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Travel and energy implications of ridesourcing service in Austin, Texas

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ABSTRACT

This paper identifies major aspects of ridesourcing services provided by Transportation Network Companies (TNCs) which influence vehicles miles traveled (VMT) and energy use. Using detailed data on approximately 1.5 million individual rides provided by RideAustin in Austin Texas, we quantify the additional miles TNC drivers travel: before beginning and after ending their shifts, to reach a passenger once a ride has been requested, and between consecutive rides (all of which is referred to as deadheading); and the relative fuel efficiency of the vehicles that RideAustin drivers use compared to the average vehicle registered in Austin. We conservatively estimate that TNC drivers commute to and from their service areas accounts for 19% of the total ridesourcing VMT. In addition, we estimate that TNC drivers drove 55% more miles between ride requests within 60 min of each other, accounting for 26% of total ridesourcing VMT. Vehicles used for ridesourcing are on average two miles per gallon more fuel efficient than comparable light-duty vehicles registered in Austin, with twice as many are hybrid-electric vehicles. New generation battery electric vehicles with 200 miles of range would be able to fulfill 90% of full-time drivers' shifts on a single charge. We estimate that the net effect of ridesourcing on energy use is a 41–90% increase compared to baseline, pre-TNC, personal travel.

1. Introduction

In the late 2000s pervasive use of smartphones, GPS systems, and digital mapping/routing applications gave rise to ridesourcing services. In a ridesourcing service, a smartphone application connects an individual seeking a ride with a nearby driver willing to provide transportation. The application gives real-time information about wait and travel times, enables passengers to pay via credit card, and allows passengers and drivers to evaluate each other once travel has been completed. The providers of such services classified as "transportation network companies" or TNCs (Rayle et al., 2016). In some cities, the application allows travelers to share the ride (and cost) with a stranger. In this case, the ridesourcing trip can be referred to as "ridesharing".

Ridesourcing services have grown dramatically over the past decade. As of early 2018, Uber—the largest U.S. provider—reported service in 633 cities worldwide, with exponential growth in the number of rides provided. Uber accumulated its first 1 billion rides in about 6 years, the next billion in 6 months, and 3 billion more in about another year (Uber, 2017). In early 2018, Lyft—the second-

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largest U.S. TNC—reported among its "community" 23 million passengers, 1.4 million drivers, and service in all U.S. states and more than 300 airports (Lyft, 2018), and in September 2018 announced their first billion rides. China's Didi Chuxing, Uber's main competitor in global growth, reported having more than 450 million users and 21 million drivers, with its 25 million daily rides eclipsing the combined rides given by the rest of the world's ridesourcing services combined (Sreeharsha and Isaac, 2018). Continued evolution of this concept consists of a range of similar services including conventional car-sharing, bike-sharing, scooter-sharing, and micro-transit services (e.g., on-demand shuttle buses) (Burgstaller et al., 2017; Clewlow and Mishra, 2017). Taken together, these types of emerging travel services are referred to as "mobility as a service" (MaaS); many envision travelers eventually purchasing access to a portfolio of travel services through a monthly subscription (Goodall et al., 2017). The TNC service providers have expressed their intention to eventually replace their contract drivers with automated vehicles, thereby greatly reducing the cost of providing a ride (Uber, 2019; Lyft, 2019). Using mesoscopic simulation experiments, Loeb et al., 2018 estimated that shared autonomous electric vehicles could serve 40% of all trips under 50 miles in Austin Texas, with a nearly 20% increase in VMT. Such services could lead to significant reductions in taxi ridership (Contreras and Paz, 2018; Nie, 2017), one of the major competitors of TNCs.

TNC companies typically do not release their data to the public or researchers, but a number of independent studies show that these services greatly impact urban transportation patterns and trends. For example, recent studies in San Francisco suggest that around 6000 ridesourcing vehicles operated in the city at peak times—outnumbering taxis by more than a factor of 15. In addition, ridesourcing vehicles accounted for around 10% of all person-trips and vehicle miles traveled (VMT), as well as about half of the change in traffic congestion in San Francisco between 2010 and 2016 (San Francisco County Transportation Agency, 2017; San Francisco County Transportation Agency, 2018). Another study of seven major U.S. cities found that 21% of adults used ridesourcing services and 9% more used them with friends but had not installed the application themselves; of ridesourcing adopters in metropolitan areas, 24% used the service on a weekly or daily basis (Clewlow and Mishra, 2017). A 2016 Pew Research Center study estimated that 21% of urban Americans and 15% of suburban Americans had used ridesourcing services (Smith, 2016).

Ridesourcing can decrease energy use in the following ways. In the cities where ridesharing (or pooling) is offered, sharing a ride with a stranger can as much as halve vehicle miles of travel compared to two travelers driving their own personal vehicles along a similar route. Second, in the medium term, by concentrating VMT in fewer vehicles, the owners of those vehicles have an incentive to purchase more efficient automobiles; high-mileage use means that the initial increase in the purchase price of a more efficient vehicle will be offset sooner by lower fuel costs. Finally, in the long term, riders may retire an existing vehicle, and, no longer facing a fixed cost for their transportation needs, may eliminate trips they made previously with their own vehicle (Cervero et al., 2007; Xue et al., 2018). An analysis of U.S. state-level data found that per-capita vehicle registrations decreased 3% after entry of ridesourcing services in metropolitan areas, with no effect on VMT (Ward et al., 2018).

On the other hand, ridesourcing services can increase energy use by a number of different ways. Miles driven without a paying passenger onboard are referred to as "deadheading"; deadhead miles can offset any energy benefits of ridesourcing services, and can lead to greater traffic congestion. There are two major components of deadheading: commuting since some drivers commute relatively long distances into urban areas to begin and end their shift of driving; and between-ride deadheading, which includes drivers circling areas waiting for riders to summon them, potentially driving longer distances as directed by their mobile app to take advantage of surge pricing, and the additional miles driven after accepting a ride request to pick up the passenger.

The few studies analyzing deadheading from ridesourcing services vary considerably in terms of data sources, methods, and areas of study. Among recent studies, estimates of the fraction of total ridesourcing VMT that are deadhead miles range from 36% to 45%, yet none of these studies capture all empty miles accumulated by ridesourcing vehicles. Henao and Marshall (2018) calculated a conservative (lower end) empty mile rate of 41% for a single Uber/Lyft driver in Denver due to deadheading and accounting for commuting only at the end of shifts. Komanduri et al., 2018 used the RideAustin data set to estimate that 37% of all ridesourcing VMT are deadhead miles, including commuting at the beginning and end of shifts. Their estimate assumed a uniform commute distance of two miles, which also applied when picking up passengers after more than 30 min of idle time. They also accounted for straight-line distances between the rides without adjusting for the real street network distance. Cramer and Krueger, 2016 obtained from Uber the city-wide average percentage of drivers' miles driven with a passenger in five cities.[2] They report empty miles rates of 45% in Seattle and 36% in Los Angeles, excluding miles driven with the Uber app turned off, which might exclude empty commuting miles at the beginning and end of shifts. Drawing primarily on operational data collected by the New York City Taxi and Limousine Commission, a non-peer-reviewed report estimates an empty VMT rate of 40% for weekday ridesourcing rides that started and/or ended in Manhattan's Central Business District, again not accounting for commuting miles (Schaller, 2017). In San Francisco, a method based on the public-facing APIs of Uber and Lyft was used to estimate an empty VMT rate of 20% for rides starting and ending within the city's core area (San Francisco County Transportation Authority, 2017). However, their method excludes commuting, and understates the share of deadheading as the authors attributed the distance from ride request to passenger pickup to passenger miles instead of to empty miles.

Whether ridesourcing increases VMT and energy use depends on the mode of travel replaced by the ridesourcing trip. Taxis likely generate comparable, or perhaps even more deadheading miles than TNCs: taxis are more likely to circle areas seeking riders, while ridesource vehicles in theory can wait parked until a ride is requested through the smart phone app. Private auto trips often add additional VMT from searching for parking at the end of the trip, depending on the destination, whereas ridesourcing drivers never have to search for parking (although they may have to find a safe location to drop off their passengers). In principle, deadheading and

[2] Data for Boston are for three days, and for San Francisco three months, in 2015; data for Los Angeles, New York City, and Seattle are for all of 2015.

ridesourcing inefficiency can be reduced over time by TNC providers better matching driver supply with passenger trip demand, thereby reducing the distance driven to reach riders (Xu et al., 2019).

A third factor of ridesourcing that may increase energy use is that such trips may substitute for a trip in a more energy-efficient mode or even induce new travel; for example, a trip shifted from public transit to ridesourcing service would, on average, increase the amount of energy consumed per passenger during that trip.[3] On the other hand, ridesourcing service may supplement conventional public transit service, by providing first-/last-mile travel to or from transit stops. An analysis using transit agency data found that ridership increased 5% two years after Uber entry, but ranged from a 7% increase to an 8% decrease based on the size of the metro area and its transit system (Hall et al., 2018). In addition, by encouraging more to drive part-time (as opposed to fewer full-time taxi drivers), ridesourcing services reduce the average number of rides provided per driver or vehicle, which may increase traffic congestion. The stop-and-go driving from increased traffic congestion leads to a slight increase in energy use (Gately et al., 2017).

