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Impact of Ridesharing on Vehicle Miles Traveled

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EXECUTIVE SUMMARY

Due to the rapid development of the ridesharing industry, there is very limited data available for researchers and practitioners to draw a comprehensive conclusion regarding resultant changes in vehicle miles traveled (VMT). Current research on ridesharing is inconclusive and conflicting. This report summarizes our findings on the impacts of ridesharing on VMT as presented in the literature. Depending on the data used and perspective of the researchers, the discrepancies arise from the following aspects:

Optimization and pairing modeling. Transportation network companies utilize optimization and pairing models that must execute quickly and easily in the field. The deadhead travel—time spent cruising between customers—is typically high using these commercially developed models. Models developed by academic researchers are more efficient and powerful but are also more computationally intensive. Multiple researchers have verified that ridesharing companies can decrease VMT using more advanced optimization approaches. A well-balanced optimization and pairing model is needed for ridesharing to show positive impacts on decreasing VMT.

Relationship between ridesharing and public transit. One of the major issues that critics of ridesharing raise is its competition with public transit. Drawing conclusions from survey questionnaires, these critics believe that ridesharing attracts travelers away from public transit and therefore generates more VMT. Proponents of ridesharing, however, argue that ridesharing offers first- and last-mile connectivity with public transit and complements train and bus services. Detailed spatial analysis is needed to clarify the relationship between ridesharing and public transit.

Induced trips. Induced trips by ridesharing in different traffic environments are not universally the same. Spatial location, availability of public transit, and land use, as well as the educational, social, and economic levels of travelers in an area, all contribute to the number of induced trips. A comprehensive survey is needed to cover different traffic environments and different groups of potential users. Determining the exact number of induced trips is vital because the tradeoff between induced trips and combined trips will influence changes in VMT.

Car ownership. The change in car ownership is a good indicator of the change in VMT. Changes in car ownership associated with ridesharing should be investigated over a longitudinal time period. Changes in car ownership over time, rather than existing car ownership, should be studied. Whether the choice to use a ridesharing service is the result of, or the reason for, a change in car ownership should be investigated to fully understand the associated change in VMT.

In summary, ridesharing impacts on VMT, which is directly related to crash risks. The existing studies are not conclusive. This report will discuss the data and modeling needs for studying ridesharing and make recommendations for future research.

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LIST OF ABBREVIATIONS AND SYMBOLS

ACS	American Community Survey
TNC	Transportation Network Company
VMT	vehicle miles traveled
NHTS	National Household Travel Survey
TAZ	Travel Analysis Zones
NYC TLC	New York City Taxi and Limousine Commission
DID	difference in difference modeling
DOT	Department of Transportation
UZA	urbanized area
FHV	for-hire vehicle

CHAPTER 1. BACKGROUND AND INTRODUCTION

Ridesharing, sometimes called ride-hailing, is a service provided by a commercial transportation network company (TNC) for peer-to-peer carpooling arrangements. Major TNCs in the United States include Uber, Lyft, Via, Juno, Getaround, Sidecar, and Gett (discontinued). TNCs match passengers with drivers through a website or mobile app and combine multiple trips into one using ridesharing drivers' personal vehicles. According to the National Household Travel Survey (NHTS), among the sampled population, there were 3,463 taxi/limo/Uber/Lyft vehicle trips reported out of a total of 924,000 vehicle trips in the 2016–2017 survey on the travel day surveyed.(1) According to Schaller, TNC ridership has increased dramatically over the last several years (as shown in Figure 1),(2) with total ridership more than doubling in the last 3 years (data estimated from 2016-2017 National Household Travel Survey).

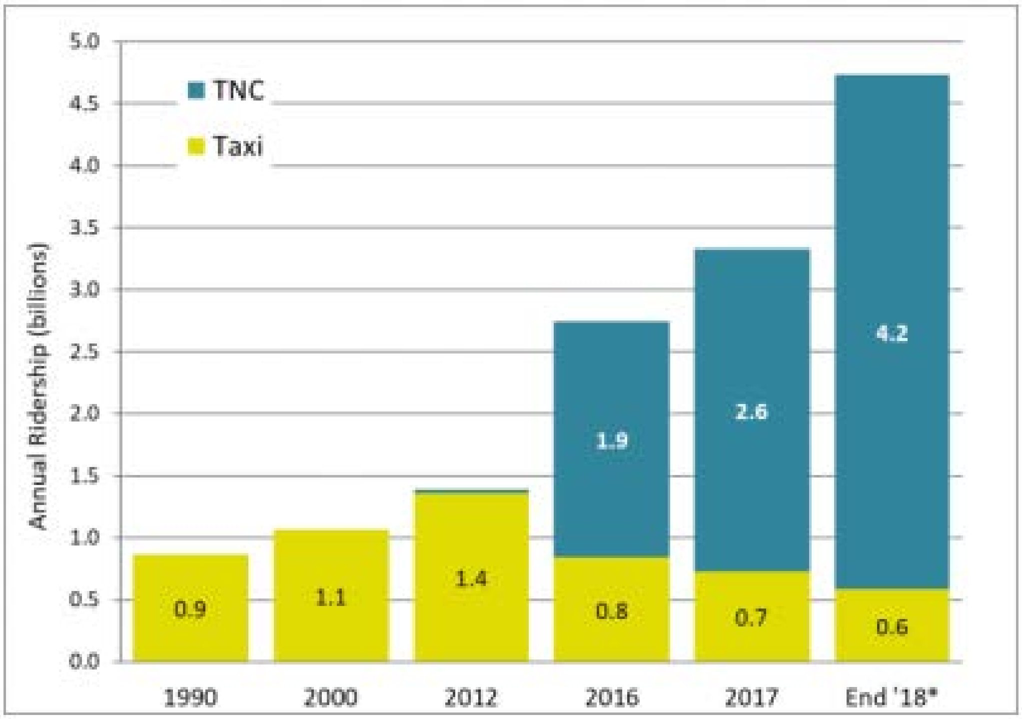


Figure 1. Graph. Ridership changes in TNCs and taxis.(2)

With such a dramatic increase in ridesharing trips, the impacts of this new industry on the transportation network need to be carefully studied, and corresponding policies are needed to regulate TNC operations. Existing research has drawn conflicting results regarding the impacts of ridesharing on crash exposures. Some studies have concluded that by combining multiple trips into one vehicle, TNCs will decrease vehicle miles traveled (VMT) and crash exposure will decrease accordingly. Other studies, however, have concluded that ridesharing induces additional trips and attracts those who previously used public transit, biked, and walked to the use of passenger vehicles. Additionally, extra vehicle mileage will be generated during the period that a TNC driver is cruising and waiting for passengers ("deadhead" mileage). Therefore, it is argued, ridesharing will have a detrimental effect on traffic safety by adding extra VMT to the system.

The reasons for the conflicting conclusions found in the existing research are complicated. First, to investigate the impacts of ridesharing requires multiple data sources at a high granularity over a long enough time period. Ideally, data to conduct a comprehensive and systematic analysis will include detailed ridesharing trip information (trip purpose, departure time, origin and destination, etc.), ridesharing users' personal and demographic information (income, social and economic status, travel habits, frequency of using ridesharing, car ownership, and the mode used if no ridesharing is available, etc.), and the alternative traffic modes available in the vicinity during the ridesharing trip. However, since ridesharing is a newly developed traffic mode and the market share has increased so rapidly, there has not yet been enough time to collect and analyze a sufficient quantity of this data. Also, to protect users' privacy, there is a lack of public access to ridesharing records at the trip level.

