hailing includes both the vehicle cost and the operational costs (fuel, insurance, and maintenance). However, the variable cost of personally owned vehicles only includes operational costs; the purchase price of the vehicle is a sunk cost. As a result, these individuals are likely to drive less using ride-hailing services than they would traveling in their own vehicles. All else being equal, the net effect would be a reduction in VMT and GHGs. This review focuses on the user effects of ride-hailing; however, it is possible that auto ownership may increase among drivers who want to work as a ride-hailing driver.
- Trip Generation: If ride-hailing services affordably fill geographic and time gaps in transit or taxi services, then new vehicle travel may be induced among those who cannot drive due to physical or cognitive limitations, lack of a driver's license, no access to a private vehicle, and a desire to avoid drinking and driving. This new vehicle travel would tend to increase VMT and GHG emissions, all else being equal.
- Mode Choice: Given a destination, ride-hailing services may provide lower overall travel time and monetary costs relative to transit, carpooling, walking, and bike modes and, all else being equal, increase vehicle mode share, VMT, and GHGs. However, ride-hailing services that bridge the first and last mile gap to rail and bus service may reduce the overall travel time and monetary cost of transit use, increase transit mode share, and reduce VMT and GHGs, all else being equal.
- Network Travel: Ride-hail vehicles generate additional VMT when driving without a passenger to pick up a new passenger. This is also known as empty relocation travel or travel without passengers.
- Destination Choice and Land Use: If overall travel time and monetary cost for all modes is reduced to central areas relative to outlying areas, then demand for travel to central areas and residential and employment space in central areas will be greater and, all else being equal, VMT and GHGs are likely to increase. On the other hand, if overall travel time and cost for all modes is reduced to outlying areas relative to central areas, then demand for travel to outlying areas and residential and employment space in outlying areas may be greater and, all else being equal, VMT and GHGs are likely to decrease.

Table 2. Effect of Ride-Hailing Services on Vehicle Miles Traveled and Greenhouse Gas Emissions

Category	Possible Outcomes	Change Direction
Auto Ownership	Reduce auto ownership because ride-hailing allows users to meet their travel needs at a lower cost.	- VMT/GHG
Trip Generation	Increase auto ride-hailing trips by people who cannot drive due to physical and cognitive limitations, no driver's license, no private vehicle, and alcohol consumption.	+ VMT/GHG
Mode Choice	Increase auto mode share when ride-hailing has an overall lower time and money costs than transit, carpooling, walk, and bike modes.	+ VMT/GHG
	Increase transit mode share when ride-hailing bridges the first and last mile gap to rail and bus transit.	- VMT/GHG
Network Travel	Relocation travel (i.e., ride-hailing vehicle travel without passenger to pick up new passenger).	+ VMT/GHG
Destination Choice and Land Use	If overall travel time and cost for all modes is reduced to central areas relative to outlying, then demand for travel to central areas and residential and employment space in central areas may be greater.	- VMT/GHG
	If overall travel time and cost for all modes is reduced to outlying areas relative to central, then demand for travel to outlying areas and residential and employment space in outlying areas may be greater.	+ VMT/GHG

Summary of Studies Reviewed

Eight studies present findings on the travel behavior effects of ride-hailing based on stated responses from surveys of adults in the U.S. and measured ride-hailing service (driver and passenger) activity, as of the fall of 2017. These are listed in Table 3.

The national use of ride-hail is explored through a survey (on-line and mail) of a representative panel of randomly selected U.S. adults administered in November and December of 2015 (Smith, 2016). 68% of those invited to complete the survey did so and the final dataset includes 4,787 samples. The sample was weighted to match the gender, age, education, race, Hispanic origin, and regional distributions of the U.S. Census's 2013 American Community Survey (ACS). The response rate of the final weighted sample was 3%. 15% of the sample had used ride-hailing apps (718 adults) and 3% (143 adults) used ride-hailing at least once per week. This study provides summaries of responses to survey questions.

Ride-hailing among residents in urban and suburban neighborhoods in seven metropolitan areas, Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle, and Washington, D.C., is analyzed with the results of an on-line survey conducted between August 2015 and January 2016 (Clewlow and Misha, 2017). The survey employed density (housing and population) and metropolitan area demographic (age, income, and gender) sampling targets from the 2011-2015 ACS. The data was weighted to match these demographic distributions. The final sample size is not reported and the response rate for this survey is not available. This study provides summaries of responses to survey questions.

Ride-hailing in the Seattle region (Washington) is examined with data from the region's household travel survey, which was conducted in 2015 (Dias et al., 2017). This study uses a subsample of this data, which includes 2,789 adults who report directly about their travel. The regional travel survey used income and geographic recruitment targets (PSRC, 2015). The final dataset was weighted for geographic and demographic characteristics (household size, workers, income, vehicles, and lifecycle) targets from the 2009-2013 ACS. The final response rate was 6%, of which 15% were regular ride-hail users (N=430) and 3% used ride-hailing at least once per week (N=72). In this study, survey responses are summarized and tests of the significance of demographic and land use variables on ride-hailing propensity are conducted by estimating bivariate ordered probit models.