Table 1 summarizes six aspects of ridesourcing services that influence their VMT and energy use. The first three likely result in reduced VMT and energy use, while the last three likely result in increased VMT and energy use, relative to travel before the introduction of ridesourcing services.

Our analysis uses data of individual rides conducted by a TNC, RideAustin, in Austin Texas, to quantify VMT and energy use effects of ridesourcing. TNCs Uber and Lyft pulled their services out of the Austin, Texas market on May 8, 2016 (Solomon, 2017). One month later a local non-profit company, RideAustin, was formed to provide such transportation services in the city. In addition to RideAustin, several other providers began operation in Austin in the same timeframe. An online survey of nearly 1840 riders, conducted in November and December 2016, found that 42% used one of these new ridesourcing services after Uber and Lyft left the market, and of those that used one of the new services, 47% used the RideAustin service (Hampshire et al., 2017). Lavieri et al., 2018 also used RideAustin data to model the spatiotemporal distribution of ridesourcing rides, the demographics of passengers, and mode substitution in relation to public transit.

This study estimates the fraction of RideAustin drivers' VMT without passengers, as well as the VMT attributed to drivers' travel into the city at the beginning and the end of their shift, using both measured and estimated distances. We categorize drivers based on their weekly working hours and compare travel patterns of occasional, frequent, and full-time drivers. In addition, the distribution of rides to and from certain major locations and land uses in Austin are analyzed. Vehicle fuel economy of the RideAustin vehicles is reviewed and compared with that of the personally owned fleet in the region, to determine if vehicles used through the service are more efficient than comparable vehicles registered in Austin. Finally, the impacts of the RideAustin ridesourcing service on net energy use, based on estimates of five of the six factors shown in Table 1, are estimated. This study demonstrates the value of detailed data on individual rides provided by TNCs, as well as other necessary data, to fully assess the net impact of this emerging type of transportation service on mobility and energy use of urban transportation systems.

2. Data and methods

We obtained publicly-available data from RideAustin on nearly 1.5 million individual rides made over an 11-month period from June 2016 to April 2017 (RideAustin, 2017). The RideAustin data on nearly 1.5 million rides, conducted by almost 5000 drivers, includes the datetime stamp at five points along each ride: when the ride request was dispatched to a driver; when the driver accepted the dispatched request; when the driver reached the rider; when the ride started; and when the ride was completed (RideAustin, 2017). The database also includes two GPS measured distances in meters: the distance traveled between the time the driver accepted the ride request and reached the rider, and the distance between the start and the end of the ride. However, the distance to the rider was not recorded until October 27, 2016, so the analysis of this trip segment excludes data prior to that date. In addition, location coordinates, rounded to three decimal places, are available for where the ride started and ended; this degree of precision identifies ride start and end locations only to within roughly 100 m. Individual drivers and riders are identified, so individual rides can be aggregated by driver and rider to analyze the travel patterns of each. The model year, make, and model of drivers' vehicles is also identified, which can be used to determine the Environmental Protection Agency rated fuel economy of each vehicle.

Fig. 1 shows the total number of rides and drivers per month from when the program started on June 6, 2016 through April 13, 2017. The figure indicates that the program use was ramping up between June and October 2016, with the number of rides increasing from 3700 to 190,000, the number of drivers increasing from 230 to 2100, and the average number of rides per month per driver increasing from 16 to 90 (or from one ride every other day to three rides per day).[4] Between October and March 2017 the number of rides and drivers increased, but at a slower rate, while the average number of rides per driver initially decreased and then increased back up to 90 in March. Peak activity occurred in March, the last month for which we have a full month of data, with 320,000 rides provided by 3560 drivers, each providing on average three rides per day.[5] The most rides provided by one driver in each month fluctuated between 500 and 600 rides, or 17 to 20 rides per day, between September and January, and then increased to 740 rides, or

[3] Although a TNC trip may increase accessibility over a transit trip, as the traveler is delivered directly to their destination rather than to a transit stop a short distance from their destination.

[4] Presumably many of the drivers for Uber and Lyft began driving for RideAustin shortly after the program was started in June 2016; however, fingerprinting and other licensing requirements likely delayed how quickly these experienced drivers could drive under the new RideAustin program.

[5] City of Austin data on taxicab trips in previous years indicates that October and March are the peak months for taxi trips, which correspond to the peak months of RideAustin rides.

Table 1
Aspects of changes in VMT and energy use from ridesourcing, and method used in this analysis.

Aspect of ridesourcing	Method used in this analysis
1. Sharing rides	Estimated based on assumptions informed by literature
2. More fuel-efficient vehicles	Measured by comparison with rated fuel economy of RideAustin fleet with overall fleet registered in Austin
3. Car-shedding and fewer trips	Not estimated
4. Commute deadheading	Measured using RideAustin ride start and end locations, based on estimated driver home location
5. Between-ride deadheading	Measured using distance between RideAustin ride end and start of next ride, adjusted for travel on the road network
6. Modal shift	Estimated based on assumptions informed by rider surveys in the literature

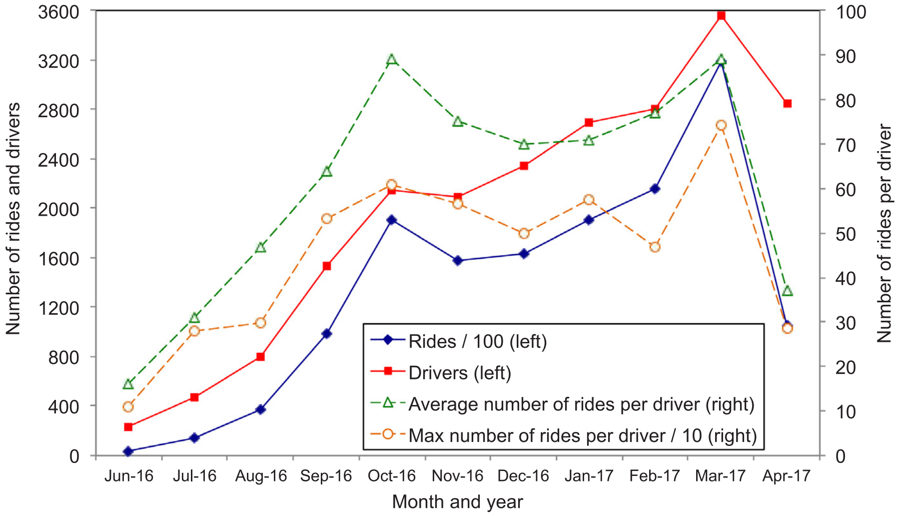

Fig. 1. Total number of rides, drivers, and average and maximum number of rides per driver, by month.

25 rides per day, in March. The peaks in October and March are coincident with major events occurring in Austin: the Austin City Limits music festival (October 6 through 8, and October 13 through 15) and the South by Southwest festival (March 10 through 19).

Fig. 2 shows the distribution of rides between October 27, 2016 and April 13, 2017 by day of the week and hour of the day. Distributions of hourly rides for the four weekdays Monday through Thursday are combined because they are quite similar to each other, but distinct from the distributions on Friday, Saturday, and Sunday. The total number of rides given Monday-Thursday and the total number of Friday-Sunday rides are presented as the distribution of total rides by day and hour. Fig. 2 indicates that the distribution of rides peaks on Friday and weekend nights (from 7 pm through 2 am the next morning), while the lowest number of rides occurs between 4 am and 8 am on weekend mornings, and 3 am to 6 am on weekday mornings. The number of rides during the morning commute hours (5 am to 10 am) during weekdays are comparable to the number during those hours on weekends. The hourly distributions of rides and the monthly peaks (that roughly correspond to the Austin City Limits music festival in October and the South by Southwest festival in March) suggest that the majority of RideAustin rides are taken for entertainment or recreational purposes, rather than as part of a regular work or school commute. In contrast, Dong et al., 2018 using DiDi Chuxing data to describe ridesourcing patterns in Beijing, found that peak hours are during commute hours: between 7:30 and 9:30 in the morning, and 4:30

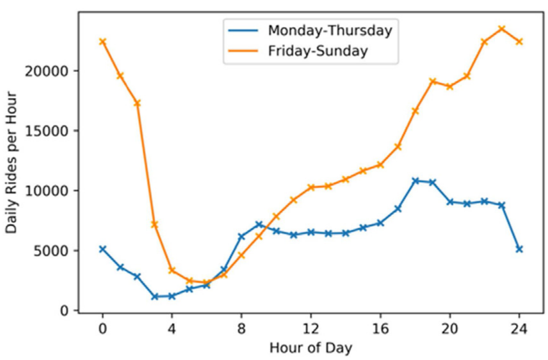

Fig. 2. Distribution of total rides by day of week and hour.