Second, ridesharing involves multiple disciplines, including traveler behavior, economics, traffic engineering, and consumer psychology. The choice to use ridesharing is typically driven by multiple factors, such as the reliability of traveling and arrival time, cost, availability of public transit, convenience, and comfort level. Thus, ridesharing needs to be investigated from multiple perspectives.

Third, ridesharing can induce traffic in addition to its impacts on the redistribution of travel demand among other travel modes. In surveys, some users have claimed that their trip would not have occurred if ridesharing were not available. Quantifying the impacts of induced traffic adds another challenge to studying ridesharing.

All of these factors add to the complexity of investigating the impacts of ridesharing on changes in VMT. Therefore, four goals were established for this research:

1. Conduct an extensive literature review on ridesharing.
2. Identify the gaps in the research on ridesharing in terms of data collection and processing, modeling methodologies, and policy issues.
3. Propose modeling methodologies to address one or more aspects of the impacts that the ridesharing industry has generated on the traffic system.
4. Provide suggestions on improving the understanding of ridesharing, regulation, and policies.

This report is organized as follows. Chapter 2 provides an extensive literature review. Chapter 3 illustrates the impacts of ridesharing from multiple perspectives. Chapter 4 lists the data sources available to help us understand ridesharing for future research. Chapter 5 provides the conclusions of the study.

CHAPTER 2. LITERATURE REVIEW

Previous research has drawn conflicting conclusions regarding the impact of ridesharing on the transportation system. Some research has concluded that pooling multiple travelers together will help to decrease the overall number of cars and the resulting VMT through a pairing and optimization process. Typically, this research has been based on mathematical modeling that groups trips (typically trips collected from taxis) spatially and temporally to minimize VMT. Other studies, however, have concluded that ridesharing increases the overall mileage traveled by personal vehicles. This increase has been attributed to multiple causes: detour driving for picking up and dropping off passengers, induced travel by individuals who are not be able to drive if no ridesharing service is available, diverted travelers from public transit, etc. The conclusion that ridesharing increases VMT is generally based on stated-preference survey data, where researchers collected information on ridesharing users' socioeconomic status, travel habits, and opinions towards ridesharing. There are also studies stating that ridesharing's impact on VMT is inconclusive and should be analyzed case by case.

The review of the literature that follows divides the discussion along the lines presented above. The first subsection covers research indicating that ridesharing will reduce VMT, and the second presents the research indicating that ridesharing will increase VMT. Note that each study is based on unique conditions (including locations), and therefore specific results might not apply to other studies.

RIDESHARING REDUCES VMT

Li et al.[(3)] modeled the congestion indices from the *Urban Mobility Report* using independent variables, including Uber entry time dummy variables, socio-economic characteristics, and traffic characteristics in a difference-in-difference (DID) framework and concluded that ridesharing services have significant positive impacts on congestion. The reasons include increased vehicle occupancy, reduced car ownership, shifted demands, diverted peak hour demands, and increased utilization of vehicle capacity.

Alexander and Gonzalez[(4)] proposed that the impacts of ridesharing need to be evaluated from the balance of two competing forces. One is the potential increase of traffic resulting from users who are attracted away from other transportation modes to cars (cost of ridesharing). The other is the potential to decrease traffic by combining multiple trips into one (benefit of ridesharing). They tried to answer two research questions in their study: (1) What proportion of trips can be matched by a real-time ridesharing service; and (2) What should be the change in the number of vehicles and traffic congestion. The results showed that under moderate- to high-adoption rate scenarios, ridesharing will decrease congestion.

Cici and Markopoulou[(5)] used mobile and social data to demonstrate that there is a significant overlap in peoples' urban commutes, which indicates a high potential benefit from a ridesharing system. They found that a two-hop en-route ride-sharing trip (people who shared the trip are from their own social contacts) offers a good trade-off between "technological feasibility, people's security concerns, and a substantial impact on traffic reduction." For example, if combining trips with a wait time up to 10 minutes and proximate origin and destination with one kilometer of distance, there is a 24% reduction of cars in Madrid. If passengers are allowed to be picked up along the way, this yields a notable boost in ride-sharing potential with or without time constraints.

Santi et al.[6] studied the benefits of vehicle pooling with sharable networks through a theoretical model where the records of 150 million taxi trips were analyzed. Using a selected time window to combine spatially close origins and destinations, the authors concluded that cumulative trip length can be cut by 40% or more.

Similar research was conducted by Ma et al. using taxi data in Beijing, where researchers proposed a taxi searching and scheduling algorithm to serve queries from passengers. They believe their algorithm can save 13% of the travel distance while serving 25% more passengers.[7]

Jacobson and King[8] built a mathematical model to estimate the fuel savings from ridesharing. They combined both the mileage increase from extra travel to pick-up/drop-off passengers and the fuel saved by grouping individuals into fewer vehicles and reducing mileage. Their results showed that ridesharing can be quite attractive under certain circumstances. For example, when travelers' time value is less than $4.24 per hour or when the parking fee and road toll costs increase, ridesharing decreases fuel consumption.

Alonso-Mora et al.[9] built a robust mathematical model using data from New York city. Their conclusions show that assuming one person per ride, 98% of the taxi rides currently served by over 13,000 taxis could be served with just 3,000 ridesharing vehicles with four occupants in each vehicle. The waiting time can be decreased to 3.2 and 2.7 minutes, individually, and a mean delay of 1.5 and 2.3 minutes, respectively, for a capacity of 2 or 4 passengers, individually.

Amey[10] concluded that, for current single-occupancy vehicle commuters at the Massachusetts Institute of Technology, approximately 78% of staff and faculty could be matched, with 67% capable of sharing rides on any given day. If those staff and faculty members for whom ridesharing was feasible all decided to share rides on a given day, it would result in a 19% reduction in institute-wide VMT. Similar results were observed for Volpe Center staff: 71% of single-occupancy vehicle commuters could be matched, with ridesharing possible among 62% of commuters on a given day. If all employees for whom ridesharing was feasible decided to share rides on a given day, VMT would be reduced by 6%.

Agatz et al.[11, 12] tested the mileage savings with a ridesharing algorithm they developed. They tested three different ridesharing participation rates of 1%, 2%, and 4%, and two dynamic optimization algorithms: greedy and bipartite. With only 2% participation rate announcement streams (one announcement is one trip need, either a driver announcement or a passenger announcement), substantial improvements were made: an absolute increase of approximately 15% on the success rate, and 10% in vehicle mileage savings (as shown in Figure 2, where S = success rate, M = average mileage savings, and C = average individual cost savings[11]; see Figure 3 for a map of the study area).

