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The impact of ride-hailing on vehicle miles traveled

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Abstract

Ride-haling such as Uber and Lyft are changing the ways people travel. Despite widespread claims that these services help reduce driving, there is little research on this topic. This research paper uses a quasi-natural experiment in the Denver, Colorado, region to analyze basic impacts of ride-hailing on transportation efficiency in terms of deadheading, vehicle occupancy, mode replacement, and vehicle miles traveled (VMT). Realizing the difficulty in obtaining data directly from Uber and Lyft, we designed a quasi-natural experiment—by one of the authors driving for both companies—to collect primary data. This experiment uses an ethnographic and survey-based approach that allows the authors to gain access to exclusive data and real-time passenger feedback. The dataset includes actual travel attributes from 416 ride-hailing rides—Lyft, UberX, LyftLine, and UberPool—and travel behavior and socio-demographics from 311 passenger surveys. For this study, the conservative (lower end) percentage of deadheading miles from ride-hailing is 40.8%. The average vehicle occupancy is 1.4 passengers per ride, while the distance weighted vehicle occupancy is 1.3 without accounting for deadheading and 0.8 when accounting deadheading. When accounting for mode replacement and issues such as driver deadheading, we estimate that ride-hailing leads to approximately 83.5% more VMT than would have been driven had ride-hailing not existed. Although our data collection focused on the Denver region, these results provide insight into the impacts of ride-hailing.

Keywords Ride-hailing · Ridesourcing · TNC · Lyft · Uber · Deadheading · Vehicle occupancy · Mode replacement · VMT · Vehicle miles traveled

Introduction

The main services provided by companies like Uber around the globe, Lyft in the United States, Cabify in South America, or Didi in China can be called ride-hailing, ridesourcing, or transportation network companies (TNCs). As ride-hailing continues to grow, the

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importance of understanding its impacts becomes more critical. City officials and transit advocates have expressed concerns about the lack of open data and potential problems with ride-hailing such as congestion, competition with public transportation, and equity issues (Flegenheimer and Fitzsimmons 2015; Grabar 2016; Rodriguez 2016). Thus, the first gap this study aims to fill is around the lack, need, and difficulty to obtain data (Bialick 2015; Levitt 2016). The second gap in the literature that we aim to fill is to provide a basic of ride-hailing impacts including deadheading, vehicle occupancy, car ownership, mode substitution, and changes in vehicle miles travel (VMT).

To do so, one of the authors collected data by serving as an independent-contractor driving for both Uber and Lyft. This quasi-natural experiment was designed to look specifically at the impacts of ride-hailing and includes two inter-related datasets: (i) the "driver dataset"; and (ii) the "passenger dataset". With these novel datasets, we estimate the impact of ride-hailing on deadheading, vehicle occupancy, mode replacement, and impacts on transportation efficiency by measuring passenger miles traveled (PMT) versus VMT, and comparing VMT with and without ride-hailing. We believe that this research will help stress the importance of data and has already proven to be helpful for cities and transportation agencies in new strategies for data collection (CommonWealth 2018). This research could also serve as a window of opportunity to understand the impacts of future autonomous vehicles (AVs).

The next section provides a background for ride-hailing including a history and overview of Uber and Lyft, followed by a literature review on research in this area. We then cover the quasi-natural experiment, data collection, and research methods before presenting the analysis and results. We conclude with recommendations, limitations, and suggestions for future research.

Background

Many factors—including social networks, real-time information, and mobile technology—allow passengers and drivers to connect through mobile smartphone applications (i.e. apps). This technology led to the creation and popularization of app-based on-demand transportation platforms such as Uber and Lyft. These companies, in their current form, are mostly known for their regular UberX and Lyft services as well as their carpool options: LyftLine and UberPool. Uber started as a black-car limousine service called UberCab, launched in San Francisco in 2010 (McAlone 2015), while Lyft co-founders Logan Green and John Zimmer previously co-founded Zimride in 2007, a true rideshare platform created to connect drivers and passengers through social networking (Green and Zimmer sold Zimride to Enterprise Holdings in July 2013) (Lawler 2014). While Lyft was launched in June 2012 with its original regular Lyft service, Uber did not unveil its regular UberX service until July 2012. The LyftLine and UberPool carpool options started in 2014 but are only available in certain metropolitan cities (Lyft Blog 2016; Uber Newsroom 2014, 2016).

As of early 2018, Uber was already operating in over 600 cities across 78 countries, while Lyft was in over 300 U.S. cities and expanded outside of the U.S. for the first time by launching in Toronto, Canada, in November 2017. Uber completed its first billion rides in six years, while the second billion rides were completed in just six months (Somerville 2016). It then took Uber only ten months to add three billion more and reach a total of five billion rides by May 2017 (Holt et al. 2017). Uber's estimated valuation was around $50 billion in early 2018 (Boland 2018), while the latest funding round values Lyft at $11 billion (Loizos 2017; Fiegerman 2017). These valuations put these TNCs as the most valuable transportation companies in the U.S., despite little in the way of transportation infrastructure, vehicle ownership, or even having to hire drivers as employees. However, both Uber and Lyft are investing and teaming up with vehicle manufacturers for automated vehicle technology (Hawkins 2017a, b; Isaac 2017; Scrutton 2016) and might have their own fleets of vehicles in the future.

The number of rides and valuation numbers show the magnitude of Uber and Lyft and their influence on the way people get around. Their path, however, has not been worry free. They constantly deal with situations regarding regulations, protests, and lawsuits from taxi companies, city officials, and drivers seeking employment rights. They also have taken advantage of the terminology in their marketing strategies. The terminology of new and evolving transportation services can be confusing and sometimes incorrectly used, which can mislead public perception and general use of the services. An example is the misused word ‘ridesharing’ when referring to ride-hailing companies in their original form (Goddin 2014). A ridesharing trip should, in theory, carry two or more passengers; yet, most ride-hailing trips carry only one passenger per trip. Some of the other names include: Transportation Network Companies (TNCs), ride-hailing, ridesourcing, ride-booking, ride-matching, on-demand-rides, and app-based rides. TNCs originated as the legal term for regulation purposes; ridesourcing has been used in academic publications; and ride-hailing has been used in more recent academic publications and media articles. The Associated Press Stylebook in January 2015 presented an update on the topic:

> Ride-hailing services such as Uber or Lyft let people use smartphone apps to book and pay for a private car service or in some cases, a taxi. They may also be called ride-booking services. Do not use ride-sharing (Warzel 2015).

While there seems to be a consensus that these services are not ridesharing, there is still no clearly a defined term. In an attempt to correct and use the right terminology, be consistent with more recent academic and media publications, and capture a larger audience, we are using the term ride-hailing for this paper.