Two studies examine the use of ride-hailing by California millennials (age 18 to 34) and Generation Xers (age 35 to 50) in California, in urban, suburban, and rural areas, with the results of an on-line survey administered in the fall of 2015 (Alemi et al., 2017a and Alemi et al., 2017b). A quota method was used to collect samples from the different regions in California and urban, suburban, and rural neighborhoods. In addition, recruitment targets, included gender, age, household income, race and ethnicity, and presence of children. The final sample was weighted to these targets, plus student/employment status, from the 2014 ACS (1-year estimate) with neighborhood classifications from Salon (2015). The final dataset included 1,731 samples, which represent 36% of those invited to complete the survey. 26% of the sample had used ride-hailing in the past (N=483) and 10% of the sample used it at least once per month (N=209) (Alemi et al., 2017a). Alemi et al., 2017a summarize survey responses and Alemi et al., 2017b conduct significant tests of factors influencing the propensity to use ride-hailing services by estimating ordered probit models with sample selection and zero-inflated ordered probit model.

Another study reports on a survey of ride-hailing users in central San Francisco. The survey was administered at locations and times of the day where high concentrations of ride-hailing users were observed in the spring of 2014 (Rayle et al., 2016). This survey likely oversamples recreational trips and underestimates other types of trips and it is not a representative sample of ride-hailing users. This study was included in the analysis because of its relatively large sample size of ride-hailing users. In addition, many of the questions addressed the topic of this white paper and were repeated in the studies with representative samples (described above). Approximately half of those invited to take the survey did so. 17% of survey respondents were intercepted after exiting a ride-hailing vehicle and were then asked to report on the ride-hailing trip they had just completed. 83% were asked to complete the survey, if they had used ride-sourcing within the last two weeks. Both samples completed the same survey. The total sample size is 380 adults. This study provides summaries of responses to survey questions.

In another study in Denver (Colorado), the author served as a ride-hailing driver and administered a survey to passengers that explored their use of ride-hailing services. In addition, the author collected data on the productivity of ride-hailing travel (i.e., share of time and distance a driver is not transporting a passenger relative to total driver time and distance traveled) by recording driving time, distance, and locations with and without a passenger (Henao, 2017). The author collected data on 416 rides and 311 passengers completed the survey. This is a 75% response rate. Prior to collecting the data, the author conducted exploratory research to understand typical ride-hailing driver behavior, which included extensive pre-data collection ride-hailing driving and attending ride-hailing driver meetings. As a driver, he mimicked what he identified as typical driver behavior but did not randomly vary start locations and driving times. Instead, he chose typical driver start locations and worked during peak demand times of day. He also implemented protocols to minimize travel time and distance without passengers and excluded “commute travel” to locations where he turned on his ride-hailing applications. As a result, the study provides a conservative representation of driver productivity. This study was included in the analysis because it includes a relatively high number of surveys completed by high frequency users; however, there is no way to determine whether the passenger survey or trip activity sample are representative of ride-hailing passengers or trips. This study also includes questions that are consistent with those implemented in population representative studies (described above) and addresses the topic of this paper.

The productivity of ride-hailing travel analyzed with 2,000 randomly selected UberX driver logs in each of five U.S. cities, Boston, Los Angles, New York, San Francisco, and Seattle (Crammer and Krueger, 2015). The sample in this study should be representative of Uber driver and passenger activity; however, Uber provided the productivity statistics for each city and the study authors did not independently verify the results.

The San Francisco County Transportation Authority (SFCTA) also reports on the productivity of ride-hailing services in San Francisco (SFCTA, 2017). They collected ride-hailing data from Uber and Lyft APIs at five second intervals over a period of six weeks. The API data provide information on approximate vehicle locations, estimated pick up times, and when a vehicle becomes available and unavailable. Extensive data cleaning, trip identification, trip matching, and attribute imputation were required to produce the final data set. Limitations of this data include approximate, rather than exact, pick-up and drop-off locations and exclusion of trips that end outside San Francisco as well as unknown errors due to data processing.

Three studies that include stated response surveys and/or recorded observations were not included in this literature review. Two studies are not reviewed in this report because they report on non-representative convenience samples (APTA, 2015; Hampshire et al., 2017). The APTA (2015) study sampled survey respondents from carsharing and bikesharing organizations, which are known to include about 5% of the population that is affluent, well-educated, and pro-environment (Clewlow and Misha, 2017). Shaller (2017) summarizes the growth of ride-hailing services and use in New York City, but uses results from Rayle et al. (2016) and Henao (2017) to estimate mode shares without the availability of ride-sharing services. These last two studies are directly included in the review.

Note that all survey studies that ask respondents to describe their use of the ride-hailing services may suffer from inaccuracies due to, for example, recall bias and estimation errors. Some of the surveys described here have small sample sizes, which make it difficult to conduct summary statistics and/or tests-of-significance. Most surveys today suffer from low response rates, due in part to consumers being inundated with survey requests, which raise questions about non-response bias and the generalizability of results the larger population.