	S (%)	M (%)	C (%)
—1%—			
GREEDY	28.2	10.5	26.2
BIPART	58.3	18.3	25.2
a posteriori	60.3	19.9	26.3
static	62.2	20.8	26.8
—2%—			
GREEDY	28.7	11.4	27.4
BIPART	67.0	22.3	27.3
a posteriori	68.7	23.8	28.3
static	70.3	24.6	28.6
—4%—			
GREEDY	28.3	12.2	29.0
BIPART	74.5	26.6	29.6
a posteriori	75.8	28.0	30.5
static	77.1	28.8	31.0

Figure 2. Screenshot. Study results.[11]

Figure 3. Map. Study area.[11]

Contreras and Paz[13] obtained data from the Regional Transportation Commission of Southern Nevada and other third-party sources and built a linear regression model to investigate the correlation between transit ridership and for-hire services. Their results showed that there was a positive correlation between transit ridership and taxicab use. As transit ridership volume increased, taxi ridership increased as well, from which they concluded that transit agencies should partner with the ridesharing industry. Additionally, the authors concluded that future work should focus on average daily traffic counts or VMT to explore the effects of ride-hailing on travel behavior, and how ride-hailing affects residential transit ridership specifically.

Murphy[14] explored shared modes of transportation in metropolitan cities and their respective impacts on public transportation. His conclusions were as follows.

1. The more that people use shared modes, the more likely they are to use public transit, own fewer cars, and spend less on transportation overall.

2. Shared modes complement public transit—ridesourcing is mostly used for social trips between the hours of 10 p.m. and 4 a.m., a period of time where transit runs less frequently, or is not available.
3. Shared modes will continue to grow in significance, and public entities should seize opportunities to collaborate with private TNCs to improve urban mobility and receive benefits that share equity through paratransit options.
4. Ridesourcing appears more likely to be a substitute for automobile trips than for public transit.

Tayle et al.[(15)] conducted research to explore the role of TNCs in the San Francisco area. Their data and analysis yielded a relationship between ridesourcing and taxis that exhibited very similar market demands. Ridesourcing customers experienced significantly shorter wait times, and the wait times exhibited less variance than those of taxis. Additionally, wait times were considerably shorter for customers located on the outskirts of the city; thus, it is evident that ridesourcing is filling the gap created by public transit and taxi's lack of presence in less-dense and more-automobile-dependent areas.

Stiglic et al.[(16)] found that when ridesharing is integrated with transit (as opposed to ridesharing by itself) and if the traveler is willing to extend their arrival time by a certain amount of time, ridesharing and ride-matching technology are beneficial for the transportation system.

RIDESHARING INCREASES VMT

Graehler et al.[(17)]conducted a longitudinal analysis on factors that are contributing to the decline in transit ridership. They found that the entry of a TNC in a market is associated with a decrease of heavy rail and bus ridership by 1.3% and 1.7%, respectively. Furthermore, they concluded that the relationship between entry of the TNC and transit ridership varies by mode. There is a significant negative relationship between heavy rail and bus ridership and the entry of TNCs, which shows that TNCs reduce transit ridership with respect to heavy rail and bus.

Rayle et al.[(18)] surveyed 757 passengers using ridesharing services in San Francisco with a valid sample of 380 participants. They asked questions regarding trip origin, destination, purpose, previous and alternative modal choice, car ownership, and basic demographics. They found that (1) the average number of passengers per vehicle is 1.8; (2) 40% of respondents who owned a car said they drove less since ridesharing became available; (3) 92% replied that they would still have made the trip if no ridesharing service were available (among them, 39% said they would have used a taxi, 33% said bus or rail, and 6% said they would drive; about 25% of trips were plausibly rail transit substitutes, and 63% were bus accessible).

Clewlow and Mishra[(19)] had similar conclusions in their study. About 49% to 61% of ride-hailing trips would have not been made or would have been made by walking, biking, or transit. The authors concluded that ride-hailing is likely to contribute to growth in VMT in major cities, including Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle, and Washington, D.C. They found that after using ride-hailing, the average net change in bus services was a 6% reduction and that light rail services saw a 3% reduction.

Schaller[2, 20] concluded that TNC users added 5.7 billion miles of driving annually in the Boston, Chicago, Los Angeles, Miami, New York, Philadelphia, San Francisco, Seattle, and Washington, D.C., metro areas. The author found that ridesharing competes with public transportation, walking, and biking rather than competing with personal automobiles, as claimed by TNCs. Overall, the results showed that, were ridesharing not available, about 60% of TNC users would have taken transit, a different non-auto mode, or not made the trip, while about 20% would have used their own cars and 20% would have used a taxi. Findings also revealed that TNC users are those who (1) would have taken public transportation (15% to 50%); (2) would have walked or biked (12% to 24%); or (3) would not have made the trip at all (2% to 22%). The major reasons that TNCs add to mileage traveled are accounted for by extra travel between trips, detour driving, and replacing other modes of travel rather than replacing travel by personal vehicle, as shown in Figure 4.[2]

Column:	A	B	C	D	E	F	G
	Personal vehicle	Private ride (all switch from personal auto)	Private ride (switch from auto and other modes)	20% shared ride (switch from auto and other modes)	50% shared (Lyft goal)	Highly optimistic scenario	Suburban scenario (90% from auto)
Mileage							
Between passenger trips	0	3.0	3.0	3.0	3.0	1.1	4.0
Per passenger	5.2	5.2	5.2	5.2	5.2	5.2	7.0
Shared trips							
Pct of all trips		0%	0%	20%	50%	75%	10%
Amount of trip shared		0%	0%	52%	65%	75%	52%
Pct with 3+ pax		0%	0%	2%	13%	38%	1%
Amount of trip shared		0%	0%	67%	80%	80%	67%
Previous mode							
Driving		100%	20%	20%	20%	20%	90%
Taxicab		0%	20%	20%	20%	20%	0%
Transit/walk/bike/no trip		0%	60%	60%	60%	60%	10%
Total vehicle miles per passenger							
Using TNCs		8.20	8.20	7.62	6.46	4.14	10.61
Using previous mode	5.2	5.20	2.93	2.93	2.93	2.93	6.30
Change		3.00	5.27	4.69	3.53	1.20	4.31
Percent change in vehicle miles		**58%**	**180%**	**160%**	**120%**	**41%**	**68%**

Figure 4. Screenshot. VMT changes under different scenarios.[20]

As part of his dissertation research, Henao[21] signed up as a contractor driver for Uber and Lyft and surveyed more than 400 passengers covering 4,951 miles. While driving passengers, he asked them to fill out a survey and collected data regarding their opinions and reactions to the trips and ridesharing. He found that 22.2% of Uber/Lyft users would have used public transportation and 12.2% would not have traveled at all (Figure 5). He found a similar trend for the between-trip, deadhead mileage[21] as that found in the study conducted by Schaller,[2, 20] where 1.2 cruising miles are used for a trip of 3.55 miles (33% average cruising distance; Figure 6). Henao concluded that ridesharing increases VMT by 185%. Henao and Marshall[22] found that 40.8% of ride-hailing miles are deadhead miles; for every 100 miles traveled with 1+ passenger, an additional 69 miles are traveled for deadhead. Moreover, they expressed concern about the complexity of mode substitution and called out the need for further research in this area. Additionally, they concluded that future studies should focus on how these results would vary between different environments, such as cities and suburban areas with different layouts and populations.