Literature review

The early academic studies on this topic compared ride-hailing mostly to the taxi industry and ridesharing services (Anderson 2014; Rayle et al. 2016; Cramer and Krueger 2016). Rayle et al. (2016) compared ride-hailing services with traditional taxis in San Francisco using an intercept survey in spring 2014. The findings from this study indicated that ride-hailing users tend to be a lot younger, have higher incomes and lower car ownership, as well as frequently travel with companions more so than the general San Francisco population. This study also showed that, compared to taxis, customers experienced shorter waiting times. Participants in this study said that ride-hailing both substitute and complement public transit, walking, and biking; moreover, 8% of survey respondents stated that they would not have traveled if ride-hailing services were not available (i.e. induced travel effect). The website FiveThirtyEight.com also published a few non-peer reviewed articles regarding ride-hailing using data acquired via a Freedom of Information Act request. Their results suggest that in New York City, most of the mode substitution for Uber comes from taxis (Fischer-Baum and Bialik 2015; Bialik et al. 2015; Silver and Fischer-Baum 2015).

In terms of driving efficiency, Cramer and Krueger (2016) compared the capacity utilization rate of UberX drivers against taxi drivers in a few U.S. cities. Using aggregated data across all drivers available for both cities, the findings suggest that the mileage-based capacity utilization measure (i.e. percent of miles driven with a passenger) was calculated at 39.1–40.7% for taxis, and 55.2–64.2% for UberX. The main limitation of this study is that the Uber data only included the time and distance when drivers have the app on. They excluded other segments such as the mileage and time drivers must travel from origin to point of log-in as well as from the point of log-out to the end location, which would overestimate their capacity utilization rate.

Regarding literature focusing more on the overall impact to the transportation system, a non-peer reviewed report investigated the relationship between public transportation and shared modes, including bikesharing, carsharing, and ride-hailing in seven U.S. cities. This report found that the higher the use of shared modes, the more likely people use public transportation, own fewer cars, and spent less on transportation. This report also showed that shared modes complement public transportation (Murphy 2016). These statements should be analyzed in more detail since these correlations do not necessarily mean causation. Do users of services like Uber and Lyft also use public transportation at higher rates and own fewer cars? Or could it be that people who use public transportation and own fewer cars are more likely to add Uber and Lyft to their transportation menu of options?

A case study in Austin, Texas, surveyed people to examine how their habits changed after Uber and Lyft left the city due to a local law change regarding driver fingerprinting and background checks. After Uber and Lyft ceased operation, they found that 41% of respondents shifted to a personal vehicle while 3% shifted to public transit. Additionally, 9% of respondents stated that they purchased a vehicle after the ride-hailing companies left (Hampshire et al. 2017). More recently, a report surveying over 4000 adults in major U.S. metropolitan areas found that 21% of adults personally use ride-hailing services. Of those ride-hailing users, 39% were substituting driving, 15% public transportation, 23% bike or walk, and 22% would not have made the trip (Clewlow and Mishra 2017).

Still, the literature on ride-hailing remains limited, in part due to their relative novelty and lack of open data. Thus, it is difficult for municipalities, states, and transportation agencies to know whether they should be encouraging or prioritizing these options. This study aims to begin filling these gaps by looking in more detail at deadheading, vehicle occupancy, car ownership, mode replacement, VMT changes in order to find where ride-hailing stands in terms of efficiency compared to other modes.

Quasi-natural experiment

The first step in understanding the impacts of ride-hailing was to develop a framework to guide the research and fill the important gaps in the literature. This framework lays out the data and research needed to investigate ride-hailing, emphasizing the need to employ a combination of travel attributes (e.g. travel times), revealed-behavior data, and stated-response data structures (Henao and Marshall 2017). Realizing the difficulty obtaining data directly from Uber and Lyft and finding the lack of ride-hailing research, we sought to gain access to exclusive driver data and real-time passenger feedback by signing-up and driving for these companies. We submitted a research proposal to the Colorado Multiple Institutional Review Board (COMIRB) and obtained IRB approval to interview passengers (COMIRB Protocol 16-0773, Exception APP001-3) in spring 2016 (Henao 2017).

There are two interconnected datasets on the data collection: "driver dataset" and "passenger dataset". The first is the exclusive data that Lyft/Uber drivers can obtain by giving rides to passengers. This "driver dataset" contains information about travel attributes from actual trips including date, time of the day, origin and destination (O–D) locations, travel times, travel distances, passenger cost, and driver earnings. The second dataset is the information gathered by surveying passengers during the actual rides (i.e. "passenger dataset"), similar to the traditional on-board survey developed by transit organizations.

We conducted the data collection using a sedan vehicle (2015 Honda Civic) and a smartphone (iPhone 5s). The main apps in the smartphone used for this research were "Lyft", "Uber-driver Partner", "GoogleMaps", and "My Tracks". GoogleMaps and MyTracks GPS apps helped tracking and recording ride-hailing travel data.

Driving strategy

Based on previous research (Anderson 2014) and extensive conversations with ride-hailing drivers, there are three main driving strategies: (i) circulate around until you get an app request; (ii) strategically locate to increase the chance of getting a request (e.g. drive to downtown areas, hotels, or airports); and (iii) minimize driving by parking immediately after a ride is finished. Most ride-haling drivers use a combination of these strategies. The driver-author also used a combination of these strategies, with an emphasis on the parking strategy since it is the most conservative option in terms of minimizing deadheading (i.e. driving without a passenger).

On a typical driving day, for instance, the driver-author turned on both Uber and Lyft apps and waited until a passenger requested a ride. To be consistent with our conservative strategy, unnecessary driving was minimized by not picking-up passengers if the location was more than 15 miles away from the driver location at request, by parking as soon as possible after a passenger was dropped-off, and using conservative commute distances at the end of the shift (we did not include commuting at the start of the shift). Once the ride was accepted, driving mode was turned-off for the other service. For example, if it was a Lyft request, the Uber driver mode was turned-off, or vice versa. Then, the driver traveled to the passenger pick-up location and drove the passenger to the desired destination.

Once the ride ended at the destination location, the other app was turned on to wait for a new passenger request. Once the passenger left the car, the driver-author tried to find the closest parking space available with the intent to minimize cruising distance without a passenger. For this study, we also kept in mind the rationale of what would a passenger have done if he/she was driving and needed to park (e.g. free parking, on-street metered parking, and garage parking under some circumstances). We recorded the cruising to park time and distance using the same methodology with the GPS-based apps.