Table 3. Description of Stated Response Surveys and Recorded Observations about Ride-Hail Travel.

Author(s)	Location(s)	Method (date collected)	Sample	Representative
Smith (2016)	US	On-line and mail survey (2015)	4,787 adults (718 ride-hail users; 143 at least 1x per week)	Age, education, gender, race, ethnicity, population density
Alemi et al. (2017a)	California (urban, suburban, and rural)	On-line survey (2015)	1,731 adults 18 to 50 (483 ride-hail users; 209 at least 1x per month)	Age, income, gender, race and ethnicity, presence of children, geographic area and neighborhood types (urban, suburban, rural)
Dias et al. (2017)	Seattle, Washington	On-line and telephone survey (2015)	2,789 adults* (430 ride-hail users; 72 at least 1x per week)	Geographic area, income, household size, worker, vehicles, lifecycle
Clewlow and Mishra (2017)	Urban and suburban Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle and Washington, D.C.	On-line survey (2015-2016)	Not reported.	Metro area age, income, gender; screened to systematically varied on population and housing density
Rayle (2016)	Central San Francisco at high demand locations and time of day	Intercept survey (2014)	380 ride-hail users (83% within last 2 weeks & 17% just completed trip)	No
Crammer and Krueger (2015)	Boston, Los Angeles, New York, San Francisco and Seattle	Driver activity and passenger use recorded by Uber (2015)	2,000 ride-hail drivers in each city (10,000 total)	Randomly selected UberX drivers
Henao (2017)	Denver	UberX/Lyft driver reported activity and passenger use; self-administered passenger survey (2015)	416 passenger rides; 311 passenger surveys	No
SFCTA (2017)	San Francisco	Vehicle location data from UberX and Lyft APIs collected every 5 seconds for 6 weeks	Not Available	San Francisco Uber and Lyft

** = Directly reporting about their travel*

Insights into the travel effects of ride-hailing services can also be gained from the growing body of modeling studies that examine fleets of personal automated vehicles and automated taxis that are fully operational without a driver (i.e., level 5 automation). See Table 4. Most of these studies employ dynamic traffic assignment (DTA) route choice models that represent the empty repositioning travel necessary to pick up and drop off passengers. DTA route choice models are widely considered to do a better job of representing the interaction of vehicles and resulting traffic flows compared to static assignment (SA) models. Two studies also represent the mode choice effects of automated vehicles.

An early study of automated taxis in the U.S. simulated travel for small downtown areas in a hypothetical U.S. city similar to Austin (Texas) (Faganant and Kockelman, 2014). Travel demand was randomly generated with limited reference to the 2009 National Household Travel Survey (NHTS). The physical representation of the city includes a 10-mile by 10-mile gridded area, but no physical representation of roadway networks. As a result, automated taxis are simulated with constant peak and off-peak travel speeds for a typical weekday.

Later studies conducted by Faganant, Kockelman, and others (Fagnant et al., 2015 and Faganant and Kockelman, 2016) improve their representation of daily travel in Austin by increasing the size of the core city to a 12-mile by 24-mile area, using a roadway network with link-level travel times, and origin and destination travel demand data from the regional Metropolitan Planning Organization's (MPO's) four step model. They also use the MATsim dynamic assignment model (see Horni et al., 2016).

Bishoff and Maciejewski (Maciejewski and Bischoff, 2016; Bischoff and Maciejewski, 2016) examine automated taxis and shared taxis in Berlin (Germany) with the MATsim modeling framework, which includes a dynamic assignment model with vehicle relocation capabilities. These studies use a Berlin street network, travel times by time of day, and travel behavior data from Berlin travel activity surveys.

Chen and Kockelman (2016) simulate an automated electric taxi fleet that competes with other modes by per mile cost of use and with travel time benefits (i.e., lower value time because passengers can pursue other activities) in a hypothetical mid-sized region (100-mile by 100-mile gridded area), which is similar to Austin. The agent-based MATsim framework is implemented with MPO trip generation rates by population densities, trip length distributions from the 2009 NHTS, and fixed peak and off-peak travel speeds that vary by area type (downtown, urban, suburban, and exurban). The model represents both mode and DTA route choice with vehicle repositioning.

Martinez and Christ (2015) use a SA route choice model with a rule-based mode choice model (using only proximity and trip length) to simulate an automated taxi fleets with and without transit. The models use population attributes and travel demand data from a local travel survey and travel times are based on hourly updated link speeds from a roadway network.

Table 4. Description of Modeling Studies Applicable to Ride-Hailing Travel.