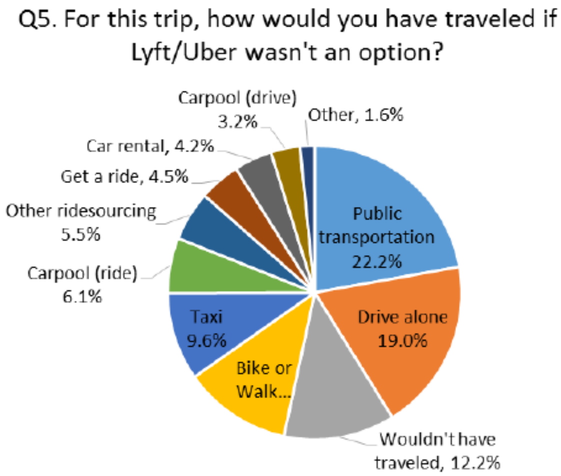
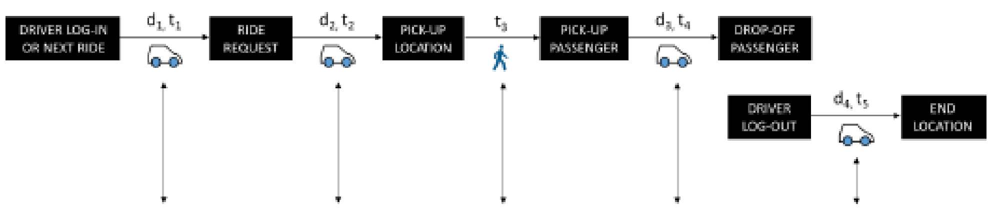


Figure 5. Chart. Modes split if no Lyft/Uber available.[22]



		Waiting/Cruising for a ride	From Request to Pick-up (en-route to passenger)	Waiting for Passenger	From Pick-up to Drop-off (WP ride)	From last Drop-off to End Location	Totals (t_T & d_T)
Time (minutes)	Total (Σt)	4,965.00	2,511.00	531.00	6,106.00	1,416.00	15,529.00
	Mean	11.94	6.04	1.28	14.68	21.78*	37.33
	St. Dev.	15.46	3.65	2.10	10.04	12.27*	20.30
	Median	7.50	5.00	1.00	11.50	20.00*	32.83
Distance (miles)	Total (Σd)	635.91	600.56		2,929.94	784.29	4,950.69
	Mean	1.53	1.44		7.04	12.07*	11.90
	St. Dev.	3.94	1.44		8.60	7.43*	10.37
	Median	0.20	1.00		3.55	12.00*	8.30
Average mph			14.35		28.79	33.23	19.13

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

* Commute based on 65 shifts

Figure 6: Screenshot. Distance and time distribution within a TNC trip.[22]

Tsao and Lin[23] developed an entropy optimization (gravity) model to model the effects of ridesharing among commuters. The research area was Los Angeles, which has a well-known urban sprawl problem. Assuming two different densities, 581 jobs/square mile and 660 jobs/square mile, they found that trip numbers were very small between the origin zone and any zone 10 miles or more away. Ridesharing, therefore, has little potential for demand reduction.

Circella et al.[24] studied shared mobility in California and found that (1) individuals with a higher education are more likely to use ridesharing; (2) environmental variables (land-use mix and activity density) explain more variation in the frequency of using ride-hailing than sociodemographic variables; and (3) net VMT impacts of single-passenger services are uncertain because many ridesharing users are converted from public transit and non-mobile modes, such as biking and walking.

In summary, the existing literature is divided, with studies drawing opposite conclusions regarding the impacts of the ridesharing industry on VMT. In the next chapters, we will summarize the reasons for this conflict and make recommendations for future research.

CHAPTER 3. IMPACTS OF RIDESHARING

As the literature review illustrates, most of the research concluding that ridesharing reduces VMT concentrated on optimizing existing trips by combining spatially and temporally proximate trips. Such studies view the problem as one of optimizing the existing demand for ridesharing. Most of them did not evaluate the impacts of ridesharing in terms of induced trips or its relationship with other traffic modes.

On the other hand, research concluding that ridesharing increases VMT typically identified existing ridesharing trips, analyzed the percentage of deadhead, or surveyed users regarding alternative modes to compute changes in VMT. In other words, these studies emphasized the supply side of ridesharing.

The compound effect of ridesharing on the transportation system will never be a simple question. It should be investigated from multiple perspectives. As shown in Figure 7, ridesharing interacts with mode shift, traveler matching, and routing. Meanwhile, it induces traffic demand. All of these aspects then affect VMT and change safety exposure. To evaluate the impacts of ridesharing, a systematic modeling framework is needed that will incorporate all the factors. Due to the complexity of these factors and their intercorrelation, we need to start by examining the following aspects individually in order to answer this research question by integrating the aspects together.

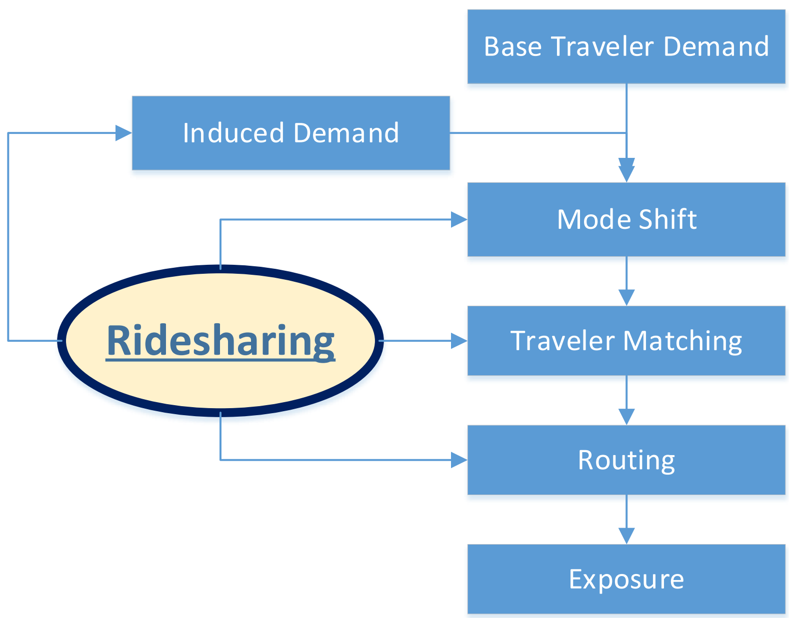


Figure 7. Chart. Ridesharing interacting with other factors.

INDUCED TRAVEL

The induced demand typically comes from travelers who cannot or are not willing to drive due to physical or financial limits. In the surveys from previous studies, many users claimed that their ridesharing trips would not have occurred if no ridesharing service were available.

The exact amount of induced travel demand is an important contributing factor to study the change in VMT. In previous research, induced travel estimates have varied widely, ranging from as high as 20% to less than 5%. We recommend conducting a categorical survey, including varied traffic environments, different user groups, and different land use setups, etc., to obtain a comprehensive picture of induced travel.

1. The amount of induced travel will vary in different travel environments. Whether or not ridesharing is serving a network with ample public transit available versus a remote area, or a high-density metropolitan area versus a sprawling urban environment, may be the deciding factor on how ridesharing works in the network. Induced travel will be lower in an area with an existing and extended public transit system. As shown in Table 1, the previous preferred travel mode varies significantly from city to city. As the table shows, for areas with highly accessible public transit, ridesharing pulls a lower percentage of users from public transit (as in New York and Boston).
2. Population density and road network configuration will contribute to the effects of ridesharing. Cici et al. found that Barcelona, which is denser in population than Madrid, has a 14% higher ridesharing potential; Los Angeles, on the other hand, has a 46% lower ride-sharing potential than New York.(5)
3. Income level and education level in the area will generate a different amount of induced travel. Previous studies have found that populations with higher income and education levels are more likely to use ridesharing services.
4. Land use is another factor. Areas with a high density of restaurants and bars will have significantly higher induced ridesharing trips because patrons want to avoid drinking and driving.