Driving shifts ranged from as low as 2 h to as high as 9 h. All seven days and times (24-hour period) were covered during the study period, but higher number of rides came during high demand times such as Friday and Saturday nights, representing typical ride-hailing services. Driving for both Uber and Lyft helped minimize the waiting times and cruising distances since the chances of getting a request from either service increased (it is also common that ride-hailing drivers work for both Uber and Lyft). For example, there were occasions where new requests came in even before finishing parking. We decided to conduct all the data collection by the driver-author to eliminate bias between drivers, to control travel without a passenger (i.e. deadheading minimization), to reduce surveyor errors, and to ensure data quality.

Passenger survey

The driver-author invited passengers to participate in a short survey about ride-hailing both verbally and with signs in the car, reading:

> Hi rider, I am a grad student doing research on transportation. Would you help me by doing a short survey (~6 min) about this ride? You can use my tablet or go to this link www.ride-survey.com. Thank you!

As the sign indicated, passengers had the option to take the survey using their own device or via a provided tablet device. Details of the survey are included in the Data section.

Study area

The Denver metropolitan region comprises a variety of contexts, covering both urban and suburban areas. For example, it contains very urban places such as the area around Union Station in downtown Denver as well as low-density areas such as those surrounding the Denver International Airport (DIA), located about 24 miles northeast of Union Station. The Denver metropolitan region also includes a college town, Boulder, and suburban cities like Westminster. This diversity of characteristics (e.g. density, race diversity, income levels) makes the Denver region a good place to study ride-hailing.

Our sample was random by design since the driver-author did not know where each ride would end up; this entailed driving all over the study area and providing transportation to passengers across a wide variety of socio-economic and socio-demographic characteristics. The only location that we had control over is where the app was turned on at the beginning of the shift. Thus, we varied the starting location from urban to suburban areas.

While Uber and Lyft originated in what is considered an unregulated space, Colorado was also the first state in the U.S. to authorize Uber and Lyft services to operate with a bill signed by Governor Hickenlooper in June 2014 (Vuong 2014).

Data

This study includes 416 ride-hailing trips—198 regular Lyft, 164 UberX, 39 LyftLine, and 15 UberPool—for the "driver dataset" and 311 surveys for the "passenger dataset," collected over a period of 14 weeks during fall 2016.

Driver dataset

The "driver dataset" contains several pieces of information for each ride including date, time, weather, pick-up/drop-off location, passenger cost, driver earnings, travel times, distances, and parking information. Figure 1 presents mileage for all 416 passenger O–D rides, and the remaining data derived from this dataset is the focus of the results section.

Passenger dataset

The 311-survey passenger dataset included three groups of questions:

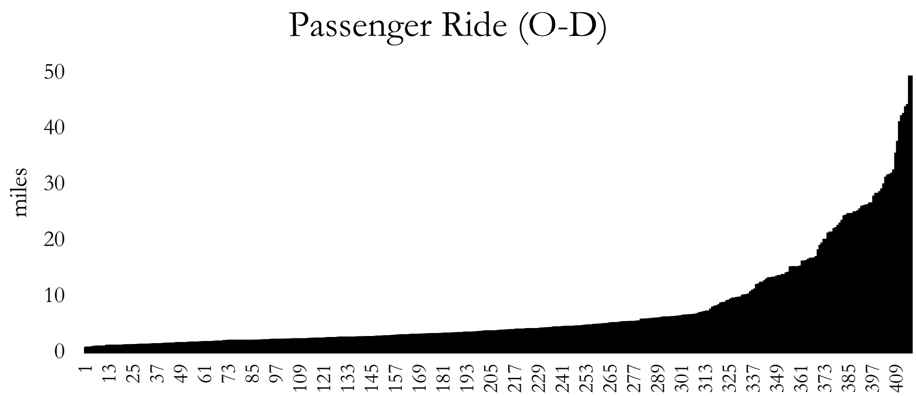


Fig. 1 Ride-hailing rides (n = 416)

Specific Trip Questions (Q1–Q10):

> The first section asks passengers questions regarding the specific Lyft/Uber ride and includes questions such as trip purpose, travel mode replacement, and reasons to shift from a previous mode.

General Use Questions (Q11–Q25):

> The second part of the survey covers broader questions about travel behavior in general such as modality resources (e.g. car ownership, transit pass, etc.), general ride-hailing use, frequency of use for different modes, travel behavior changes, and more general trip purposes and reasons.

Demographic Questions (Q26–Q37):

> The third section of the survey includes questions regarding characteristics of the individual and household (i.e. socio-economic demographics).

Table 1 provides descriptive statistics from passengers' survey answers. Previous studies have shown that ride-hailing (and carsharing) users do not usually represent the overall population in terms of income, age, and ethnicity (Murphy, 2016; Rayle et al., 2016). The authors from these papers suggest that these services mostly serve certain populations. Comparing the summary statistics of this study to the Denver population, our study results somewhat agree with these previous studies but are slightly more aligned with the representative populations than the existing literature. Different from previous studies—where researchers used intercept surveys at specific locations or online—our research has the advantage of being random by design since the passengers' destination location is unknown. Thus, this study covered a larger area and included populations that may not be represented in the existing literature. The sample has a very close split of male–female population. Passengers were mostly younger adults, but compared to other studies, we had higher participation from elderly people. While two-thirds of the sample were white, we had representation from various races and ethnicities. In contrast to previous studies, income and education demographics were also better distributed between different ranges, although still skewed compared to the Denver population. These services are mostly used by single or never married individuals, as well as people working full-time or part-time.

Table 1 Demographics of ride-hailing passengers

	Survey	Responses (%)	Denver (%)		Survey	Responses (%)	Denver (%)
Gender (n = 309)				Marital status (n = 295)			
Female	145	46.9	50.0	Single or never married	185	62.7	41.7
Male	162	52.4	50.0	Married	80	27.1	39.2
Prefer not to answer	2	0.6	–	Separated, divorced, or widow	28	9.5	19.1
Resident (n = 309)				Other	2	0.7	–
Local resident	254	82.2	–	Household size (n = 292)			
Visitor	55	17.8	–	Household size of 1	65	22.3	–
Age (n = 309)				Household size of 2	129	44.2	–
18–24	78	25.2	10.0	Household size of 3	56	19.2	–
25–34	132	42.7	21.8	Household size of 4	30	10.3	–
35–44	56	18.1	15.4	Household size of 5+	12	4.1	–
45–54	30	9.7	11.7	Children (n = 229)			
55–64	7	2.3	10.5	Children in household	47	20.5	25.1
65+	6	1.9	10.7	No Children in household	182	79.5	74.9
Race/ethnicity (n = 308)				Education (n = 297)			
Asian	24	7.8	3.5	Less than high school	9	3.0	13.9
Black/African American	16	5.2	9.4	Graduated high school or equiv.	49	16.5	17.7
Hispanic or Latino	39	12.7	30.9	Some college, no degree	58	19.5	18.3
White	206	66.9	53.1	Associate or Bachelor's degree	124	41.8	32.5
Other	16	5.2	3.1	Advanced degree (Master's, PhD)	57	19.2	17.6
Prefer not to answer	7	2.3	–	Employment (n = 301)			
Household income (n = 296)				Working (Full-time or Part-Time)	246	81.7	70.9
$30 K or less	34	11.5	28.3	Volunteer	1	0.3	–
$31 K–$45 K	56	18.9	14.0	Unemployed	15	5.0	6.3
$46 K–$60 K	58	19.6	11.1	Retired	8	2.7	–
$61 K–$75 K	30	10.1	10.0	Not applicable	31	10.3	–
$76–$100 K	40	13.5	11.9	Student (n = 300)			