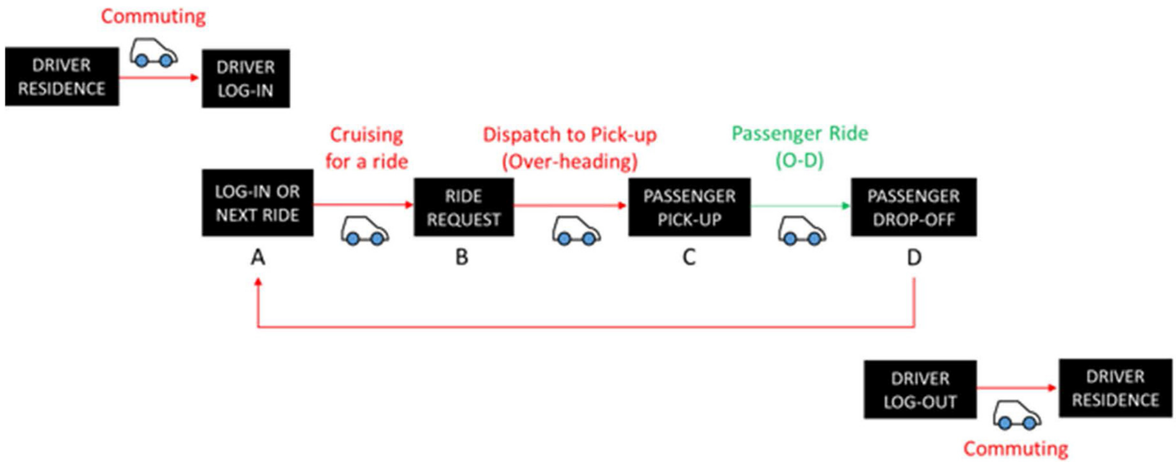

Fig. 3. Ridesourcing driving segments, with empty vehicle miles segments shown in red (Henao and Marshall, 2018).

and 6:30 in the evening.

Table 1 lists the methods and data used to estimate the net impacts on VMT and energy use from five of the six aspects of TNCs listed in the table. We estimate the decrease in VMT and energy use from sharing rides based on estimates in the literature and assumptions regarding the fraction of ridesourcing rides that are shared, as well as the amount of person miles of travel reduced by sharing. We calculate the decrease in energy use from TNC drivers using more efficient vehicles by comparing the distribution of the vehicles used by RideAustin drivers with those of all registered vehicles in Austin Texas. We calculate the increase in VMT and energy use from driver commute and between-ride deadheading based on the straight-line distance between the starts and ends of the RideAustin rides, using estimated home locations for drivers (for commute deadheading) and a calculated adjustment factor for additional miles driven over the local street network derived from the measured distance of the RideAustin rides. Finally, we estimate the increase in energy use from travelers shifting from other travel modes to ridesourcing based on observed modal shift from two rider surveys in the literature. Of the six factors listed in Table 1, we do not estimate the long-term impacts of travelers' car-shedding and eliminating some discretionary trips.

3. Results and discussion

In this section we describe the detailed methods used to estimate the effect of ridesourcing service on between-ride and commute deadheading, more efficient vehicles, and modal shift, as well as an analysis of ride distributions by location and land use.

3.1. Ridesourcing VMT and deadheading

The segments of deadheading VMT considered in our analysis are illustrated by red arrows in Fig. 3. The RideAustin dataset is unique as it provides two GPS measured distances: between when the driver accepted a ride request and picked up the rider (from B to C in Fig. 3), and between the start and end of the ride (from C to D). Other ride-level databases only provide origins and destinations, and not measured distances on the road network. To estimate deadheading while cruising for a ride request (from A to B), we use the straight-line distance between the start of each ride and the end of the previous ride, adjusted for travel over the road network, minus the measured distance from when the driver accepted the ride request and the ride itself. In this section we describe how we estimated the total amount of deadheading between rides (from A to C); in the next section we describe how we estimated the deadheading from driver commuting.

Components of a sample ride from the RideAustin database are shown in Fig. 4, which illustrates how deadheading miles are estimated in this study. The locations of the driver's vehicle are shown in circles, the inferred routes based on measured travel distances are indicated by solid lines, and straight-line distances are indicated by dashed lines. Location 1D is the recorded end of the driver's previous ride (Ride 1), while locations 2C and 2D are the recorded start and end of the driver's next ride, respectively (Ride 2). The dashed lines indicate the straight-line distances between the end of the previous ride (1D) and the start of the next ride (2C), and the straight-line distance between the start (2C) and end (2D) of the next ride. The database also provides the measured distance the driver travels to reach the rider once the ride request is accepted (solid line between 2B and 2C) and the measured distance of the ride itself (solid line between 2C and 2D). Although the measured distances are provided, the exact route taken over the road network is not. In Fig. 4, we select routes to reach the rider and the ride itself that nearly match the measured distances, for this one illustrative ride.

The network route the driver takes between rides must be inferred based on where the driver ended the previous ride (1D) and where the next rider was reached (2C). However, the location of the driver at the time the ride request was accepted (2B) could be anywhere within a 1.3-mile measured distance from where the rider was reached. The route shown minimizes the additional distance

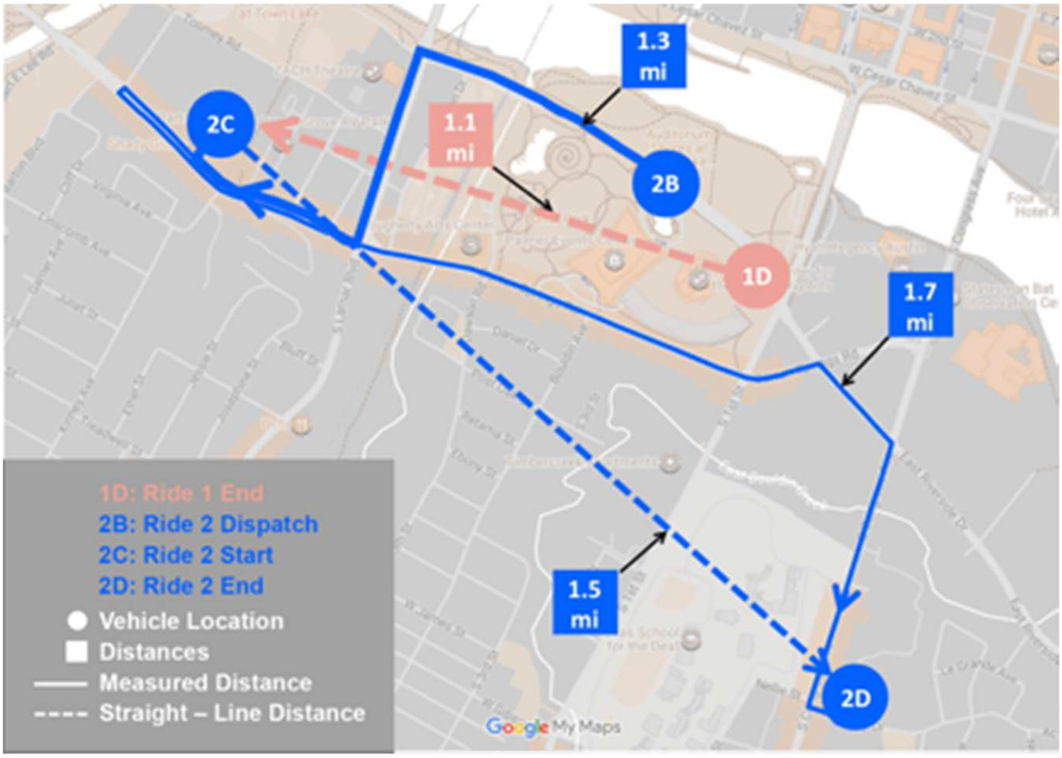

Fig. 4. Components of a sample ride.

driven between the time the driver ends the previous ride (1D) and accepts the next ride request (2B). Note that the measured distance between where the driver accepts the ride request (2B) and where the rider is reached (2C) is 1.3 miles, which is 18% further than the straight-line distance between the end of the previous ride and the start of the next ride (1.1 miles). In this example the distance between the end of the previous ride (1D) and the inferred location where the next ride request is accepted (2B) is minimized (it could have been even farther).

In summary, the RideAustin data provides the straight-line distance between rides, the measured distance between when the ride request was accepted by the driver and when the driver reached the passenger, and both the straight-line distance and the measured distance of the ride itself. We first examine the two measured distances to calculate the additional miles RideAustin drivers drove to reach passengers after they had requested a ride. We find that on average a driver drove 21% more miles after accepting the ride request to reach a rider than the ride itself; that is, the total distance to reach the rider plus the ride itself was 21% farther than the distance of just the ride itself. While on average drivers drove 21% more miles to reach the rider, this amount fluctuated between 16% and 26% of the ride distance depending upon the hour of the day, with the highest percent additional miles driven during morning and evening passenger commute hours, and the lowest percent additional miles in the early morning and during the afternoon.