Table 1. Where ridesharing users shift from.

City	Drive Alone	Rail/Train/ Public Transit	Walk/Bike	Taxi	Would Not Make Trip
Boston(25)	18%	42%	12%	23%	5%
New York(26)	12%	50%	16%	43%	2%
Denver(21)	26%	22%	12%	10%	12%
California(24)	35%	33%	19%	51%	9%
Aggregated area (7 large metros)(19)	39%	15%	24%	N/A	22%

Therefore, to better study the induced travel from ridesharing, a more comprehensive, carefully designed survey is needed. Previous induced travel calculations were based on survey data collected from existing ridesharing users, generating a self-selection bias. A survey covering different types of traffic networks with varied population densities is needed and the data should be collected from existing and potential ridesharing users.

CAR OWNERSHIP

Car ownership was studied by almost all the previous survey-based research. Decreased car ownership is seen as an evidence that ridesharing will help decrease VMT. We believe that car ownership is a good indicator for studying impacts on VMT. However, a larger amount of longitudinal data is needed to illustrate changes in car ownership. The following data collection and analysis activities would shed more light on car ownership trends:

1. Collect users' ownership data before and after using ridesharing services over a longer time period. Existing car ownership or self-claimed car ownership changes could be the result or the cause of using ridesharing. Some users may choose to use ridesharing because they do not own or do not want to own a car. Some users may decide to give up their cars after they adopt ridesharing as their major travel mode. The impacts of ridesharing under the two circumstances are different and should be calculated differently.
2. Survey TNC companies for changes in fleet size simultaneously. Any changes of car ownership by private parties need to be combined with changes in TNC fleet sizes to account for changes in VMT.
3. Survey a wider population of car owners. Only if the size of the user group increases and the ridesharing service covers a larger area is it likely that more users will be willing to give up their cars. Such potential users have not typically been included in previous studies. A better understanding of these potential users' choices will help us calculate changes in VMT more accurately.
4. Differentiate car ownership by whether or not the subject is a ridesharing driver.

RELATIONSHIP WITH TRANSIT AND OTHER NON-MOBILE MODES

Existing research regarding the relationship of ridesharing with public transit and other modes relies on drawing conclusions from self-statements made by survey participants. Participants were asked about the modes they would have used if ridesharing were unavailable. The shortcoming of survey data use is that participants were asked the question at a different time from when they made their travel choices. Some factors that would have restricted their choices typically were not taken into consideration. For example, the departure time of the trip could fall into a time frame when public transit is not available. Previous studies have shown that a large portion of ridesharing happens at night from 10 p.m. to 4 a.m. The time factor was not usually considered by participants when they answered the mode choice questions afterwards. Also, some ridesharing trips start and/or end at locations where public transit is not within walking range. It was also possible that using public transit would involve transferring and was therefore not likely to replace the ridesharing trip. Detailed ridesharing trip data, with information regarding departure time, origin, and destination, need to be analyzed jointly with public transit service times, public transit stops, and frequency of public transit arrivals/departures to draw more valid conclusions.

OPTIMIZATION AND PAIRING MODEL

Much previous research has found that deadhead travel makes up a large portion of the mileage traveled by ridesharing providers. Some negative conclusions about the effects of ridesharing have been based on the estimated percentage of deadhead travel obtained from survey data (as shown in Figure 4 and Figure 6). However, one assumption made in such analyses is that the deadhead travel between trips is fixed. This high percentage, however, is based on the existing pairing/optimization process adopted by TNC companies. If an advanced optimization and pairing model were adopted, deadhead travel could be decreased. Consequently, positive conclusions about the effects of ridesharing have been generated from mathematic modeling. According to proponents, a suitable optimization process can save up to 40% of VMT. However, there is a discrepancy between the optimization modeling adopted by the ridesharing industry and academic research. A more advanced optimization and pairing model needs to be adopted by TNCs for ridesharing to work more efficiently. The cost, complexity, and computational burden of the models need to be weighed to balance effectiveness and feasibility.

OTHER RELATED ISSUES

Two other issues are important to factor into research on ridesharing:

1. Ridesharing market penetration

The user pool of ridesharing needs to be expanded enough to allow benefits to show. Currently, critics believe that ridesharing generates too much deadhead travel. If the user pool is large enough, deadhead driving can be minimized.

2. Mileage savings omitted by previous research

One major component in calculating VMT change has been ignored by all previous research. According to a previous study, up to 30% of cars need to cruise to find street parking during rush hours, increasing average travel time by as much as 8 minutes.(27) The reduction in this extra driving has not been identified as a benefit of decreased VMT when using ridesharing.

CHAPTER 4. DATA NEEDS FOR MODELING

As the discussion above has illustrated, the data sources used to study ridesharing have played a large role in the conclusions that have been drawn. This chapter lists the data sources that were used in previous studies and offers some potential sources to broaden future research.

DATA SOURCES FOR PREVIOUS RIDESHARING STUDIES

Previous studies have relied on multiple sources of data, such as the NHTS, aggregated traffic volumes, and total trip volumes from TNCs. Table 2 lists the data sources used in the research previously discussed in this report.

Table 2. List of data sources in previous studies.

Reference ID, Location	Datasets and Data Sources
(2), Boston	1. 2017 ridership report by Lyft (365 million trips) 2. Lyft's market share based on credit card transactions compiled by Second Measure 3. TNC trip counts reported to city and state agencies 4. 2016–2017 NHTS 5. Data from industry sources showing relative trip volumes for different size metro areas and urban and suburban population densities 6. TNC trip volumes released by the Massachusetts Department of Public Utilities 7. Customer survey data conducted in the Boston area
(3), Texas	1. Urban mobility report provided by Texas A&M Transportation Institute (Travel time index, commuter stress index, delay time, delay cost, fuel consumption due to congestion) 2. Uber entry time data 3. Census Bureau and Bureau of Economic Analysis (fuel cost, socio-economic characteristics of the urban areas including gross domestic product, population, income, characteristics of road transportation system including VMT) 4. Federal Highway Administration (monthly traffic data)
(4), Massachusetts	1. Aggregated cell phone data (call detail records into census tracts (from American Community Survey [ACS]) 2. NHTS 2009 3. Census Transportation Planning Products 2006–2010 4. Geographic information system (GIS) shapefile of town boundaries by MassGIS 5. Massachusetts Travel Survey 2010/2011. 6. Road network for traffic simulation
(5), Multiple locations	1. Cell phone data 2. Twitter and Foursquare geotagged posts
(6), New York	1. Origin and destination data and GPS data of 172 million trips with passengers of all 13,586 taxicabs in New York City (NYC) in 2011 2. Open Street Map data