Table 1 (continued)

	Survey	Responses (%)	Denver (%)		Survey	Responses (%)	Denver (%)
Over $100 K	50	16.9	24.9	Student (Full-time or Part-time)	70	23.3	34.2
Prefer not to answer	28	9.5	–	Not currently a student	230	76.7	65.8

Notes: Denver data is from 2011 to 2015 ACS 5-Year estimates, First age category for ACS is 15–24 years old, Income ranges for ACS differ slightly from survey

Methodology

This section is divided in several sub-sections covering the specific methodology to calculate deadheading, vehicle occupancy, and VMT changes with mode replacement.

Deadheading

The term deadheading is mostly used for the taxi and trucking industry and refers to distance traveled without passengers or freight. Exclusive to ride-hailing, there are four specific segments of deadheading: commuting from driver residence; cruising for a ride (this is the most commonly known form of deadheading); from dispatch to pick-up location (we propose to name this new form of deadheading, somewhat exclusive to ride-hailing, overheading); and commuting at end of shift. Figure 1 illustrates these four segments, in addition to the actual passenger ride, for a total of five segments (Fig. 2).

The total ride-hailing driving distance (VMT_R) is calculated by Eq. (1) where for each shift i and ride j:

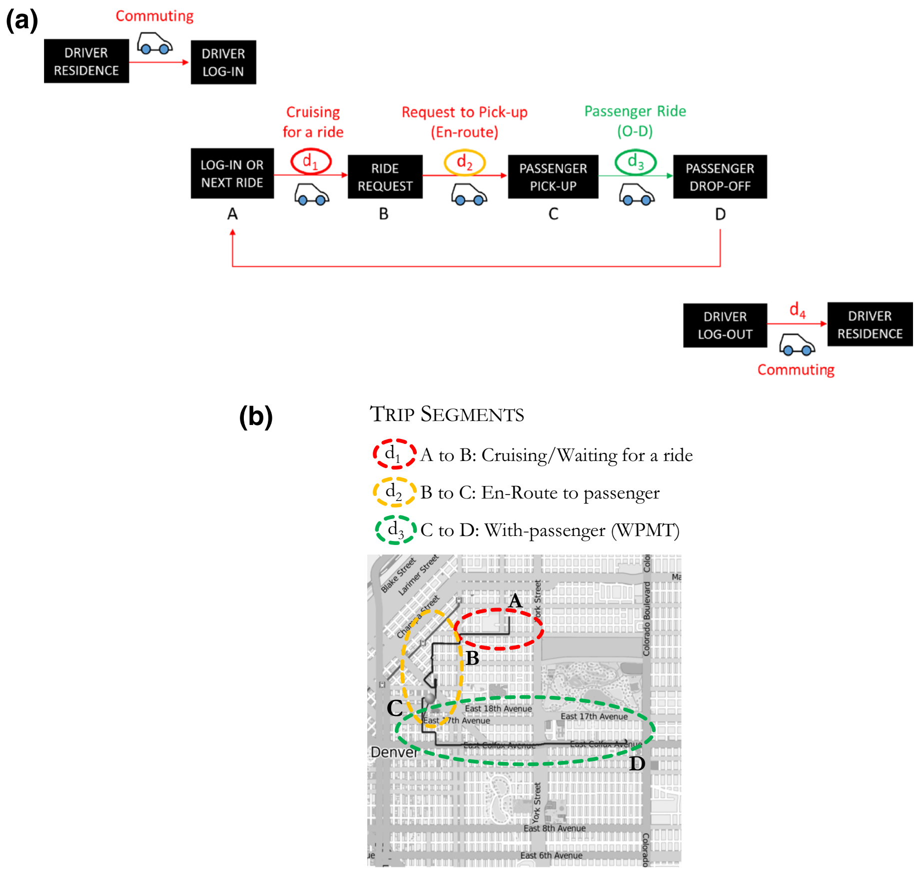


Fig. 2 **a** Travel Segments of a Lyft/Uber Driver, **b** GPS Tracking of a Lyft/Uber Ride

$$VMT_R = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} \left[d_{1(\mathrm{i,j})} + d_{2(\mathrm{i,j})} + d_{3(\mathrm{i,j})} \right] + d_{4(\mathrm{i})} \right) \tag{1}$$

where m is the last ride of each shift i; n is the last shift; d_1 is the miles cruising for a ride; d_2 is the "overheading" miles; d_3 is miles for the O–D ride; and d_4 is commute miles at end of shift.

Equation (1) can also be expressed as:

$$VMT_R = \sum_{i=1}^{n} \sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n} \sum_{j=1}^{m} d_{2(\mathrm{i,j})} + \sum_{i=1}^{n} \sum_{j=1}^{m} d_{3(\mathrm{i,j})} + \sum_{i=1}^{n} d_4 \tag{2}$$

In terms of passenger O–D rides and deadheading, the total driving distances is expressed as:

$$VMT_R = \mathrm{OD} + deadheading \tag{3}$$

where:

$$\mathrm{OD} = \sum_{i=1}^{n} \sum_{j=1}^{m} d_{3(\mathrm{i,j})} \tag{4}$$

$$\mathrm{Deadheading} = \left(\sum_{i=1}^{n} \sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n} \sum_{j=1}^{m} d_{2(\mathrm{i,j})} + \sum_{i=1}^{n} d_4 \right) \tag{5}$$

We estimated the ride-hailing deadheading percentage by comparing deadheading versus $\mathrm{VMT_R}$, as follows:

$$Deadheading\ Percentage = \frac{Deadheading}{VMT_R} \tag{6}$$

Finally, we calculated the ratio of "deadheading without commuting" and O–D to estimate the amount of deadheading (no commute) occurring per vehicle miles traveled with passengers (O–D) as:

$$Deadheading\,(no\,commute)rate\,per\,O{-}D = \frac{\left(\sum_{i=1}^{n} \sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n} \sum_{j=1}^{m} d_{2(\mathrm{i,j})} \right)}{\sum_{i=1}^{n} \sum_{j=1}^{m} d_{3(\mathrm{i,j})}} \tag{7}$$

Vehicle occupancy

For every ride-hailing trip, we recorded the vehicle occupancy defined as the number of passengers in the vehicle for each ride, ranging from 1 to 4. For the deadheading segments, the vehicle occupancy equals zero. We calculated the average vehicle occupancy based on total rides as well as the distance weighted average, with and without deadheading.