Author(s)	Location	Method	Travel Effects
Faganant and Kockelman (2014)	Hypothetical US city like Austin	Agent-based model; 10 by 10 miles gridded area; demand randomly generated with some basis in 2009 NHTS; constant peak and off-peak speeds (no network)	DTA route choice with relocation travel
Faganant et al. (2015)	Austin	Agent-based dynamic assignment (MATsim); 12 by 24 miles core city; demand from MPO 4 step model; network with link-level travel times	DTA route choice with relocation travel
Faganant and Kockelman (2016)	Austin	Same as above	Same as above
Maciejewski abd Bischoff (2016)	Berlin, Germany	Agent-based (MATsim); dynamically schedules fleet in response to demand; network with link level travel times by time of day; Berlin travel behavior data	DTA route choice with repositioning travel
Bischoff and Maciejewski (2016)	Berlin, Germany	Same as above	Same as above
Chen and Kockelman (2016)	Hypothetical mid-sized city like Austin	Agent-based (MATsim); MPO trip generation rates; 2009 NHTS trip distance; fixed vehicle speeds	Mode and DTA route choice with vehicle repositioning
Martinez and Christ (2015)	Lisbon, Portugal	Model with population and travel demand from travel survey data; travel times based on hourly updated link occupancy	SA route choice and rule based mode choice (proximity and trip length)

Relocation travel=vehicle travel without a passenger; NHTS=National Household Travel Survey; DTA= Dynamic Traffic Assignment Model; SA=Static Traffic Assignment Model

Evidence for Potential Travel and Greenhouse Gas Effects of Ride-Hailing Services

In this section, we use the framework from Section 2, Framework for Understanding the Travel and Greenhouse Gas Effects of Ride-Hailing, to categorize and synthesize the evidence from the studies described in Section 3, Summary of Studies Reviewed.

Auto Ownership

As described above, travelers may give up a personally owned vehicle, if their travel needs can be more cost-effectively met by ride-hailing than through vehicle ownership. Two studies show a modest reduction in auto ownership. Clewlow and Mishra (2017) find that 9% of ride-hailing respondents, in their survey of major U.S. cities, gave up one or more household vehicles. They also find a correlation between the frequency of ride-hailing use and disposing of a household vehicle. Similarly, Rayle et al. (2016), in their survey of ride-hailing users in central San Francisco, find that 10% of respondents gave up a personal vehicle since using ride-hailing services.

Trip Generation

Four studies show that the availability of ride-hailing services induces new trips. Clewlow and Mishra (2017) find that 22% of ride-hailing trips in major U.S. cities would not have been made at all. Alemi et al. (2017a) survey of Millennials and Generation Xers in California show that 8% of respondents would not have made the trip, if the ride-hailing service had not been available. Two survey studies that target high ride-hailing demand in city locations rather than a representative population sample find that new trip making is as low as 8% (Rayle et al., 2016) and as high as 12% Henao (2017). Discrepancies may be explained by differences in the geographic areas (population and modal transportation attributes).

Reducing Physical and Legal Limits to Driving

Ride-hailing services may increase vehicle use among those who cannot drive due to physical or cognitive limitations and/or driving age-restrictions. Some insight into the magnitude of this effect can be gleaned from the literature on automated vehicles, which identifies specific non-driving populations and applies driving rates of typical drivers. It is important to note that the attributes of a driverless vehicle and one with a driver could make it more or less likely for younger people and people with disabilities to use the respective services. Our review of the literature identified only four studies that attempt to quantify the magnitude of this increase.

Sivak and Schoettle (2014) conducted an on-line survey of young people (age 18 to 39) without a driver's license and asked the primary reason why they did not have a driver's license. The distribution of respondents without a driver's license aged 18 to 39 is consistent with that of the U.S. population (Schoettle and Sivak, 2014). They find that four of these reasons would be eliminated by the availability of fully automated vehicles: too busy, disability, lack of driving knowledge, and legal issues. If respondents indicated one of those four reasons, then it was assumed that they would travel in a fully automated vehicle. The increase in total vehicle users was estimated by age group. These figures were then applied to the 2009 NHTS data. The study reports a 10.6% total average increase in annual VMT with fully automated vehicles for the U.S. population aged 18 to 39.

Wadud et al. (2016) used the 2009 NHTS to estimate the increase vehicle travel among those aged 62 and older that may result from the introduction of fully automated vehicles. Their analysis applies the driving rates of those aged 62 to everyone older than 62. The results indicate a 2% to 10% increase in VMT.

Harper et al. (2016) also use data from the 2009 NHTS data to estimate the potential increase in VMT by non-drivers, seniors (65 years and older), and individuals with travel-restrictive medical conditions. The study assumes that, with fully automated vehicles, non-drivers will use vehicles at the same rate as drivers, seniors will drive at the same rate as those under 65, and that working age adult drivers (19-64) with travel-restrictive medical conditions will travel at the same rate as working age adult drivers without medical conditions. They estimate a 14% increase in annual VMT for the U.S. population aged 19 and older.

Avoiding Drinking and Driving

Surveys of ride-hailing passengers show that the most common reason for using ride-hailing services is to avoid drinking and driving. 33% of respondents indicate that this is the case in Clewlow and Mishra (2017), 21% in Rayle et al. (2016), and 60% in Alemi et al. (2017). 20.6% in Henao (2017) state that “going out/drinking” is their primary reason for ride-hailing. While not all of this travel would be new vehicle travel, the popularity of ride hailing for this purpose suggests that some of this travel is likely induced.