<table>
<tr><th>Reference ID, Location</th><th>Datasets and Data Sources</th></tr>
<tr><td>(7), Beijing</td><td>1. Beijing road network (106,579 nodes and 141,380 road segments)
2. Taxi trajectories (GPS data from over 33,000 taxis during a period of 87 days in 2011; 20 million trips)</td></tr>
<tr><td>(9), NYC</td><td>1. Three million rides extracted from the NYC taxicab public dataset
2. Daily home-based work-related vehicle trips between all 2,024 travel analysis zones from demand model of local travel planning agency</td></tr>
<tr><td>(13), Las Vegas</td><td>1. Historical data from the Regional Transportation Commission of Southern Nevada —This dataset contains monthly counts for a number of transport operators in the region.
2. Data from the Las Vegas Convention and Visitors Authority
3. Data from the Las Vegas City Employees' Association.
• Total taxi pick-ups and drop-offs at the McCarran International Airport per month
• Ride-hailing trip counts to and from the McCarran International Airport per month
• Monthly transit ridership revenue for the entire region and resort corridor
• Average daily traffic counts on major highways per month
• Total number of visitors passing through McCarran International Airport per month
• Total number of rental cars made at the McCarran International Airport per month
• Average daily hotel room rate per month ($)
4. Population of the Las Vegas Valley</td></tr>
<tr><td>(14), Multiple locations</td><td>1. Interviews with transportation officials
2. Self-administered survey of shared mobility users
3. Transit and ridesourcing capacity demand
4. Federal Transit Administration Report No. 0081 (2014)
5. National Cooperative Highway Research Program Research Results Digest 319
6. Transit Cooperative Research Program Report 121</td></tr>
<tr><td>(15), San Francisco</td><td>1. Self-administered intercept survey in San Francisco during May and June 2014
2. Existing and proposed legislation and public policies on ridesourcing in the U.S.</td></tr>
<tr><td>(16), San Francisco</td><td>Computational study on a theoretical metropolitan area (20 miles by 10 miles) with an urban center (radius = 2.5 miles). This network was designed to reflect the Bay Area Rapid Transit network in San Francisco.</td></tr>
<tr><td>(17), Multiple locations</td><td>1. Monthly transit ridership data from the National Transit Database from 22 transit agencies and for four modes
2. Metropolitan population data from the ACS
3. Metropolitan land areas for the 22 urbanized areas (UZAs) studied from the U.S. Census Bureau
4. Employment data from the Bureau of Labor Statistics</td></tr>
</table>

Reference ID, Location	Datasets and Data Sources
	5. Historical price per gallon of gasoline from the U.S. Energy Information Administration 6. Uber entry dates for each of 22 cities from Uber press releases 7. Bike share entry dates for each of the 22 cities
(19), Multiple locations	1. ACS data 2011-2013 from seven major metropolitan areas: Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle, and Washington, D.C. In total, 4,094 completed responses were collected. 2. Regional transportation survey (e.g., California Household Travel Survey)
(20), NYC	1. NYC electronic trip logs (yellow cab data from 2009 and TNC data from 2015) 2. Uber trip data in 2014 and 2015 (selected months) 3. For-hire vehicle (FHV) weekly summaries for 2015 from Taxi and Limousine Commission (TLC) 4. Monthly taxi trip volumes (TLC websites) 5. Current licensees 6. Vehicle mileage data from TLC of selected months (June 2013, June 2015, and June 2016), subway and bus ridership (provided by Metropolitan Transportation Authority NYC Transit), bike ridership (NYC Department of Transportation [DOT]), ferry ridership (Mayor's management report), personal travel by all modes (Household travel survey 2010-2011)
(21), Minnesota	Author interviewed passengers and collected in-field data by becoming an independent contractor to drive for Uber and Lyft (416 rides total)
(22), Minnesota	Self-administered, quasi-natural experiment yielding two datasets: (1) driver dataset and (2) passenger dataset. Over 14 weeks, Henao and Marshall conducted 416 ride-hailing trips via UberX, Lyft, UberPool, and LyftLine.
(24), California	Online survey data collected in 2015 – California Millennials Dataset
(28), Multiple locations	Two self-administered, Internet-based, travel and residential choice surveys with questions deriving from the ACS. In total, 4,094 responses were collected from the two surveys. Survey sampling was done in seven major cities, targeting their suburban and urban populations.
(29), Multiple locations	1. Six fields of data from the National Transit Database (NTD) per UZA. The six fields were (1) number of agencies, (2) number of cities, (3) unlinked passenger trips, (4) utilization, (5) average trip length in miles, and (6) average fare per trip in dollars. These fields of data were collected per mode of transit. 2. Date of ride-hailing service entry into a geographic UZA 3. Labor force size and unemployment rates per UZA, from the Bureau of Labor 4. Monthly gasoline prices from the U.S. Energy Information Administration per Petroleum Administration Defense District 5. Transit agency-level characteristics for each city and transit mode from the NTD
(30), Multiple locations	Travel frequency data, at the granularity of an individual, from the 2017 NHTS. A zero-inflated negative binomial regression was performed on the data to analyze the relationship between ridesharing and public transit.

Reference ID, Location	Datasets and Data Sources
(31), NYC	NYC TLC dataset spanning from 2009 to 2015 on yellow and green taxicabs
(32), Multiple locations	1. In-home qualitative research: in-home interviews with riders in different cities 2. Self-administered online maximum differentiation survey
(33), California	2009 National Household Survey – socioeconomic characteristics, travel capability, and land use characteristics
(34), NYC	Three million rides extracted from the public NYC taxicab dataset (NYC TLC)
(35), Multiple locations	Internet-based survey examining the demographics of ridesharing adopters, reasons for non-adopters, and differences between travel behavior between non-adopters and adopters. Survey was deployed in Boston, Chicago, New York, Seattle, and Washington, D.C.
(36), San Francisco	California Household Travel Survey (2010–2012) from the San Francisco Bay area. Data collected on characteristics of households, socio-demographic data (education, income, and household structure), types of vehicles owned, and travel diaries.
(37), NYC	1. 2016 dataset from the New York Metropolitan Transportation Authority 2. Yellow and green taxicab trip records from the NYC TLC 3. Data from FiveThirtyEight retrieved from NYC TLC via Freedom of Information law. 4. CitiBike geotagged bike share data from Citi Bike website
(38), Multiple locations	August 2017 Adjusted Database via Monthly Module Adjusted Data Release from the Bureau of Transportation Statistics and the Federal Transit Administration
(39), Multiple locations	1. Current Population Survey – annual estimates of demographics over an extended period of time 2. NHTS

OTHER POTENTIAL DATA SOURCES FOR FUTURE STUDIES

In addition to the datasets that were utilized by prior research, we also identified several external potential data sources that can be used in the next step of our research.

Uber-sponsored Data

The Uber driver-partner app records a location entry every 1 or 2 seconds. This location entry includes latitude, longitude, speed, course, and a timestamp (date/time) of the GPS location ping. These GPS location pings are ingested in real-time (every 4 seconds) to power multiple Uber business products (e.g. turn-by-turn navigation for driver-partners, fare calculation, matching driver-partners with riders, as well as user experience elements, such as displaying the position of the car in the Uber rider app). The GPS location data are also stored for offline processing, and, when aggregated, can be used to derive average, median, and percentile speed data on any given street segment where there is sufficient data. It is important to note that the number and quality of the GPS location data impacts the quality of speed data that we are able to derive on a given street segment.

Recently, Uber has published a website called Uber Movement (movement.uber.com), which offers the public anonymized data from 10 billion trips from metropolitan areas around the world. There are three different datasets, but only one is completely published and not in the beta phase. This dataset is called “Travel Times” and depicts the zone-to-zone travel times for major cities. The cities included from the U.S. are:

- Boston, Massachusetts
- Cincinnati, Ohio
- Los Angeles, California
- Miami, Florida
- New York, New York
- Orlando, Florida
- Pittsburgh, Pennsylvania
- San Francisco, California
- Seattle, Washington
- Tampa Bay, Florida
- Washington, D.C.