Combining the driver and passenger datasets

Both interconnected datasets—driver and passenger—are necessary to compare with- and without- ride-hailing scenarios. For example, in the without scenario, we need to know what passengers would have done without ride-hailing; thus, the question of interest from the passenger survey is Q5: *"For this trip, how would you have traveled if Lyft/Uber wasn't an option?"*. The survey response options to the multiple-choice question were: *"wouldn't have traveled; drive alone; carpool (drive); carpool (ride); public transportation; bike or walk; taxi; and other"*. After reviewing the "*other*" responses, we created new categories including "*get a ride*" and "*car rental*". If the passenger response to question Q5 was carpool, the survey was designed to ask the number of people that the passenger would have carpooled with (Q6), with the intent to make a fair comparison. For this study, we included a question on whether the passenger was using Lyft/Uber for the entire length of the trip (origin to destination), or if he/she was making a connection to another mode of transportation (Q9), and if so, to which mode of transportation (Q10). Finally, we included survey questions about car ownership/access (Q19). In summary, the information of interest for each ride includes:

- Date of ride
- Time at request
- The service the ride was requested from: Lyft, LyftLine, UberX, or UberPool
- Travel distances
- Number of passengers
- Trip Mode replaced (Q5)
- If passenger would have carpooled, the number of people carpooling (Q6)
- Connection with another mode of transportation (Q9 & Q10)
- Own or have access to a personal car (Q19)

Based on the data previously described, including the mode replaced and travel behavior if Uber and Lyft were not in place, we calculated passenger miles traveled (PMT) and replaced VMT (or $VMT_{WITHOUT}$), as follows:

- $VMT_{WITHOUT}$ for "*wouldn't have traveled*" is 0
- $VMT_{WITHOUT}$ for "*bike or walk*" is 0
- $VMT_{WITHOUT}$ for "*car rental*" is the same as the VMT from the origin to the destination (O–D) plus parking distance
- $VMT_{WITHOUT}$ for "*carpool (drive)*" is the same as O–D VMT plus parking distance
- $VMT_{WITHOUT}$ for "*carpool (ride)*" is calculated based on O–D VMT, the number of passengers in the ride, and the number of people that they stated would have carpooled with
- $VMT_{WITHOUT}$ for "*driving*" is the same as O–D VMT plus parking distance
- $VMT_{WITHOUT}$ for "*get a ride*" is equal to two times the O–D VMT. This is the case when someone else (e.g. parent, spouse, or friend) would have driven the passenger from the origin to the destination and then gone back to origin, thus incurring in a round-trip doubling of miles from the original O–D trip.
- $VMT_{WITHOUT}$ for "*other ride-hailing*" is the same as ride-hailing VMT_R,
- $VMT_{WITHOUT}$ for "*public transportation*" is 0 for walk-to-transit (WTT) and 3.4 miles for drive-to-transit (DTT). The selection of WTT and DTT rides were based on ride

distance, the answer to connection mode (Q9 & Q10), the answer to car access (Q19), the percentage of WTT and DTT based on data from a previous study in the Denver area (Marshall and Henao 2015), and DTT distance based on another paper in the study area (Truong and Marshall 2014).

- $\mathrm{VMT}_{\mathrm{WITHOUT}}$ for "*taxi*" is equal to 2.5 times O–D VMT based on the taxi distance efficiency of around 40% (Cramer and Krueger 2016). We used the same ride-hailing VMT for trips to the airport.
- If the ride included a connection, the previous distance replaced is based on total VMT and PMT. For example, if a passenger was dropped-off at a transit station to ride a train to the airport, and the mode replaced was "*get a ride*", the $\mathrm{VMT}_{\mathrm{WITHOUT}}$ is equal to two times the total distance (O–D VMT plus the train distance) because the person taking the passenger would have traveled all the way to the airport and back.

Ride-hailing VMT (or $\mathrm{VMT}_{\mathrm{R}}$) was calculated using all distances—with and without a passenger—as described in Eqs. (1) or (2). Then, we calculated PMT/VMT ratios for before and after rides-hailing scenarios to understand the efficiency (Eq. 8) of moving people (PMT) versus moving vehicles (VMT). Finally, to understand the additional VMT put into the system because of ride-hailing, we calculated the ratio of $\mathrm{VMT}_{\mathrm{R}}$ versus $\mathrm{VMT}_{\mathrm{WITHOUT}}$ (Eq. 9) for every mode replaced and overall.

$$PMT\ per\ VMT\ Efficiency = \frac{PMT}{\mathrm{VMT}} \tag{8}$$

$$VMT\ Ratio = \frac{Ridehailing\ VMT}{Replaced\ VMT} = \frac{VMT_R}{VMT_{WITHOUT}} \tag{9}$$

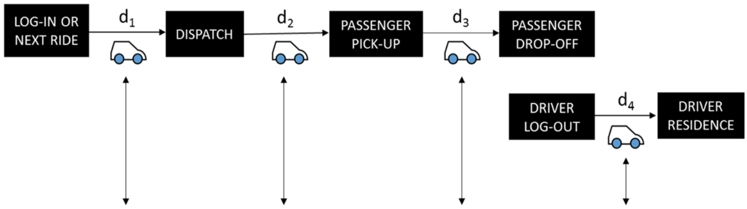
Results

The total ride-hailing VMT ($\mathrm{VMT}_{\mathrm{R}}$) distance based on all 416 rides was 4951 total miles driven. Using the mean and median travel distances summary statistics (Table 2) from the datasets, a representative day from the sample would be as follows. The driver-author logs-on both apps, trying to minimize cruising for a ride (mean: 1.5 miles, median: 0.2 miles) until getting a passenger request. Once the driver accepts the request, he travels approximately 1.4 miles (median: 1.0 miles) from the dispatch location to the passenger pick-up location (i.e. overheading). The average distance for a passenger ride (or O–D) is 7.0 miles (median: 3.6 miles). After the passenger is dropped-off, the driver starts the process again by waiting for a new ride request but also by minimizing unnecessary driving. When the driver is done for the day, he travels to the desired end location, commuting and average of around 12 miles (based on 65 commuting trips or shifts).