Lack of Auto Ownership

Individuals who lack access to a personal vehicle due to low-income may increase their trip making given the availability of affordable ride-hailing services. Alemi et al.’s (2017a) summary of survey results show that lack of vehicle availability was an important motivation for ride-hailing by 35% of frequent ride-hailing users and only 17% of non-frequent users. Alemi et al. (2017b) also estimate probit models and find a significant positive relationship between adoption and use of ride-hailing for those who live in households without access to a vehicle. Henao (2017) reports that 19% of survey respondents use ride-hailing when they don’t have a car available. Dias et al. (2017) finds a significant positive relationship in bivariate probit models for zero vehicle households and the propensity to ride-hail. Smith (2016) finds that frequent (daily to weekly) ride-hailing users have lower access to a personal vehicle than infrequent and non-ride-hailing users (78%).

In contrast to these findings, Clewlow and Mishra (2017) find that ride-hailing users do not have significantly less vehicles than non-ride-hailers. Their survey categorizes respondents as ride-hail only, transit and ride-hail, transit only, and neither (i.e., do not have ride hail app, infrequent transit users, and largely travel by car) based on their use of these modes "for their commute or for regular trip generating activities (social, shopping, services, and eating) for the last three months" (p. 18). They find similar auto availability levels between ride-hailing only and car-centric travelers (78% vs. 81%, respectively) and somewhat higher auto availability levels for transit and ride-hail users relative to transit only users (52% vs. 46%). Similarly, they found no significant difference in average auto ownership between ride-hail users and car-centric travelers and somewhat larger average auto ownership levels for transit and ride-hail users (1.07 cars per household) and transit only users (1.02 cars per household). The discrepancy between the findings in Clewlow and Mishra and other studies cited in this section may be categorization of vehicle ownership and ride-hail use categories.

Mode Choice

One of the more controversial issues surrounding ride-hailing is whether these services support transit use by increasing first and last mile access to transit or lure transit riders away from some of the more profitable routes, which would tend to undercut the ability of transit providers to maintain their services. This section outlines the evidence to date for both effects as well as the relative importance of modal time and cost variables for ridesharing.

Substitution Effects

Four studies examine the mode choice effects of ride-hailing by asking survey respondents who ride-hail how they would have traveled without the availability of the service (Clewlow and Mishra, 2017; Alemi et al., 2017; Henao, 2017, and Rayle et al., 2016). These studies and survey responses are summarized in Table 5 below. All studies indicate that ride-hailing trips would be most frequently substituted by car or taxi trips. The share of these trips ranges from 21% to 51%. Ride-hailing also appears to substitute for a relatively large share of transit (16% to 33%) and walk/bike (10% to 24%) trips across all studies. Ride-hailing does not substitute for many carpool trips in Rayle et al. (2016), only 1%, likely because the study focused on short trips in downtown San Francisco. However, the substitution of ride-hailing for carpool trips in major cities and California is higher, ranging from 14% to 18%. It appears that ride-hailing is out competing transit, carpool, transit, and walk/bike travel in terms of overall time and cost. For example, Rayle et al. (2016) reports that the average ridesourcing trip is 10 minutes longer by transit; 66% of ridesourcing trips are twice as long by transit.

Table 5. Mode(s) ride-hailing respondents would have used if ride-hailing not available.

Study	Car + Taxi	Carpool	Transit	Walk/Bike
Clewlow and Mishra (2017) * weighted by frequency of ride-hailing use	21%	18%	17%	24%
Alemi et al (2017) *weighted average of multiple allowed responses	51%	16%	16%	12%
Henao (2017)	33%	14%	22%	13%
Rayle et al. (2016)	45%	1%	33%	10%

Note shares do not sum to 100% because other responses not included (e.g., not made trip and other).

Complementary Effects

The fours studies also examine the magnitude of the complementary effects of ridesharing and transit. Clewlow and Mishra (2017) find that, since using ride-hailing, survey respondents use heavy rail transit (3%) more frequently and use bus and light rail less frequently (6% and 3%, respectively). Alemi et al. (2017) report that ride-hailing increases access and egress use of transit by 9%. Rayle et al. (2016) show that 5% of survey respondents use ride-hailing to access a specific public transit station. Henao (2017) reports that 5.5% of his riders were connecting to transit and 20.5% of respondents indicated that they had at some point used ride-hailing to connect to transit. On balance, these studies suggest that the substitution effect for transit appears to be stronger than the complementing effect.

Relative Importance of Travel Time and Cost Mode Choice Variables

The same four survey studies provide some insight into the relative important of time, cost, parking benefits, and lack of transit with respect to users' decision to ride-hail. See Table 6 below. Overall, lack of available transit service is ranked as the least important and time is, overall, the most important across the three studies that reported on its significance. Parking and time were also found to be significant reasons for ride-hailing.