The data range from 2015 to 2018. Figure 8 and Figure 9 are screen captures of the Uber Movement Travel Times dataset (upper) and corresponding average speed (lower) for Seattle. The user selects the origin of the origin-destination pair, and the colors depict the travel times to each zone or tract as the destination (the legend at the bottom right shows the color codes used for the travel times). Speed data modules provide aggregated roadway speed data as a percentage of free-flow speed, ranging from 100% slower to 20% faster (the legend at the bottom right identifies the color codes used for the percentage from free-flow speed).

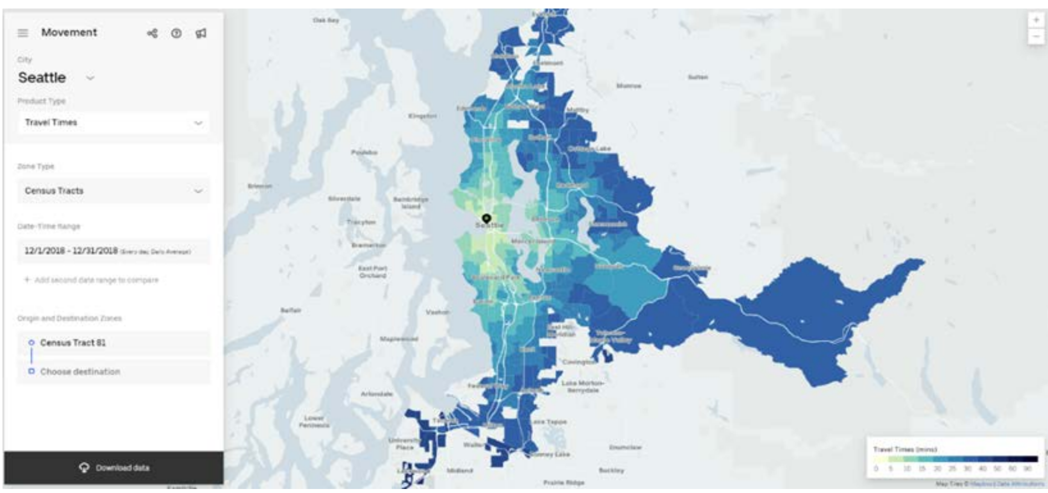


Figure 8. Map. Uber Movement travel times for Seattle.

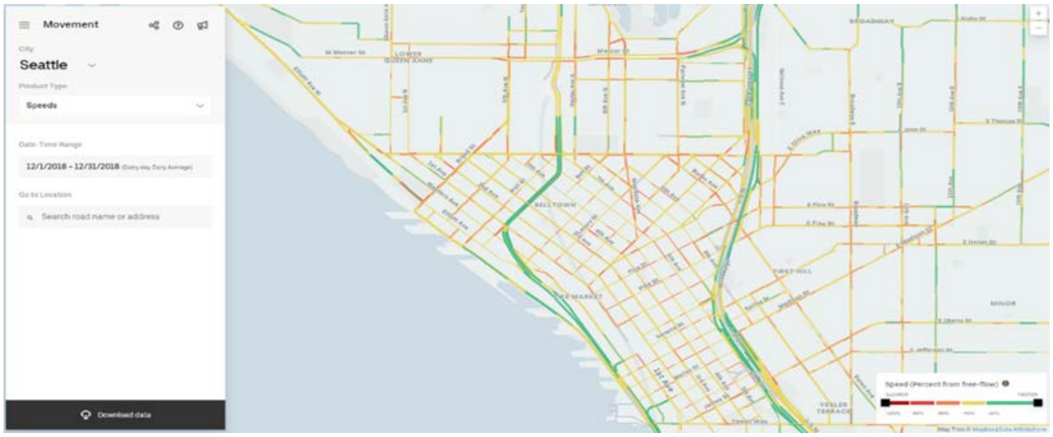


Figure 9. Map. Uber Movement speeds for Seattle.

Data from Chicago

In November 2018, the City of Chicago began collecting trip data from TNCs such as Uber and Lyft. The data are published to their open data portal (Chicago Data Portal) and are available to the public. Three datasets are available: (1) trips, (2) drivers, and (3) vehicles.

Trips

This dataset contains 21 fields:

- Trip ID
- Pick-up: time, date, location, community area
- Drop-off: time, date, location, community area
- Trip duration (seconds)
- Fare (rounded to the nearest $0.50)
- Tip (rounded to the nearest dollar)
- Additional charges
- Total trip cost
- Shared trip (true/false)
- Trips pooled
- Centroid pick-up: latitude, longitude
- Centroid drop-off: latitude, longitude

Drivers

- Month reported
- Driver start month
- City
- State
- Zip
- Number of trips
- Working for multiple transportation network companies (Yes or No)

Vehicles

- Month reported
- State
- Make
- Model
- Color
- Year
- Last inspection month

The trips dataset from Chicago is particularly of interest because of the granularity of the data. It provides detailed trip information, including trip time, trip distance, origin, destination, the fare, and whether the trip was pooled or not. If combined with other external datasets, such as public transit data and NHTS data, this dataset could help us better understand the impacts of ridesharing.

New York City

The NYC TLC collects records per trip from all taxicab, livery car, and FHV providers. The trip record data vary based on vehicle classification (taxicab versus FHV) but contain fundamental trip characteristics. The data collected are offered to the public in aggregated, report, and raw formats. For the raw data, all datasets are separated by vehicle classification—yellow taxi, green taxi, and FHV—and are then sorted per month and year. These sets are offered in CSV format, downloadable to Excel. All of the data are available on the NYC TLC Open Data Portal. Figure 10 shows a screenshot of the data portal and the organization of datasets. The screen capture is of all datasets from 2018.

Figure 10. Screenshot. NYC TLC open data portal.

Yellow and Green Taxicab Records

For the yellow and green taxi trip records, the following fields are available:

- Pick-up: location, time, date
- Drop-off: location, time, date
- Trip distance
- Itemized fare
- Rate type
- Payment type
- Driver-reported passenger counts

The yellow taxicab trip records are available from January 2009 to June 2019. The green taxicab trip records are available from August 2013 to June 2019.

For-hire Vehicle Records

Specifically, for FHV trip records, the following fields are available:

- Vehicle base license number
- Pick-up: time, date
- Dispatch number
- Availability of pick-up and drop-off locations varies between months and years; as more data are collected, more fields are provided.

The FHV trip records are available from January 2015 to December 2018. A screenshot of the raw data is shown in Figure 11. The dataset used is of FHV trip records from January 2018.

	A	B	C	D	E	F	G	H
1	Pickup_DateTime	DropOff_datetime	PUlocationID	DOlocationID	SR_Flag	Dispatching_base_number	Dispatching_base_num	
2	1/30/2018 21:06	1/30/2018 21:15	56	129		B02884		
3	1/30/2018 21:20	1/30/2018 21:35	129	112		B02884		
4	1/30/2018 21:04	1/30/2018 21:16	47	42		B02884		
5	1/30/2018 21:11	1/30/2018 21:40	49	131		B02884		
6	1/30/2018 21:43	1/30/2018 21:49	98	121		B02884		
7	1/30/2018 21:36	1/30/2018 21:44	235	235		B02884		

Figure 11. Screenshot. FHV trip records in CSV file.