Deadheading

For this study, the conservative (low end) deadheading percentage of ride-hailing (without commuting at beginning of shift) equals to 40.8% (25.0% from "cruising" plus "overheading", and 15.8% from commuting at end). This means that for every 100 miles with a passenger, a ride-hailing driver travels an additional 69 deadheading miles

Table 2 Ride-hailing distance summary statistics



	Cruising for a ride	Dispatch to pick-up (Overheading)	Passenger ride (O–D)	Commute at end	Total VMT_R
Distance (miles)					
Total (St)	635.9	600.6	2929.9	784.3	4950.7
Mean	1.5	1.4	7.0	12.1*	
SD	3.9	1.4	8.6	7.4*	
Median	0.2	1.0	3.6	12.0*	

n = 416 (Lyft, 198; LyftLine, 39; UberX, 164; UberPool, 15)

*Commute based on 65 shifts

without a passenger. Previous to this study, the only ride-hailing data and study available was the one by Cramer and Krueger (2016), where they calculated an utilization rate of 64.2% for Los Angeles and 55.2% for Seattle, which equates to 35.8–44.8% in deadheading. Since they only had data for when the Uber app was on, they missed some information such as the commuting distance at the end of shifts. Recently, a dataset of over 1.49 million O–D trips was made available by RideAustin, a non-profit ride-hailing company in Austin, Texas, on the website Data.World for a 10-month period (June 2016 to April 2017). Using conservative estimates, the deadheading percentage for RideAustin equates to 49% (31% from "cruising" plus "overheading", and 18% from commuting). Another recent study in San Francisco (Castiglione et al. 2017), used the Uber and Lyft API to develop a research method to track vehicles (Chen et al. 2015). They estimated 20.3% deadheading for intra-city trips. Unfortunately, they incorrectly calculated this number: i) by not including "overheading" in the deadheading, and ii) by adding this "overheading" distance to the passenger O–D rides. They also excluded trips starting or ending outside of the city core such as going to and from the airport and did not account for commuting at the beginning or end of shifts. More recently, an online research article published data from Lyft for San Francisco, New York, and Chicago (RMI Outlet 2018). Although the post is not very clear about their calculation methods and analysis, one of the figures provides insights into the relationship between deadheading from "cruising" plus "overheading" and VMT with passengers (or the O–D distance).

Since these studies do not include commuting in their calculations, we decided to calculate the deadheading rate of "cruising plus overheading" (no commuting) per 1.0 "VMT with passengers" (or O–D), as defined in Eq. (7), for the sake of comparison. Table 3 presents these results.

Because we minimized cruising for a ride request, did not accept rides when the distance to pick-up a passenger was too long, and used conservative commute distances at end

Table 3 Deadheading rate per vehicle mile traveled with passengers

	Cruising for a ride + Dispatch to pick-up (Overheading)
Cramer and Krueger (2016)	0.56–0.81
RideAustin (2017)	0.61
RMI (2018)	0.46–0.67
This study	0.42

of shifts, our deadheading rate calculation is lower than the other studies. Even with this conservative calculation, ride-hailing drivers tend to travel 69.0 extra miles in deadheading (42.2 miles from "cruising and overheading" and 26.8 miles from commuting) for every 100 miles with a passenger.

Vehicle occupancy

Including all 416 rides, the average vehicle occupancy was 1.36 passengers per ride (Fig. 3). When we consider the VMT with passengers per vehicle occupancy, the distance weighted vehicle occupancy equates to 1.31 passengers per ride without including deadheading (Fig. 4). When we include deadheading, the distance weighted vehicle occupancy becomes 0.78 passengers per vehicle (Fig. 5), which is lower than a single-occupancy vehicle trip.

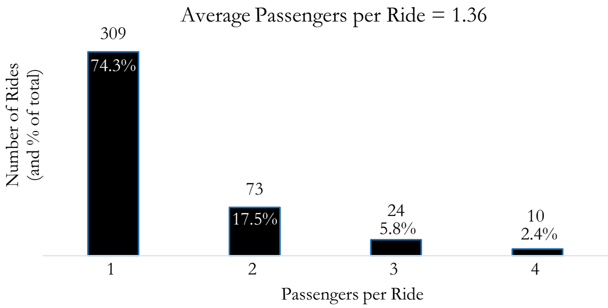


Fig. 3 Ride-hailing vehicle occupancy (n = 416)

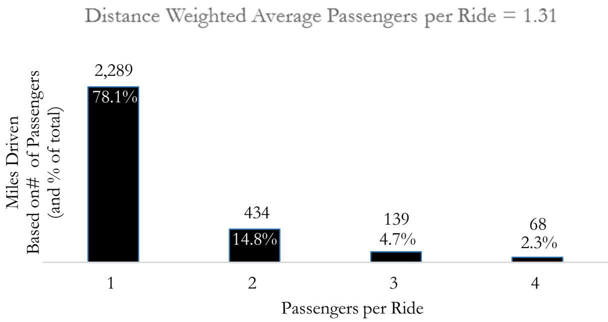
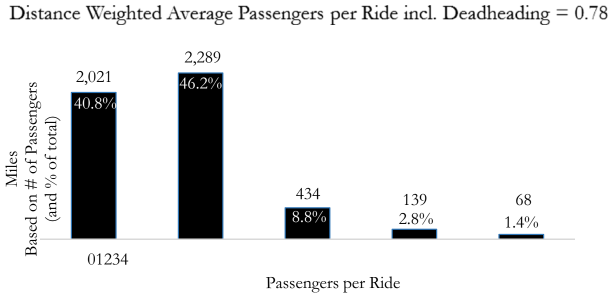


Fig. 4 VMT with passengers per vehicle occupancy (n = 2930)

Fig. 5 VMT per vehicle occupancy (n = 4951)



Pooling ride-hailing: UberPool and LyftLine

A total of 54 requests were either from UberPool or Lyftline services, representing about 13.0% of all requests. From those 54 requests, only 8 (or 14.8%) received a matching ride. This last fact is important to note because when Uber or Lyft representatives mention statistics on this type of service, they do not differentiate between requests and actual matches. They have stated that requests for these pooled services represent between 20 and 40% of total ride-hailing requests, but they have not clarified the rate of actual matches.

Car ownership

Reductions in car ownership could potentially represent one of the biggest benefits of ride-hailing services. While causation between ride-hailing and car ownership rates is difficult to discern, approximately 13% of respondents report owning fewer cars due to the availability of ride-hailing. Moreover, our results suggest that only 60% of our ride-hailing passengers own a car, which is significantly lower than average for the Denver region. However, approximately half of those that do not own a car still report having access to a car. Table 4 tests for demographic differences between passengers that own a car and those that do not. Ride-hailing passengers that owned a car tended to be older, more educated, wealthier, and were more likely to be white and married with children. They were also less likely to be a student and more likely to be from out of town.