We then estimated the total distance between rides based on the locations of the end of the previous and start of the next ride, multiplied by a factor to account for the ratio of network distance to the straight-line distance. The straight-line distance between the coordinates at the start and completion of each ride (i.e. between points 2C and 2D) was compared to the GPS-measured distance of each ride following the actual route taken on the road network. Fig. 5 shows the cumulative distribution of this ratio for all rides. For the average ride, the measured network distance was 1.4 times the straight-line distance between the ride start and end coordinates, and for about 83% of all rides the measured network distance was between 1.1 and 1.9 times the straight-line distance derived from the coordinates. Therefore, the measured network distance the driver travels between rides is estimated as 1.4 times the straight-line distance derived from the coordinates of the end of the previous ride and the coordinates of the start of the next ride. The resulting deadheading distances are conservative, as they do not account for drivers circulating after each ride awaiting another ride request, but rather heading directly over to pick up their next passenger.

We examined a subset of consecutive rides given by individual drivers, which occurred within 60 min of the previous ride, under the assumption that individual rides more than 60 min apart could include additional driving not related to providing rides for RideAustin (for example, a driver traveling to a particular spot for their lunch break or to conduct errands). About half of all rides were started within 20 min of the end of an individual driver's previous ride, while another 20% of rides were started between 20 and 60 min after the end of a driver's previous ride, as shown in Fig. 6.[6] Fig. 6 indicates that the deadhead distance between rides given by

[6] On the other hand, 10% of all rides occurred between one and three hours, and 13% occurred between three and 24 h, after the driver's previous

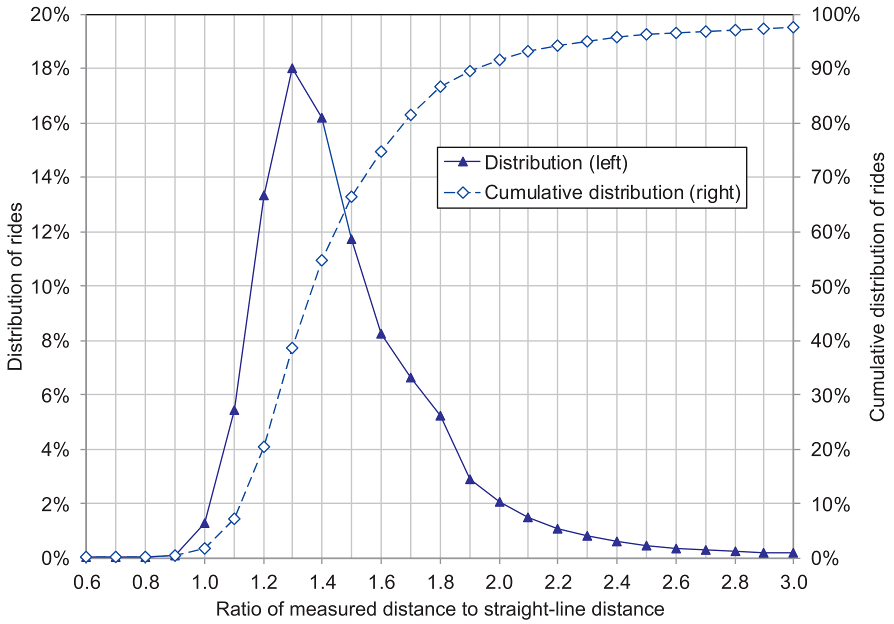

Fig. 5. Distribution and cumulative distribution of ratio of measured distance to straight-line distance between start/end coordinates of RideAustin rides.

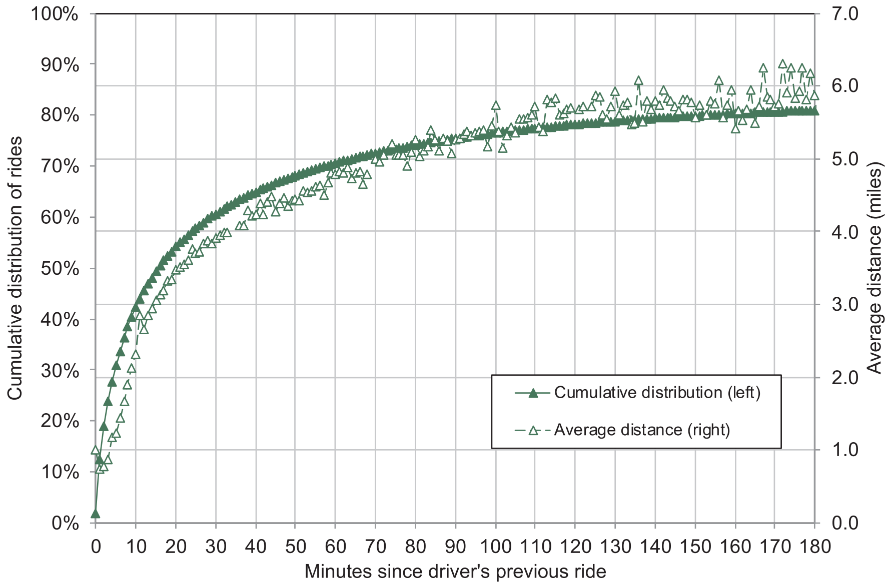

Fig. 6. Cumulative distribution of rides and average distance between rides, by time since driver's previous ride.

a particular driver increases steeply for each minute since the end of the previous ride until about 30 min after the previous ride. After 30 min from the previous ride's end, the average deadhead distance between rides continues to increase, but a much slower rate. The deadhead distance between rides levels off just under six miles after about two hours between rides.

On average, for rides that occurred within 60 min[7] of each other, the empty-vehicle deadheading adds 55% to the following ride's

(footnote continued)
ride; the remaining 10% of all rides by a specific driver occurred more than one day after the driver's previous ride.

[7] Because the database does not indicate when the RideAustin app is active, we do not know when drivers are actively seeking rides. It is possible that drivers are conducting personal travel, such as running errands or picking up a child at school, between rides. The likelihood that a driver is conducting personal travel between rides increases as the time between rides increases. We chose to use the average deadheading distance for rides up to 60 min since the previous ride to reflect the time between rides that drivers are likely still seeking rides with the app on; we assume that any

distance, including the measured distance between when the driver accepted the ride and when they reached the rider, as discussed above. The estimated distance driven between rides within 60 min of each other, is nearly three times that of the measured distance from ride request to passenger pickup (55% vs. 20% respectively).[8] This suggests that most RideAustin drivers do not park their vehicles while waiting for their next ride request; instead they are cruising while awaiting their next ride request.

Whether the number of deadheading miles driven by RideAustin drivers represents an increase in VMT or fuel use depends on what travel mode the RideAustin riders would have used in the absence of ridesourcing. If the previous mode was personal vehicle, ridesourcing likely increases VMT (as long as the VMT spent looking for parking a personal vehicle does not exceed the ridesourcing deadheading VMT). If the previous mode was a taxi, ridesourcing may not increase VMT, if the deadheading rate of taxis and ridesourcing is comparable. Future work should compare deadheading rates of taxis with those of RideAustin vehicles, as well as utilize rider surveys to determine what mode the TNC ride replaced.

3.2. Ridesourcing drivers commute distance and shifts

The distance drivers travel without passengers at the start and end of their driving shift is an often overlooked yet important component of ridesourcing that should be estimated to better understand the actual effect of ridesourcing services on VMT and energy use (Henao and Mashall, 2018). At the start of each shift, drivers may travel from their residence or garage to an area where they would then turn on the app and wait until a first request is made. Similarly, at the end of the shift, the driver travels from their last passenger drop-off (or app being turned off) to home.

Likely for privacy reasons, RideAustin drivers' addresses were not provided in the dataset. We estimated each driver's residence location by computing the spatial median of the first pick-up location of all shifts for each driver. This is a conservative estimate, as it minimizes the average commute distance for each driver. Commute distance was estimated as the straight-line distance between the approximate residence location and the first pick-up location of each shift, and the last drop-off location, of each shift. We applied the same distance adjustment factor of 1.4 to estimate the total commute distance on the street network.

Fig. 7 shows the cumulative distribution by distance of five components of a ride, four of which are deadheading: a driver's estimated pre-shift commute; measured travel between when the driver accepts the ride request and when they pick up the rider; estimated travel while cruising for the next ride request;[9] measured travel between the rider's origin and their destination; and a driver's estimated post-shift commute.

Fig. 7 indicates that the average ride is 5.4 miles long (green), higher than the average ride distance of 3.2 miles in San Francisco (Rayle et al., 2016) but lower than the average ride distance of 7.0 miles in Denver (Henao and Marshall, 2018). The deadheading distance between rides is divided into the measured distance after receiving a ride request (from B to C in Fig. 3) and the distance cruising before receiving a ride request (from A to B in Fig. 3), which is calculated by subtracting the measured distance from ride request to rider pickup from the between-ride deadheading distance estimated from the straight-line distance between ride start and end of previous ride after adjusting for the road network. The average deadhead distance from cruising before a ride request (on average 2.2 miles, in red) is twice that of deadheading between ride request and rider pickup (on average 1.1 miles in, in orange).[10] Finally, the average pre-shift (blue) and post-shift (purple) commutes, based on the estimated driver's home location, are 5.3 miles and 7.2 miles respectively, suggesting that drivers might turn on the RideAustin app close to their residence at the start of their shift, and have little control over their last passenger's destination at the end of their shift. A potential strategy to reduce empty-vehicle VMT would be to give drivers incentives to park after completing each ride and wait for the next request, instead of cruising around (Kontou et al., 2019); such a strategy would reduce or eliminate the deadheading represented by the red curve in Fig. 7.