Table 6. Relative Ranking* of Mode Choice Variables Across Studies.

Study	Time	Cost	Parking	Poor Transit Service
Alemi et al (2017)	2	1	3	4
Henao (2017)	1	3	2	4
Rayle et al. (2016)	1	3	2	4
Clewlow and Mishra (2017)	NA	NA	1	NA

**Note author's analysis of ranking based on study results.*

Alemi et al. (2017b) estimate latent class models and find that land use mix significantly reduces the frequency of ride-hailing and density significantly increases the frequency. Dias et al. (2017) find that the interaction of residential density and access to vehicles is significant in their bivariate probit model of ride-sharing propensity.

Network Vehicle Travel

Several studies use ride-hailing vehicle activity data from Uber and/or Lyft to estimate the share of time and or distance that a ride-hailing vehicle travels without a passenger. See Table 6. As described above, Crammer and Krueger (2015) randomly selected 2,000 UberX drivers in each of five large cities (Boston, Los Angeles, New York, San Francisco, and Seattle). They find that the fraction of time and VMT drivers travel without a passenger ranges from about 45% in San Francisco to about 57% in Seattle.

A more recent study uses vehicle location data in San Francisco from Uber and Lyft APIs and finds that the share of ride-hailing VMT without a paying passenger is about 20% (SFCTA, 2017). The lower estimate may be due to the significant growth in ride-hailing service availability between 2015 and 2017 and the inclusion of only trips that begin and end in the city. The direction of potential bias due to data cleaning and imputation processes is unknown.

Simulation studies of automated vehicle taxi services in the cities of Austin and Berlin also provide some insight into the magnitude of empty passenger relocation travel. Like the SFCTA study, these studies focus on intracity or region travel only. In Berlin (Maciejewski and Bischoff, 2016), market penetration of automated vehicle taxis was varied from 20% to 100% and empty vehicle relocation travel was varied from 17% to 19%, respectively. In another Berlin study (Bischoff and Maciejewski, 2016), which examined 100% penetration of AV taxis in both the central and outlying areas, found that relocation travel was 10% or less in central areas and between 22% to 45% in outlying areas. In Austin (Chen and Kockelman, 2016), electric automated vehicle taxi service that competes with other available modes is simulated with per mile costs that range from 75 cents to one dollar per mile. At higher levels of pricing, market penetration is lower and thus there are higher levels of empty passenger vehicle travel, which ranges from about 7% to 9%.

The effect of empty passenger relocation travel on total systemwide VMT is measured in the SFCTA study and in Austin. The SFCTA (2017) shows an overall increase in VMT of 6.5% on a typical weekday and of 10% on the weekend. In Austin (Chen and Kockelman, 2016), the studies show an increase that range from 8% to 11% for a typical weekday (Faganant and Kockelman, 2014; Faganant et al., 2015; and Faganant and Kockelman, 2016).

Several studies provide insight into the combined effects of mode choice and empty vehicle relocation travel. Henao (2017) uses driver trip log data and passenger surveys to estimate the change in passenger VMT before and after the introduction of ride-hailing services. He estimates an average 84.6% increase in VMT per trip for his sample of passengers. Chen and

Kockelman (2016) simulate both mode choice and route repositioning travel for an automated vehicle fleet that competes with other available modes and charges a fee. Average trip distance increases from 20% to 35% when prices range from 75 cents to 85 cents per mile, but decreases slightly (3%) when the per mile cost is high (one dollar per mile). Martinez and Christ (2015) use a rule base (i.e., not a behaviorally based) estimate of mode change with an estimate of relocation travel for an automated vehicle fleet with 50% to 100% of market penetration and find that total VMT increases by almost 90% without transit and from 43% to 50%, respectively, with transit.

Table 7. Summary of Ride-Hailing Distance Traveled Effects.

Author(s)	Method	Scenario	Location	% No Passenger		Total VMT
				Time	VMT	
Crammer and Krueger (2015)	Recorded driver activity	Ride Hailing	Boston	53.2%	53.9%	-
			LA	48.3%	49.7%	
			NY	49.1%	48.8%	
			SF	45.1%	45.7%	
			Seattle	56.5%	56.4%	
SFCTA (2017)	Recorded driver activities	Ride Hailing	SF	-	20.0%	+6.5% weekday; +10% weekend
Henao (2017)	Driver activity; passenger surveys	Ride Hailing	Denver	60.7%	40.6%	+84.6 Ride-hail Trip
Faganant and Kockelman (2014)	Model DTA relocation	100% AV Taxi	Like Austin	-	-	+10.7%
Faganant et al. (2015)			Austin	-	-	+8.0%
Faganant and Kockelman (2016)			Austin	-	-	+8.7%
Maciejewski & Bischoff (2016)	Model DTA relocation	20% AV Taxi	Berlin	-	19%	-
		40% AV Taxi			18%	
		60% AV Taxi			17%	
		80% AV Taxi			17%	
		100% AV Taxi			17%	
Bischoff and Maciejewski (2016)		100% AV Taxi	Average	-	16%	-
			Central		≤ 10%	
			Outer		22%-45%	
Chen and Kockelman (2016)	Mode choice and DTA with relocation	AV Taxi $0.75/mi.	Like Austin	-	6.8%	+35%*
		AV Taxi $0.85/mi.			7.7%	+20%*
		AV Taxi $1.00/mi.			9.4%	-3%*
Martinez and Christ (2015)	SA and rule based mode choice (proximity & trip length)	100% AV Taxi No Transit	Lisbon	-	-	+88.2%
		100% AV Taxi Transit				+43.2%
		50% AV Taxi No Transit				+89.5%
		50% AV Taxi Transit				+49.7