Table 4 Demographic differences between ride-hailing passengers by car ownership

	Car mean	No-car mean	t-stat	*df*	*p* value
Gender (female)	0.48	0.45	0.502	305	0.3082
Age	2.52	1.89	5.043	307	**< 0.0001**
Race/ethnicity (white)	0.75	0.58	3.288	299	**0.0006**
Marital status (single)	0.53	0.78	– 4.458	293	**< 0.0001**
Household size	2.24	2.40	– 1.252	290	0.1059
Children	0.28	0.09	3.658	227	**0.0002**
Education	3.99	2.90	3.658	295	**< 0.0001**
Employment	0.94	0.85	2.651	268	**0.0042**
Income	4.10	2.53	8.181	266	**< 0.0001**
Local Resident	0.76	0.92	– 3.680	307	**0.0001**
Student	0.13	0.40	– 5.643	298	**< 0.0001**

Significance of bold values is $p < 0.01$

Table 5 Ride-hailing use differences between ride-hailing passengers by car ownership

	All mean	Car mean	No-car mean	t-stat	*df*	*p* value
Ride-hailing frequency	2.83	2.50	3.40	5.043	307	**< 0.0001**
Ride distance (miles)	6.79	8.23	4.63	3.690	309	**< 0.0001**
Drive alone replaced	0.19	0.31	0.01	7.161	309	**< 0.0001**
Public transportation replaced	0.22	0.14	0.35	– 4.438	309	**< 0.0001**

Significance of bold values is $p < 0.01$

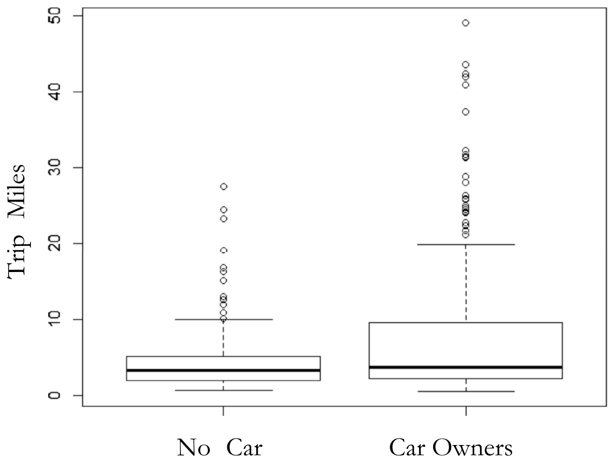


Fig. 6 Box and Whisker plots comparing ride-hailing trip mileage by car ownership

While the demographic differences related to car ownership with ride-hailing passengers were expected, Table 5 considers how these two groups used ride-hailing services differently. Ride-hailing passengers that do not own a car used ride-hailing more frequently compared to those that own a car. However, they also used ride-hailing for significantly shorter trips (4.6-mile average) than ride-hailing passengers that own a car (8.2-mile average). Figure 6 depicts the trip mileage of each group. We also found that ride-hailing passengers that do not own a car are significantly more likely to use ride-hailing to replace public transit while those that own a car are more likely to replace driving alone. The next sub-section delves further into this mode replacement issue to better understand how ride-hailing impacts VMT.

Mode replacement

Figure 7 depicts the mode replacement results. For instance, 19% of ride-hailing trips would have been single-occupancy vehicle trips while 34% would have been either walking, biking, or transit. Also, more than 12% of ride-hailing rides would not have been taken had Uber and Lyft not existed.

Regarding connections with other modes of transportation, 94.5% of passengers stated that they were using Lyft or Uber for the entire trip, and only 5.5% were using another mode of transportation in connection with the specific Lyft or Uber ride (Q9). Moreover, 187 people out of 291, or 64.3%, responded to question Q19 stating that they own or have access to a personal car.

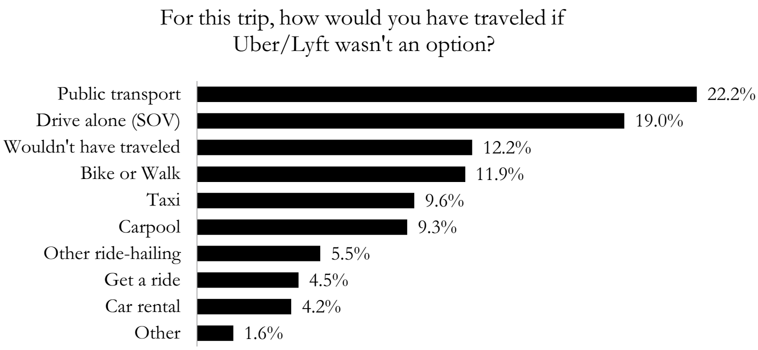


Fig. 7 Mode replacement

Passenger miles traveled (PMT) and vehicle miles traveled (VMT) efficiency

Looking exclusively at rides that included at least one passenger survey, the ride-hailing VMT distance (VMT_R) in this analysis was 3618 miles, while PMT was 2200 miles. The average passenger surveyed traveled a mean distance of 7.1 miles (median: 3.5 miles) with a range from 0.5 miles to 49.1 miles. Based on the mode replaced and the calculations discussed above, the replaced VMT ($VMT_{WITHOUT}$) would have been approximately 1972 miles. This suggests that the ride-hailing passengers would have put 1972 VMT into the system if Uber/Lyft did not exist. With Uber/Lyft, they now put 3618 VMT into the system. The before travel behavior based on the replaced mode was 111.6% efficient in terms of how much PMT (2200 miles) per VMT (1972 miles) would have happened if Lyft or Uber were not available, meaning that all the modes replaced were transporting passengers at a rate of 111.6 miles for every 100 vehicle miles. With the introduction of ride-hailing, the PMT/VMT efficiency dropped to 60.8%, meaning that the miles passengers travel is lower than the vehicle miles at a rate of only 60.8 PMT for every 100 VMT from Lyft/Uber. This equates to a 45.8% percent reduction.

VMT change

Table 6 presents the total, mean, and median distances of PMT as well as the total and mean distances for $VMT_{WITHOUT}$ and Ride-hailing VMT_R for each mode replaced and total. The last column of this table shows the percent change in VMT for every mode and the total. Overall, our results suggest that ride-hailing adds approximately 83.5% more VMT to the system than if these services did not exist.