Due to considerable heterogeneity of driving frequency for such a service, understanding drivers' behavior is critical to understand how the number of drivers on the road and the number of ride requests relate to passenger wait times and deadhead miles at any given time. In the RideAustin dataset, while most are occasional drivers who drive only a few shifts per week, others are regular drivers for whom ridesourcing is the primary source of income, much like professional taxi drivers. Since the RideAustin data do not provide information on how long the driver has the app turned on before accepting a ride request, we have to estimate shifts for individual drivers based solely on the duration between consecutive rides. We divided each driver's activity in the RideAustin database into separate shifts, using a threshold of eight or more hours between consecutive rides to delineate separate shifts.

To estimate the number of shifts and rides per shift, we first calculated the "sample duration", the total period of time over which drivers used the RideAustin app during the 11-month period for which we have data (i.e. the date of their last ride minus the date of their first ride). Many drivers drove for the service for only a short period of time; only half of all drivers drove for a period of up to 3 months of the 11-month data period. Then, we calculated the average number of hours per week per driver by dividing the sum of

(*footnote continued*)
travel conducted more than 60 min after the previous ride includes at least some personal travel.

[8] Even the estimated distance driven between rides driven within 20 min of each other is nearly double that of the measured distance from ride request to passenger pickup (36% vs. 20%).

[9] Which is calculated by subtracting the measured distance between acceptance of ride request and pick up of rider from the estimated distance between the ride start and the end of the previous ride.

[10] The computed deadheading distance is highly sensitive to the assumptions used, as noted above. The between-ride deadheading travel of 3.0 miles is for rides provided by the same driver within 60 min of the previous ride. For rides provided within 20 min of the previous ride, the average deadhead distance is only 1.9 miles; while for all trips conducted by an individual driver within a driving shift, the estimated between-ride deadheading travel is 3.8 miles.

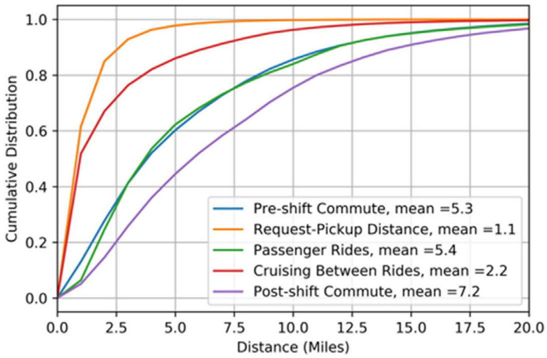

Fig. 7. Cumulative distribution of distance by ride segment and commuting.

all shift durations (difference between the end of the last ride and the start of the first ride in a shift) by the number of weeks driven.[11] Drivers are then categorized into three groups, based on the average weekly hours driving for the service: occasional drivers (less than 10 h/week), frequent drivers (10 to 35 h/week) and full-time drivers (over 35 h/week). We classified drivers who drove fewer than two weeks for the service over the 44-week period as occasional drivers, regardless of the number of hours per week they drove. Table 2 shows the shift characteristics of driver segments, using the 8-hour definitions of driver shifts; annualized VMT is calculated by dividing the total ride VMT by driver over their sample duration, multiplied by 365.25 days per year. Full-time drivers account for only 11% of all drivers, work on average 49 h and 5 shifts per week, and provide 10 rides over 10 h and 104 miles per shift. Frequent driver segments account for 41% of all drivers, work on average 20 h and 4 shifts per week, and provide 7 rides over 6 h and 70 miles per shift. On the other hand, occasional drivers account for nearly half of all drivers, work on average 11 h and 3 shifts per week, and provide 5 rides over 4 h and 50 miles per shift. If each driver segment drove their average intensity over an entire year, occasional drivers would accumulate 7000, and frequent drivers 12,600, annual VMT just driving for the service. Full-time drivers would log nearly 28,000 miles just driving for the service, nearly 2.5 times the national average annual VMT of 11,500 miles for personal vehicles (FHWA, 2016).

Taking a closer look at the distribution of shift VMT can provide important insights on the potential for TNC drivers, especially full-time ones, to use battery electric vehicles (BEVs). BEVs have lower operating costs but longer refueling times than conventional gasoline or hybrid electric vehicles, and TNC drivers may be reluctant to interrupt their shift and take a BEV out of service in order to recharge the battery, especially when charging infrastructure is not available. Fig. 8 indicates that about 94% of full-time drivers' shifts are under 200 miles, and around 35% of full-time drivers never exceeded 200 miles in any shift during the study period.[12] As longer electric range BEVs become available, they could be suitable for most ridesourcing trip operations. Similar findings are presented in previous research studies (Hu et al., 2018). Full-time drivers who accumulate many annual miles for ridesourcing services have an incentive to purchase a BEV because the time it takes to offset the initial additional purchase price with lower operating costs becomes shorter as annual VMT increases. Electrification of the vehicle could lead to faster return on investment from lower operational costs compared to conventional vehicles. Although the total fare of each ride is provided in the dataset, the portion that is earned by the driver is not, so the ability of even full-time drivers to afford the capital cost of a new gasoline or BEV cannot be determined.

In summary, we estimated between-ride deadheading from (1) the straight-line distance between rides, adjusted for the street network distance, for rides up to 60 min apart, and from (2) the measured distance from ride request to rider pickup for rides more than 60 min apart until the end of the driver's shift. Commute distance was estimated based on the straight-line distance between the last ride of a driver's shift and their estimated home location, also adjusted for the street network distance. About 55% of all miles driven is with a passenger, while 26% is between-ride deadhead miles and 19% commute deadhead miles with no passengers. The combined 45% percentage of empty miles is similar to studies in Seattle and Los Angeles which estimate that empty miles accounted for 45% and 36% of ride distances, respectively (Cramer and Krueger, 2016), excluding driver commuting segments.

3.3. Ride distributions by specific locations and land use

RideAustin pick-up and drop-off locations were spatially joined with a detailed land use dataset made available on the city of Austin's open data portal (City of Austin, 2010). Residential locations are among the most common ride attractors (29% of rides, evenly split between single family homes and apartments), along with commercial locations (26% of rides, including retail, restaurants, bars, etc.) and offices (12% of rides). The airport is another significant ride attractor; 6% of all rides end there. These ride

[11] Since this is an average, it includes drivers who may have driven intensively for most weeks but took several weeks off from driving entirely.

[12] These are conservative estimates, and are sensitive to the shift definition described above. For example, one driver provided 203 rides over 211 h between March 9 and March 18 (the South by Southwest festival). Relaxing the constraint from 8 h to 4 h between shifts divides that single shift into 10 mini-shifts, each separated by 5 h of inactivity on average, leaving ample time for the driver to recharge a BEV between mini-shifts. It is possible that in this case the single "driver" is actually multiple drivers using the same RideAustin driver account.

Table 2
Summary of differences between three Ride Austin driver segments.

Characteristic	Occasional drivers	Frequent drivers	Full-time drivers
Number of drivers	2415	2012	534
Distribution of drivers	49%	41%	11%
Total VMT (millions)	2.2	8.8	4.5
Distribution of VMT	14%	57%	29%
Annualized VMT*	7300	12,800	29,000
Hours per week	11	20	49
Shifts per week	2.8	3.6	5.4
Rides per shift	4.9	6.8	9.8
Shift duration (hours)	3.8	5.9	9.8
Shift distance (miles)	50	70	104
Shift speed (miles per hour)	13.1	11.8	10.6

* Sample VMT/sample duration in days * 365.25 days per year, averaged over individual drivers.

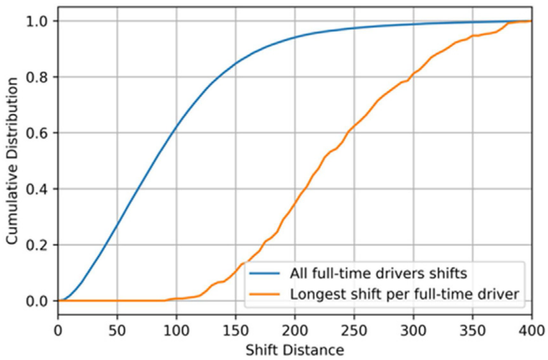

Fig. 8. Full time drivers' shift VMT distribution for all travel days and maximum shift VMT per driver distribution.

flows are presented as a chord chart in Fig. 9 (generated using Circos of Krzywinski et al., 2009), which shows the flows to and from commercial (yellow), residential (pink), office (blue), the airport (red), parking lots/garages (purple), mixed use (turquoise), and educational (green) land uses.