LA=Los Angles; NY=New York; SF=San Francisco; AV=automated vehicles; VMT=vehicle miles traveled; * Average Trip Distance Miles

Conclusion

In this study, a framework was developed to identify the range of possible travel effects, both positive and negative, of ride-hailing service users. This includes the effects of ride-hailing on auto ownership, trip generation, destination choice, mode choice, network vehicle travel, and land use. Next, the available literature (as of the fall of 2017) was synthesized using this framework. The major findings and conclusions are summarized below.

- **Auto Ownership**: 9% to 10% of respondents in two surveys stated that they gave up a vehicle after joining ridesharing. One of these studies includes a representative sample of the population in seven major U.S. cities and another targeted ride-hailing users in downtown San Francisco. These studies represent initial evidence for some reduction in auto ownership. However, the responses to specific questions in these surveys raise questions about other factors that may contribute to reduced vehicle ownership. More research is needed to verify the cause and effect relationship between reduced auto ownership and use of ride-hailing.
- **Trip Generation**: Available research currently reports a widely varying range of new vehicle trips resulting from the availability of ride-hailing: 8% to 22%. These results are from surveys of a representative sample of U.S. cities (22%), a representative sample of Millennial and Generation Xers in California (8%), and ride-hailing users in San Francisco (8%) and Denver (12%). Available research indicates that reduced physical and legal limits to driving, avoiding drinking and driving, and lack of auto ownership contribute to new vehicle trips. However, more research is needed to understand the wider range of factors that contribute to variation in induced vehicle trip generation from ride-hailing and their relative importance.
- **Mode Choice**: One of the more controversial issues surrounding ride-hailing is whether these services support transit use by increasing first and last mile access to transit or undermine transit by a providing a faster and cheaper travel alternative. The body of research to date suggest that the substitution effect is stronger than the complementary effect. In response to the question, "What mode(s) would you have used if ride-hailing were not available?" in four surveys, 16% to 33% of respondents indicated that they would have taken transit if ride-hailing was not available. These results are from surveys of a representative sample of U.S. cities (17%), a representative sample of Millennial and Generation Xers in California (16%), and ride-hailing users in San Francisco (33%) and Denver (22%). These studies also show some use of ride-hailing for access and egress purposes (3%, 9%, 5%, and 6%, respectively), but this is more than offset by reductions in transit travel. These studies show reductions in carpool, walk, and bike travel, and one study suggests that ride-hailing may also reduce carsharing. Research is needed to more carefully measure the transit ridership effects of ride-hailing and the potential to increase the use of ride-hailing as a first and last mile transit access mode.

- **Network Vehicle Travel without Passengers**: Available research suggest that empty vehicle travel can range from about 10% to 20% in high density downtown urban areas where the supply of ride-hailing vehicles is high and about 45% to 60% in lower density suburban areas where the supply of ride-hailing vehicles is lower. These results are based on three studies that use ride-hailing driver activity data and two modeling studies. Current studies are limited due to lack of access to ride-hailing activity data. More studies that use ride-hailing driver activity data are needed, particularly in suburban areas.
- **Destination Choice and Land Use.** No studies have been conducted on the destination and land use effect of ride-hailing.

In sum, the results of our analysis indicate that ride-hailing will tend to reduce auto ownership somewhat and increase vehicle trip generation, vehicle mode share, and network vehicle travel necessary to pick up new passengers. Overall, these effects would tend to increase VMT and associated GHG emissions. However, there are no studies that examine the impact of all these factors on VMT.

The effect of vehicle travel without passengers on total systemwide VMT is estimated for the City of San Francisco in a study that uses ride-hailing vehicle activity data and in several modeling studies in Austin (Texas). The San Francisco study shows an overall increase in VMT of 6.5% on a typical weekday and of 10% on the weekend and, in Austin, the increase ranges from 8% to 11% for a typical weekday.

Several studies attempt to estimate change in VMT and represent mode choice and vehicle travel without passengers. One study combines ride-hailing vehicle activity data and passenger survey data and finds an average 85% increase in VMT for each ride-hailing trip. Modeling studies in Austin and Lisbon show increases on the order of 20% to 50%.