Conclusions

Ride-hailing has quickly become a very popular service that is successfully competing and interacting with other modes of transportation, but due to the lack of open data, research on this topic is scarce. We use an innovative research methodology to gather interconnected driver and passenger datasets with a quasi-natural experiment. To our knowledge, this is the first independent study that uses Uber and Lyft data from both the driver- and passenger- perspectives to assess several impacts of ride-hailing on transportation including

Table 6 Before-and-After VMT by mode replacement

Mode replaced	n	Ride-hailing passenger miles traveled			Replaced VMT		Total ride-hailing VMT		$\frac{Ridehailing\ VMT}{Replaced\ VMT}$	% Change in VMT
		Total	Mean	Median	Total	Mean	Total	Mean		
Public transportation	69	419.6	6.1	3.5	27.2	0.4	768.9	11.1	28.27	2726.7
Drive alone (SOV)	59	661.3	11.2	5.2	670.4	11.4	935.5	15.9	1.40	39.6
Wouldn't have traveled	38	194.0	5.1	3.7	0.0	0.0	370.2	9.7	–	–
Bike or Walk	37	74.3	2.0	1.7	0.0	0.0	195.9	5.3	–	–
Taxi	30	364.2	12.1	5.8	639.5	21.3	568.3	18.9	0.89	– 11.1
Carpool (ride)	19	132.1	7.0	3.9	82.2	4.3	227.7	12.0	2.77	177.1
Other ride-hailing	17	52.8	3.1	3.0	143.3	8.4	143.3	8.4	1.00	0.0
Get a ride	14	132.6	9.5	5.7	265.3	18.9	140.5	10.0	0.53	– 47.0
Car rental	13	54.6	4.2	3.7	55.4	4.3	119.7	9.2	2.16	115.9
Carpool (drive)	10	77.1	7.7	2.7	79.2	7.9	93.6	9.4	1.18	18.3
Other	5	37.5	7.5	2.6	9.2	1.8	54.1	10.8	5.90	489.8
Total	311	2200.0	7.1	3.5	1971.7	0.9	3617.7	11.6	1.83	83.5

deadheading, vehicle occupancy, mode replacement, PMT/VMT efficiency, and VMT impacts by exploring without- and with- ride-hailing scenarios.

While ride-hailing provides mobility and convenience, our results suggest that ride-hailing adds a significant amount of VMT (+83.5%) to the system when accounting for deadheading, induced travel, and substitution of more sustainable modes.

For all 416 ride-hailing trips, we found that deadheading accounts for 69.0 extra miles for every 100 miles with passengers (or O–D). Compared to private driving trips—and even accounting for the extra mileage cruising for parking at the destination—the ride-hailing VMT is significantly higher to what would have been driven without Lyft/Uber. For example, a single-occupancy vehicle (SOV) traveler that needs to go five miles to his/her destination would add approximately 5.1 miles (accounting for parking distance) to the transportation system (+5.1 VMT); if that same person is taking a Lyft or Uber instead, he/she would still travel five miles, but the ride-hailing driver might add nine total miles to the transportation system (+9 VMT). It is obviously concerning that ride-hailing—when accounting for deadheading—seems less efficient than driving alone. Such results should be investigated in other contexts and may have significant implications for our cities in terms of congestion and environmental concerns.

In terms of vehicle occupancy, while the average passenger per ride was between 1.3 and 1.4, it is concerning that when accounting for deadheading miles, the distance weighted average passenger occupancy drops down to approximately 0.8—which is less than a single-occupancy vehicle (1.0). Ride-hailing passengers tended to have lower car ownerships rates than average. Those that did not own a car tended to use ride-hailing services more frequently but for shorter trips. For this study, a combined 34.1% of our ride-hailing passengers would have taken transit, walked, or bicycled. While mode substitution rates from more sustainable modes were significantly higher for ride-hailing passengers that did not own a car, car ownership and mode substitution is a complicated issue in need of further inquiry. For instance, if somebody owns a car and uses ride-hailing, then it is relatively easy for them to tell us what mode is being replaced. When somebody that does not own a car uses ride-hailing, the short-term thinking may be that the trip is replacing walking, biking, or transit. Still, they may have made the long-term decision not to own a car, at least in part, due to the availability of ride-hailing services. It is worth noting that 13% of our respondents report owning fewer cars due to ride-hailing. The reported mode substitution rates, however, remain based on their stated response to the question "how would you have traveled if Lyft/Uber wasn't an option". These modal shifts represent an indication of how ride-hailing affects the efficiency of transporting passengers versus vehicles, going from a PMT/VMT efficiency of 111.6% to 60.8%. In fact, ride-hailing, in its current form, is only more efficient—in terms of transportation passengers per VMT—than two other mode options: "taxis" and "getting a ride".

This study does not come without limitations. The main limitation is the trip sample size relative to the overall number of rides that Uber and Lyft provide. Secondly, our data is limited to one metropolitan area and not necessarily generalizable to other regions. Luckily, more recent datasets seem to complement our analysis. In terms of data collection, our singular driver-author approach is both a limitation and an advantage. It is a limitation because drivers have different work strategies such as searching for prime areas, having a desired location in mind, cruising unlimitedly until getting a ride request, or limiting driving without a passenger as much as possible by parking right after a passenger is dropped off. At the same time, our methods are an advantage since we were able to control the amount of driving, and in turn, design the research with conservative estimations. Future studies should also consider how these results might differ depending upon the context. For instance, there may be less deadheading in urban areas where ride requests may be more frequent and closer together. At the same time, ride-hailing may prove to help people connect to transit in more suburban locations.

Cities can use the results from this research to look at this issue in more detail and realize what they might actually gain or lose. However, we believe that much more research—especially with the newer and truer sharing services such as LyftLine and UberPool—is needed on these critical topics of vehicle occupancy, mode replacement, and VMT. Unfortunately, such research cannot be done without appropriate data, and the approach we took in this paper is not easily replicable at larger scales. Thus, cities authorizing ride-hailing companies such as Uber and Lyft should demand data sharing agreements for research purposes. Such research is needed before we start encouraging or prioritizing the use of these services (e.g. curb space and parking priorities, transit agencies contemplating removal/replacement of bus services in certain areas, subsidizing Lyft/Uber rides, etc.). Positive outcomes should come when car ownership is being reduced and the modes being replaced are SOV, taxis, or getting a ride instead of more sustainable modes like transit, walking, or biking.

This research begins to fill a gap in the academic literature by identifying, measuring, and disentangling ride-hailing data to help us better understand the impacts of ride-hailing on important aspects of the transportation system, including deadheading, vehicle occupancy, mode replacement, efficiency, and VMT. We hope this study helps cities and transportation agencies better account for the impacts of ride-hailing in their policies, planning, and engineering processes. We also hope to contribute to the conversation as to how ride-hailing companies can help better achieve sustainable transportation goals such as mode shifts away from SOV into transit, walking, and biking, better VMT efficiency, improved interconnectivity and integration with active modes of transportation, equity, and safety for both users and drivers.

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