The innermost thick ring in the figure indicates the distribution of both origins and destinations among the seven land uses, while the flows of rides by origin and destination are indicated by the bands across the chart. The scale adjacent to the thick inner ring gives the number of combined origins and destinations of rides by each land use; e.g. 650,000 for residential (evenly split between single- and multi-family), 620,000 for commercial, etc. The thin outermost ring is the distribution of all rides by land use type; the thin middle ring is the distribution to each (destination) land use type, while the thin inner ring the distribution from each (origin) land use type. For example, there are more rides to (60%) than from (40%) the airport. The color of the bands across the chart represents the origin of each ride. For example, the thick yellow diagonal ribbon represents rides originating from commercial and headed towards residential areas; most rides from the airport are to residential areas (thicker red band), while rides to the airport are more evenly distributed from residential, commercial, and office origins (pink, yellow, and blue bands).

Fig. 9 indicates that the most common ridesourcing rides are between residential and commercial areas, followed by rides between two commercial areas. Rides from residential to office land uses are less common, suggesting that commuting is not a primary purpose of TNC rides. Although rides to the airport represent only 6% of all rides, the airport is the single largest destination of TNC rides. These results are supported by passenger survey results in San Francisco that indicate that social/leisure rides, as well as rides from/to the airport, as the most common (Rayle et al., 2016). On the contrary, results from DiDi Chuxing data analysis in Beijing (Dong et al., 2018) show that common morning drop-off destinations and afternoon pick-up locations are within the city's central business district, suggesting that this service is primarily used for commuting purposes.

The most popular specific origins and destinations for ridesourcing are the Austin airport (AUS), downtown employment centers (City Hall, State Capitol, and the campus of the University of Texas), downtown entertainment areas (Sixth Street and Rainey Street), and major downtown hotels. Table 3 shows that only 16% of rides start, and only 20% end, in these nine areas. The average measured distance of rides from or to the airport is just over 12 miles, while the average distance of rides from and to the other eight areas range from 3.2 to 5.1 miles. The average distance of rides from/to all other unidentified areas is 5.3 miles, which is slightly lower than the average distances of rides from/to the nine areas, including the airport (5.67 and 5.82 miles, respectively).

Table 4 indicates the variation in deadheading distances by land use. Although rides to the airport are the longest on average, deadheading associated with the airport as a percent of the next ride is comparable to that of residential and education land uses. This is likely because not all RideAustin drivers are able to find a return trip from the airport after dropping off their previous passenger. Similarly, it appears that drivers also tend to drive back towards locations that generate more trips (i.e. commercial, office, mixed

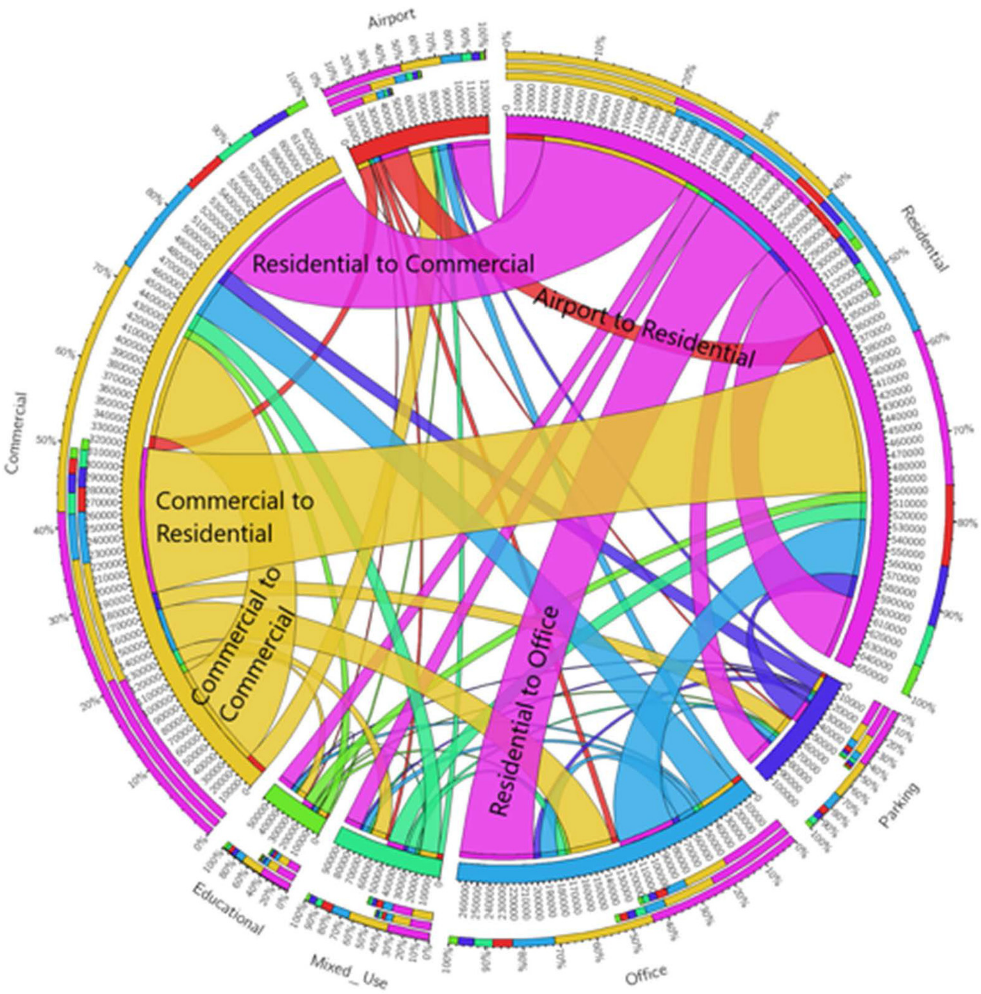

Fig. 9. Chord diagram of rides between RideAustin origin and destination land uses.

Table 3
Distribution of rides and average distance, by location of origin and destination, October 27, 2016 to April 13, 2017.

Locations	Ride origins			Ride destinations		
	Rides	Share	Avg. ride distance (miles)	Rides	Share	Avg. ride distance (miles)
AUS airport	36,219	3.1%	12.63	66,875	5.7%	12.03
Work	28,781	2.4%	4.40	38,050	3.2%	3.80
Entertainment	79,424	6.7%	4.01	83,888	7.1%	3.53
Major hotels	16,921	1.4%	4.72	24,415	2.1%	3.59
University of Texas	33,783	2.9%	3.65	36,457	3.1%	3.24
Subtotal, 9 areas	195,128	16.5%	5.67	249,685	21.1%	5.82
Others	987,683	83.5%	5.35	933,126	78.9%	5.29
Total	1,182,811	100.0%	5.40	1,182,811	100.0%	5.40

use) after dropping off passengers at residential or education locations.

Fig. 10 shows the distribution of rides at a given hour, by day of week, for the major destinations and origins listed in Table 3. The columns in each figure represent the distribution of all rides given on that day and hour to or from these five location categories; the columns do not add up to 100% because the majority of rides do not start or end at any of these locations. The highest hourly concentration of rides between the hours of 5 am and 7 am are to the airport (shown in blue), especially on weekdays, when 40% to 65% of all rides given during those hours are to the airport. Conversely, rides from the airport are evenly distributed throughout the day. The entertainment districts are popular destinations on weekend evenings, increasing from 9% of all rides given at 5 pm to 16% of all rides given at 11 pm. Rides away from the entertainment districts tend to occur a few hours later, ranging from 14% to 21% of

Table 4
Deadheading distances variation by land use, for all rides started within 60 min of the previous ride.

Land use category	Average deadheading distance (miles)	Deadheading distance as % of next ride
AUS airport	7.34	61%
Residential	3.26	59%
Commercial/entertainment	2.49	54%
Office/work	2.24	51%
Educational/UT	2.27	61%
Mixed use	2.15	52%

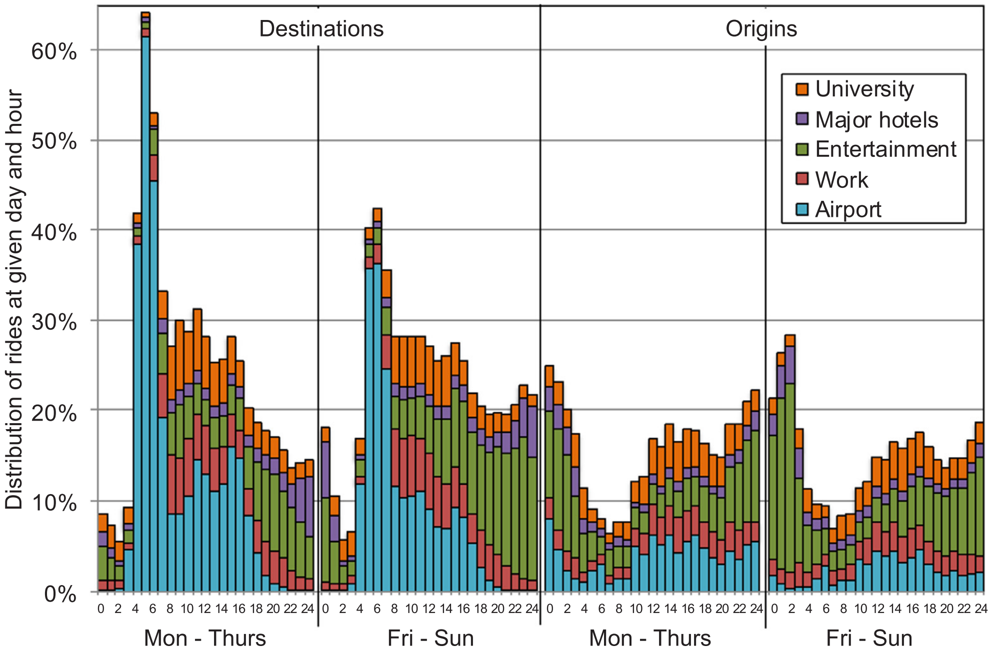

Fig. 10. Distribution of rides at a given hour, by day of week and destination.

all rides between midnight and 2 am on weekend mornings.