CHAPTER 5. CONCLUSIONS AND DISCUSSION

Ridesharing is a relatively new mode of transportation that has developed rapidly in recent years, and many researchers who have studied the impacts of ridesharing have drawn conflicting conclusions. As described in the previous chapters, there are many reasons for the discrepancies, but they can be summarized into two categories: (1) gaps in modeling methodologies and (2) gaps in data.

Some mathematical optimization modeling shows benefits of ridesharing when applying the model to existing taxi trips. Other empirical studies, however, draw different conclusions due to the optimization and pairing methodologies adopted by TNCs. A large portion of deadhead travel can be decreased if a more efficient model is used and a larger market share for ridesharing can be achieved.

Multiple factors can influence changes in VMT associated with ridesharing. Unfortunately, limited data are available for analyzing the impacts of ridesharing from a more comprehensive perspective due to the short time period ridesharing has been available. A carefully designed data collection effort is needed to cover varied traffic environments, existing users, and potential users of ridesharing.

We propose to extend our research in three ways: (1) spatial modeling of ridesharing trips and public transit; (2) DID modeling; and (3) modeling critical turning points for ridesharing to generate positive impacts.

SPATIAL MODELING OF RIDESHARING TRIPS AND PUBLIC TRANSIT

One of the discrepancies in the existing research on ridesharing concerns whether ridesharing competes with or complements public transit. Some researchers believe ridesharing is replacing public transit, while others believe that it is connecting the first and last mile of a trip and therefore complementing public transit. The majority of previous studies drew conclusions based on stated preference answers from surveys. One objective method to investigate the relationship of ridesharing with public transit is to obtain ridesharing origin-destination information and conduct a spatial analysis to see if the origin or destination of a trip falls within walking distance of a public transit station and/or overlaps with a transit route. In addition to the spatial analysis, ridesharing trips need to be analyzed by time. It was found that ridesharing services are most frequently used for social trips between 10 p.m. and 4 a.m., times when public transit runs infrequently or is not available. One good candidate city to conduct the analysis is Chicago, where detailed ridesharing trip information and public transit data are both available. As shown in Figure 12 are the pick-up and drop-off locations of ridesharing trips. A detailed spatial and temporal analysis is needed to quantify the relationship of ridesharing and public transit.

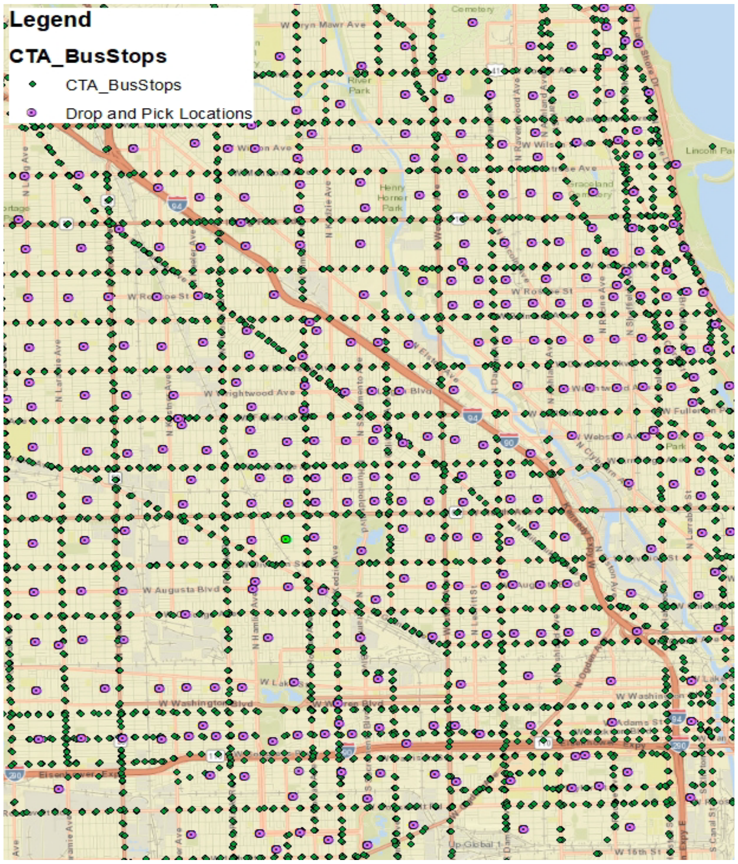


Figure 12. Map. Pick-up and drop-off locations of ridesharing trips.

DIFFERENCE IN DIFFERENCE MODELING

Induced travel and car ownership changes should be studied further to clarify the impact of ridesharing. One method is DID modeling. DID is a statistical technique that calculates the effect of a treatment on an outcome by comparing the average change over time in the outcome variable for the treatment group to the same change over time in the control group. The challenge of applying DID is choosing the treatment group and control group to mitigate the effects of extraneous factors. Ideally, we would like to define the study period such that the only changing factor in the treatment and control group is the availability of ridesharing.

Several cities have banned or restricted ridesharing and then lifted the restriction afterwards. Some of these cities are listed in Table 3. These areas serve as good candidates for DID modeling. The overall VMT and car ownership patterns before and after the ban can be compared to evaluate the impacts of ridesharing.

Table 3. Laws restricting ridesharing.

City/State	Restriction Law	Enacted By
Ann Arbor, MI	Uber and Lyft	
Georgia	HB 907	
Columbus, OH	All rideshare	City
Nebraska	Lyft	Nebraska Public Service Commission
New Mexico	Lyft	Public Regulation Commission
St. Louis, MO	All rideshare	Taxi commission
Texas	All rideshare	Austin, Dallas, Houston, and San Antonio
Virginia	Uber and Lyft	DMV
Kansas City, MO	Lyft	
New York	Lyft	

In addition to these areas, the following areas/cities have a ridesharing program where travelers can obtain monetary compensation for their ridesharing trips if they connect it with a public transit trip or any other non-mobile traffic mode: Seattle DOT, NYC DOT (via freedom of information law), SLOCOG (San Luis Rideshare program), Georgia DOT/Office of Transportation Data, City of Altamonte-partnership with Uber, The Ride by Massachusetts Bay Transportation Authority pilot program with Uber, and Pinellas Suncoast Transit Authority partnership with Uber. Modeling these areas for changes in VMT and car ownership will clarify the impacts of ridesharing.

MODELING CRITICAL TURNING POINTS FOR RIDESHARING TO GENERATE POSITIVE IMPACTS

For every mile an Uber or Lyft car drives with a passenger, it cruises a certain number of miles without a passenger, a practice known in the industry as “deadhead.” One of the major factors that has led previous research to criticize ridesharing is the percentage of deadhead drives. Estimates of total deadhead time vary from 30% to as much as 60%. The more passengers that a ridesharing trip serves, the less the negative impact of deadhead will be on the overall VMT. We can model: (1) varied percentage of ridesharing replacing other modes and (2) departure time and spatial distribution of ridesharing trips to illustrate how many trips can be combined at different levels of tolerance for additional waiting time and detour distances for ridesharing to generate positive impacts on VMT. Suitable cities to serve as modeling testbeds could be Chicago or New York City, where detailed ridesharing data are available.

SUMMARY

In summary, we need to further our data collection and modeling methodology to better understand the impacts of ridesharing and eventually better regulate it to yield a positive impact on our transportation system.

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