Note, however, there are numerous uncertainties associated with all these studies, as is detailed in the full white paper. Better understanding of the full impacts of ride-hailing can be improved with greater access to driver and passenger activity data across a wider range of geographic and socio-demographic contexts. However, the evidence available as of the fall of 2017 suggests that ride-hailing, as currently used in U.S. cities, is contributing to a net increase in VMT and associated GHG emissions; however, the total magnitude of that increase is uncertain.

As a result, policy makers may want to evaluate policies that support the use of ride-hailing services for first and last mile service to transit and for disadvantaged populations (low income, disabled, and without vehicles) to access basic services and opportunities, for example, through subsidized fares. Outside of dense city areas, policy makers may want to explore restrictions on ride-hailing services or distance-based pricing policies to minimize empty vehicle travel and support transit use. Inside dense city areas, curb-based pricing policies for pick-up and drop-off access may offset lost parking revenues and continued use of transit. Policies should also be considered that encourage ride-hailing drivers to use electric vehicles

References

Alemi, Farzad, Giovanni Circella, and Daniel Sperling (forthcoming) "Adoption of Uber and Lyft, Factors Limiting and/or Encouraging Their Use and Impacts on Other Travel Modes among Millennials and Gen Xers in California". To be presented in *TRB 97th Annual meeting* and to be submitted to Transport Policy (forthcoming). 2017a.

Alemi, Farzad, Giovanni Circella, Patricia Mokhtarian and Susan Handy (forthcoming) "On-demand Ride Services in California: Investigating the Factors Affecting the Frequency of Use of Uber/Lyft". To be presented in *TRB 97th Annual meeting* and to be submitted to Transportation Research Part C (forthcoming). 2017b.

Bischoff, Joschka, and Michal Maciejewski. "Autonomous taxicabs in Berlin–a spatiotemporal analysis of service performance." *Transportation Research Procedia* 19 (2016b): 176-186.

Chen, T. Donna, and Kara M. Kockelman. "Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes." *Transportation Research Record: Journal of the Transportation Research Board* 2572 (2016): 37-46.

Clewlow, Regina R., and Gouri Shankar Mishra. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. No. UCD-ITS-RR-17-07. Research Report–UCD-ITS-RR-17-07, Davis: University of California, 2017.

Cramer, Judd, and Alan B. Krueger. "Disruptive change in the taxi business: The case of Uber." *The American Economic Review* 106, no. 5 (2016): 177-182.

Dias, Felipe F., Patrícia S. Lavieri, Venu M. Garikapati, Sebastian Astroza, Ram M. Pendyala, and Chandra R. Bhat. *A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services*. No. 17-06359. 2017.

Fagnant, Daniel J., and Kara M. Kockelman. "The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios." *Transportation Research Part C: Emerging Technologies* 40 (2014): 1-13.

Fagnant, Daniel J., and Kara M. Kockelman. "Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas." *Transportation* (2016): 1-16.

Feigon, Sharon, and Colin Murphy. *Shared mobility and the transformation of public transit*. No. Project J-11, Task 21. 2016.

Hampshire, Robert Cornelius, Chris Simek, Tayo Fabusuyi, Xuan Di, and Xi Chen. "Measuring the Impact of an Unanticipated Suspension of Ride-Sourcing in Austin, Texas." (2017).

Henao, Alejandro. "Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior." PhD diss., University of Colorado at Denver, 2017.

Horni, Andreas, Kai Nagel, and Kay W. Axhausen, eds. *The multi-agent transport simulation MATSim*. London: Ubiquity Press, 2016.

Maciejewski, Michal, and Joschka Bischoff. "Congestion effects of autonomous taxi fleets." *Transport* (2017): 1-10.

Martinez, Luis, and P. Crist. "Urban Mobility System Upgrade–How shared self-driving cars could change city traffic." In *International Transport Forum, Paris*. 2015.

Rayle, Lisa, Danielle Dai, Nelson Chan, Robert Cervero, and Susan Shaheen. "Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco." *Transport Policy* 45 (2016): 168-178.

Salon, Deborah. "Heterogeneity in the relationship between the built environment and driving: Focus on neighborhood type and travel purpose." *Research in Transportation Economics*52 (2015): 34-45.

San Francisco County Transportation Authority. TNCs Today: A Profile of San Francisco Transportation Network Company Activity. San Francisco. June 2017.

Schaller, Bruce. "Unsustainable? The Growth of App-Based Ride Services and Traffic, Travel and the Future of New York City." (2017).

Sivak, M. and Schoettle, B. (2014) A survey of public opinion about autonomous and self-driving vehicles inthe US, the UK and Australia. Michigan: University of Michigan.

Schoettle, B. and Sivak, M. (2014). The reasons for the recent decline in young driver licensing in the United States. Traffic Injury Prevention, 15, 6-9.

Smith, A. (2016). Shared, collaborative and on demand: The new digital economy. *Washington, DC: Pew Internet & American Life Project. Retrieved May 21*, 2016.

Wadud, Zia, Don MacKenzie, and Paul Leiby. "Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles." *Transportation Research Part A: Policy and Practice* 86 (2016): 1-18.