3.4. Decreased energy use from more efficient vehicles

The RideAustin data provides the year and model of the vehicles that drivers have registered through the RideAustin mobile app. The vehicle Product Information Catalog and Vehicle Listing (vPIC) website maintained by the National Highway Traffic Safety Administration (NHTSA) was used to decode the vehicle identification numbers (VINs) in a database purchased from AIB (National Highway Traffic Safety Administration, 2018). AIB purchases updated registration information from the Texas Department of Motor Vehicles (DMV), and maintains an updated snapshot of vehicle registrations over time. We only included vehicles whose registration expiration date was in 2017 or later, as of January 2017.

VINs from the Texas DMV data provided by AIB were decoded and merged with certification fuel economy ratings (combined city-highway miles per gallon) from EPA's Fuel Economy Guide (U.S. Department of Energy, 2018), by vehicle year, make, model, engine size in cylinders and displacement, fuel type, drive configuration, and, for pickup trucks, rated capacity (1/2-, ¾-, or 1-ton) and gross vehicle weight rating. Vehicle type in the Fuel Economy Guide (DOE, 2018) was used to classify vehicles into six groups: cars, car-based crossover utility vehicles, minivans, pickup trucks, truck-based sport utility vehicles, and full vans. Since the RideAustin data do not provide the VIN of specific vehicles, and only provides year, make, and model (and not engine size variables), the weighted average fuel economy was assigned to a given model in the RideAustin database based on the average fuel economy weighted by engine configuration and other variables for vehicles registered in Austin from the AIB DMV database. Using this method, fuel economy values were assigned to over 98% of the RideAustin vehicle fleet.

The left-hand panel of Fig. 11 compares the vehicle type and powertrain distributions of the RideAustin fleet with the fleet of registered vehicles in Austin as of January 2017. Fig. 11 indicates that the RideAustin fleet has more cars, CUVs, and minivans (61%, 23%, and 6%, respectively) than the overall Austin fleet (49%, 21%, and 3% respectively), while the RideAustin fleet is comprised of fewer pickups and SUVs than the overall Austin fleet (3% and 6% vs. 14% and 12%, respectively). The three car-based vehicle types tend to have higher fuel economy than the two types of light trucks. The right hand panel of the figure indicates that the RideAustin

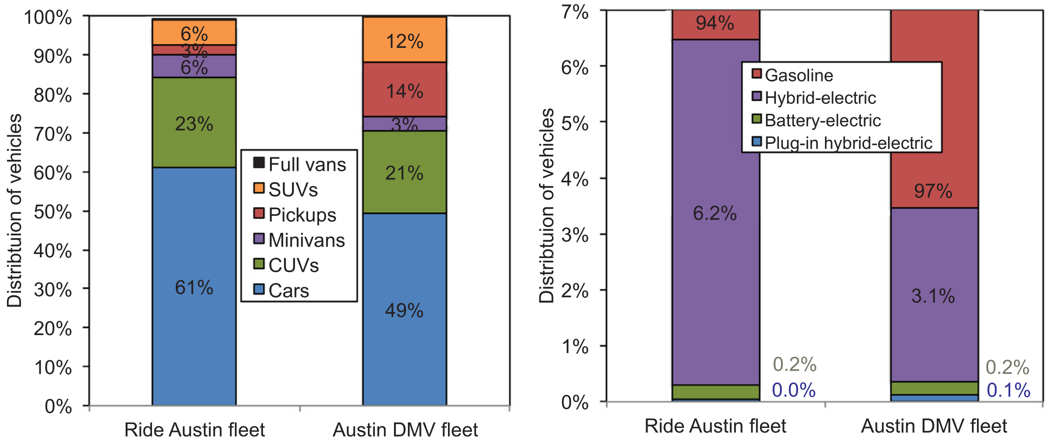

Fig. 11. Distribution of vehicles by vehicle type and powertrain, RideAustin fleet and all vehicles registered in Austin.

fleet has double the portion of hybrid-electric vehicles than the overall Austin fleet (6.2% vs. 3.1%), but comparable portions of battery-electric and plug-in hybrid-electric vehicles. The RideAustin fleet is on average two years newer than the overall Austin fleet (average model year of 2011.9 vs. 2009.7).

The larger proportion of newer cars, CUVs, and minivans with more efficient powertrains in the RideAustin fleet results in a 3.2 MPG greater fuel economy of the RideAustin fleet compared to the overall Austin fleet (25.5 vs. 22.3 MPG).[13] This suggests that TNC drivers are using more efficient vehicles than the average on-road vehicle; thus, energy consumption is reduced if they replace an equal amount of travel in a personal vehicle. The distributions by vehicle type, powertrain, and model year, as well as the average fuel economy, of the RideAustin fleet is insensitive to whether the fleet is weighted by the number of vehicles, rides provided, or miles driven. Similarly, the average fuel economy of the overall Austin fleet does not change after accounting for different average VMT by model year (with newer vehicles being driven more miles annually than older vehicles).

3.5. Mode replacement

Spatiotemporal analysis of ride origins and destinations, along the lines of the analysis in Section 3.3, can help infer what mode a specific RideAustin ride displaced. For example, in the absence of the RideAustin service, rides to and from the airport would most likely have been taken in a personal vehicle or taxi. If replacing a taxi ride or personal vehicle ride and park to the airport, the ridesourcing ride would likely have comparable VMT. However, a ridesourcing ride that replaced a friend or relative delivering a passenger to the airport in a personal vehicle likely would have lower VMT, as the return ride home in the personal vehicle would be eliminated. Ridesourcing rides that coincide with a fixed transit route could have been taken by transit, while rides to a transit stop may have enabled replacing a personal vehicle ride with a multi-modal transit trip, with the ridesourcing ride providing first- and/or last-mile travel to/from transit.

Rather than inferring modal shift using detailed spatiotemporal analysis of the distribution of individual rides, we assumed modal shifts induced by ridesourcing based on surveys from the literature. Table 5 summarizes four such surveys; we used the results from two surveys each conducted in seven US cities, as they likely are more representative of traveler behavior in the average US city. Note the large differences between the Clewlow and Mishra (2017) and Feigon and Murphy (2016) survey results for the share of car and non-motorized modal trips replaced by ridesourcing trips, even though six of the seven cities were the same in each survey. These large differences may be due to how survey respondents were sampled or how the question was asked in each survey. Due to the large differences in modal shifts between these two surveys, we use each as a bounding case of the estimated shift in travel using different modes induced by a ridesourcing service.

3.6. Net energy impact

We estimate the overall net impact of TNC operation on energy use accounting for deadheading and commuting miles and vehicle energy efficiency from the above analysis, as well as the effect of ride sharing and mode shift based on low and high energy assumptions from the literature. This impact is estimated as follows. First, the energy consumption of TNC rides is estimated using the average fuel economy of the RideAustin fleet, 22.3 miles per gallon, as computed above,[14] multiplied by the VMT of TNC rides, including deadheading and commuting, also estimated above. Then the pre-TNC energy use is estimated for each displaced travel

[13] RideAustin required its drivers to use a vehicle from model years 2001 or newer; the average fuel economy of the overall Austin fleet for these model years is 22.7 MPG.

[14] The actual fuel economy of the RideAustin fleet is used rather than the 38.6 mpg in the AFDC analysis, which assumes 1.6 occupants per light-duty vehicle.

Table 5
Modal distribution replaced by ridesourcing trips, and average per passenger fuel economy.

Mode	Survey estimates in the literature				Average passenger miles per gasoline gallon equivalent*
	Clewlow and Mishra (2017) (7 US cities)	Feigon and Murphy (2016) (7 US cities)	Rayle et al. (2016) (San Francisco, CA)	Henao (2017) (Denver, CO)	
Public transit	15.0%	–	33.0%	22.2%	–
Transit bus	–	9.0%	–	–	31.5
Transit rail	–	6.0%	–	–	44.5
Bike/walk/other	45.0%	18.5%	21.0%	25.7%	0
Driving/carpool/taxi	40.0%	66.5%	46.0%	52.1%	38.6/24.1

* Alternative Fuels Data Center (2018); for personal vehicles, first number is based on AFDC assumption of 1.6 occupants per vehicle, second number adjusts for only one occupant per vehicle.

mode, by allocating the reported VMT of TNC rides in Austin to one of two assumed distributions (low energy from Feigon and Murphy, 2016, high energy from Clewlow and Mishra, 2017) of three travel modes[15] to represent a low and high estimate of the modal distribution of trips that are displaced by TNC rides. The energy intensity (occupant miles per gasoline-gallon equivalent) of each of these modes, from the Alternative Fuels Data Center (AFDC, 2018), as shown in Table 5, is applied to these two modal distributions to estimate a low and high baseline energy consumption of the displaced trips; we assume the same distance of displaced trips on transit vehicles as the TNC ride, even though the transit ride would have likely been shorter than the point-to-point ride provided by the TNC.[16] Finally, low and high energy assumptions regarding sharing are applied. The lower estimate assumes 30% of all TNC rides are shared (George and Zafar, 2018),[17] and that two shared rides each have the same distance, thereby reducing passenger miles of travel (PMT) in half; the higher estimate assumes that only 15% of rides are shared, and that the combined distance of the two shared rides is half that of the two separate rides. The net effect of the sharing assumptions is that PMT is reduced by 30% in the low energy case, and by 7.5% in the high energy case.

Fig. 12 summarizes the net effect of five factors discussed above on the energy use from ridesourcing operation.[18] Increased VMT from between-ride deadheading and commuting, and replacing trips that were previously made by more efficient modes, increase energy use by 84–110%. On the other hand, the higher fleet efficiency and potential for sharing rides reduce energy consumption by 43–20%. The net effect is a 41% increase in energy use under our low energy assumptions, and a 90% increase under our high energy assumptions.[19] We believe that the increased energy use from TNC services is likely even greater, as our estimate of deadheading VMT from driver commuting is likely conservative, as noted above.

4. Conclusions

Data on 1.5 million individual rides were used to estimate the additional miles RideAustin drivers travel to reach a rider, as well as the additional miles driven between consecutive rides (referred to as deadheading). Relative to the distance from passenger pick up to drop off, RideAustin drivers traveled 21% more miles just to reach their passenger(s) after accepting the ride request; and drivers traveled an estimated 55% more miles between the end of a ride and the start of the next ride (including the distance traveled to reach the rider who requested the ride) for rides within 60 min of each other. The estimated distance driven by a driver between rides is greater than the measured distance between when a driver accepted a ride request and reached their rider, suggesting that RideAustin drivers are not parking their vehicles but are driving or circling while awaiting their next ride request. However, RideAustin vehicles are more efficient than the average vehicle registered in Austin, partially offsetting the increased energy use from additional VMT.

Out of the total miles driven by RideAustin drivers, 26% correspond to between-ride deadheading and 19% to drivers' commuting. Three distinct types of drivers are examined, based on the frequency of their driving shifts; the 40% of drivers that are half-time drivers conduct more than half of the ridesourcing rides, and 57% of all ridesourcing VMT, while the 11% of drivers that are full-time drivers conduct almost 30% of rides with average daily distance of 109 miles. Full-time drivers could complete over 94% of their shifts on a single charge in the latest generation electric vehicles (with around 200 miles real-world range); in addition, 35% of full-time drivers never exceeded 200 miles in one shift during the study period. In the current situation where the TNC has little control over the number of drivers and vehicles, other than pricing incentives, the supply of drivers may be short of the optimum necessary to minimize rider wait times and deadheading. When ridesourcing operations are conducted by a centrally managed fleet of automated

[15] Transit bus and rail, bike/walk/other non-motorized, and light-duty vehicles including taxis.

[16] A transit ride is likely of a shorter distance than a TNC ride to the same destination, but involves walking to and from the transit stops.

[17] This is based on the claim by Uber and Lyft that 30% of all ride requests are for shared rides; the fraction of requested shared rides that are actually shared is unknown (George and Zafar, 2018)

[18] We do not estimate the effect of ridesourcing service on retiring of personally owned vehicles and elimination of discretionary trips, which may occur over the longer term.

[19] The assumptions we used regarding the modal distributions of trips replaced by TNC rides come from cities with fairly extensive public transit systems (Feigon and Murphy: Austin, Boston, Chicago, Los Angeles, San Francisco, Seattle, Washington DC; Clewlow and Mishra: Boston, Chicago, Los Angeles, New York, San Francisco Bay Area, Seattle, Washington DC).

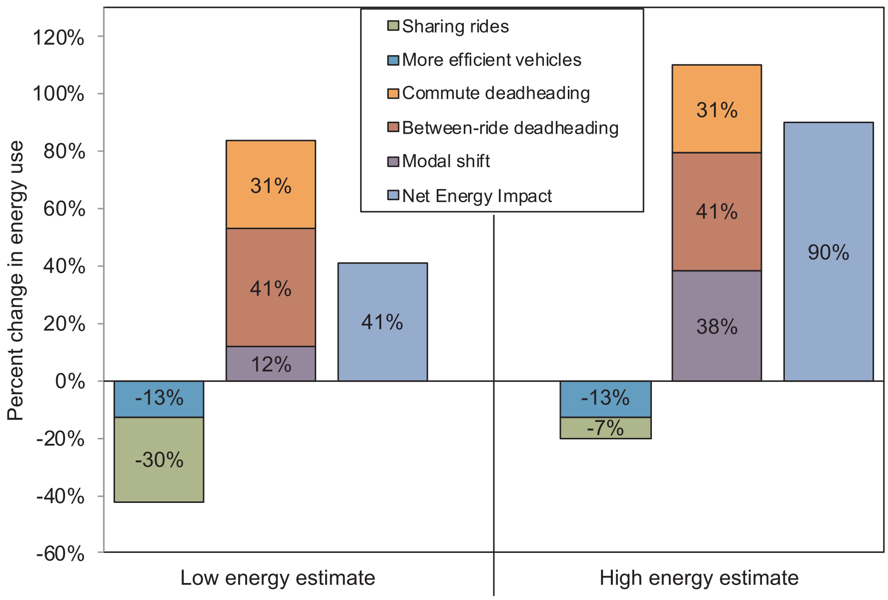

Fig. 12. Low and high estimates of net energy impact of ridesourcing in Austin.

vehicles, TNCs will have the capability to better balance the supply of vehicles in order to meet the demand for rides, thereby reducing wait times and between-ride deadheading. In addition, a centrally managed fleet of automated vehicles likely will reduce commute deadheading, as well as minimize between-ride deadheading by parking vehicles until their next ride request (Bauer et al., 2018).

The results presented here, from a single non-profit TNC operating in a unique market, are not necessarily generalizable to all ridesourcing in cities across the US. The RideAustin dataset and our analysis allow us to gain better understanding of the many aspects of ridesourcing that affect mobility and energy use. Similar data on individual rides provided by large TNCs such as Uber and Lyft in other cities would be useful in understanding many of the aspects that influence changes in overall VMT and energy use from greater use of these services in cities with different characteristics. In future analysis, geospatial analysis of detailed ride data can be used to infer whether the TNC ride may have replaced travel on public transit, as in Komanduri et al., 2018. Analyses of TNCs timing entering different regional markets can provide useful insights into the relationship between ridesourcing service and largescale changes in vehicle registrations, VMT, and public transit use. However, simultaneous surveys of riders are necessary to determine the causal effect between individuals' use of ridesourcing and modal shift, including car-shedding or eliminating discretionary travel. Other important aspects of ride-sourcing services, such as driver residence (to calculate exact commute distances), the extent to which rides are shared with separate paying passengers, and the makeup of the vehicle fleet used for ridesourcing services, also can only be obtained through surveys of drivers, or other innovative strategies to collect such data. More data on individual rides or from surveys of drivers and riders can also be used to calibrate assumptions used in agent-based, mesoscopic, travel simulation models such as BEAM (DOE, 2017) and POLARIS (Auld et al., 2016). These models, in conjunction with a long-term land use development model such as UrbanSim (Waddell, 2011, 2002; Waddell et al., 2007) can be used to simulate the short- and long-term effect of ridesourcing and other innovative transportation services on overall regional transportation systems under different scenarios, to investigate the sensitivity of overall system mobility and energy use to different aspects of these services.

This work overall provides a thorough overview of a ridesourcing dataset and sets an example for researchers and practitioners on how to use information like RideAustin trips to uncover travel, schedule, driving, land-use, and energy-related patterns of TNC services. Several of the metrics and the analysis methods presented here can be used to measure the effectiveness of such services, enhance microscopic and agent-based modeling assumptions, and inform urban policy directions that can help towards seamless integration of ridesourcing in a city's transportation system.

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Declarations of interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.03.005.

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