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# How Do On-demand Ridesharing Services Affect Traffic Congestion? The Moderating Role of Urban Compactness

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The role of information technology (IT) in managing operations that support environmentally sustainable growth has been emphasized a lot in operations management and information systems research. In this paper, we study the impact of the IT-based on-demand ridesharing platforms on an important aspect of sustainability—traffic congestion. Our theoretical prediction suggests two countervailing effects from the entry of ridesharing platforms to urban areas: the efficiency-enhancing effect that reduces traffic congestion and the demand-inducing effect that increases traffic congestion. We propose that the impacts of ridesharing services on traffic congestion should vary with urban spatial features. Given the theoretical tension, we investigate the impact of Uber entry on traffic congestion in urban areas of the United States with a focus on the moderating role of urban compactness. Based on a unique dataset that combines multiple archival sources, we empirically examine whether the entry of Uber's on-demand ridesharing service affects traffic congestion by using a difference-in-differences framework. Our empirical evidence indicates that ridesharing services significantly increase traffic congestion in compact areas. Meanwhile, we find some marginal evidence that ridesharing services decrease traffic congestion in sprawling urban areas. The results are robust to a series of additional analyses, including the use of alternative measures, relative time model, entry exogeneity test, and placebo tests. We conclude that the efficiency-enhancing and demand-inducing effects shape traffic congestion and that the net effect varies according to different levels of urban compactness. We provide circumstantial evidence for the underlying mechanisms by analyzing public transit and commuting characteristic data.

*Key words:* on-demand ridesharing services; sharing economy; sustainability; traffic congestion; urban compactness
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## 1. Introduction

The platform-based sharing economy has received significant attention from major media and policymakers.[1] Sharing economy platforms aim at the efficient use of resources (e.g., labor, capital, and assets) by leveraging information technology-enabled digital infrastructure to lower the cost of matching the two sides of the platforms (i.e., buyers and sellers). First proposed by Benkler (2004), many studies followed suit and have subsequently explored the nature, design, and effects of sharing economy platforms (Benjaafar and Hu 2020, Hu 2020, Li et al., 2021, Sundararajan 2013). In 2011, TIME Magazine named sharing economy one of the ten ideas that will change the world. According to Price Waterhouse Coopers, the global revenues of the five key sharing sectors (i.e., ride/car sharing, peer-to-peer (P2P) finance, online labor, P2P accommodation) can potentially increase from around US$15 billion in 2013 to around US$335 billion by 2025.[2]

On-demand ridesharing platforms constitute a significant part of the sharing economy, and the usage of these platforms has grown rapidly in recent years. By leveraging the affordance of the latest digital technology, on-demand ridesharing platforms provide users

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with a reliable mode of transportation that caters to each rider. These platforms improve access to mobility for individuals who are unable to operate a personal vehicle as well as reduce the waiting times and stress associated with travel. Specifically, ridesharing is based on smartphone technology, which allows customers to make real-time ride requests. The advances in computing speed and data storage have optimized the dispatch system of the ridesharing platform by using an Artificial Intelligence simulation framework,[3] which improves matching efficiency. During the trip, GPS provides the driver and customer locations along with the route navigation. After the trip, the fare is automatically calculated and charged to the payment method that the customer has linked to his/her account. These platforms also provide a rating system, which fosters trust and creates a positive experience for users. Additionally, many ridesharing platforms have a dynamic pricing system to balance supply and demand, which improves economic efficiency (Hall et al., 2015). Compared with traditional ridesharing services, the on-demand ridesharing service is cheaper, faster, and more convenient; hence, the user base has been expanding quickly in recent years (Cullen and Farronato 2020). The new user-centric services are transforming urban mobility and have the potential to create a tremendous positive impact on personal mobility, pollution, congestion, energy consumption, and quality of life (Alonso-Mora et al., 2017, Qi and Shen 2019).

Digital platforms have had an increasing impact on Operations Management (OM) from the perspectives such as new product development, supply chain management, and customer service (Gaimon et al., 2017). They create a technical basis for firms to integrate and coordinate their activities, thus increasing productivity. Specifically, the important relationship between information technology (IT) and sustainability has been strongly emphasized in the literature (Melville 2010, Watson et al., 2010). Ba and Nault (2017) pointed out that understanding the efficiency gains and sustainability impact supported by IT within the transportation system is an important part of the management of technology. Besides, in sustainable operations research, Kalkanci et al., (2019) emphasized the important role of innovation in addressing social issues. As a technology-driven service innovation, on-demand ride-sharing platforms and their impacts on sustainability are important yet unresolved issues. In this study, we answer this call and examine how on-demand ride-sharing platforms influence sustainability.

Given that traffic congestion is a key issue in sustainability, researchers have used the simulation approach to examine how on-demand ridesharing may have an effect on traffic congestion (Alexander and González 2015). A few other studies delved into this important societal issue, yet the findings are inconclusive. One study from the New York Times estimates that Uber vehicles contribute to about 10% of traffic in Manhattan during evening rush hours.[4] In a separate study, the Office of the Mayor in New York City released a report in January 2016, highlighting the city mayor's contention that the Uber vehicles and other ridesharing services worsening traffic in Manhattan is unfounded.[5]

Empirically, the entry of on-demand ridesharing services can have an impact on traffic congestion through two countervailing effects. On the one hand, providing more convenient, less expensive services, and on-demand ridesharing creates a *demand-inducing* effect by diverting non-driving trips, like public transit, to a driving mode. Hence, on-demand ridesharing could induce additional traffic volume, thus increasing traffic congestion. On the other hand, on-demand ridesharing could reduce traffic via an *efficiency-enhancing* effect. Previous studies pointed out that Uber increases the use of public transit by addressing the last mile problem (Hall et al., 2018). Uber increases the efficiency of transportation systems by facilitating the use of alternative, more traffic-friendly, and environmentally sustainable modes of transportation, thus decreasing traffic congestion. Notably, both the possibility of on-demand ridesharing services substituting public transit without major additional cost and the necessity of leveraging on-demand ridesharing services to alleviate the last mile problem are related to the spatial feature of the urban area. This suggests that the urban spatial feature may play a role as a key moderating factor. We conjecture that in more sprawling areas that are faced with a more serious (first or) last mile problem and the average trip length is longer, the *efficiency-enhancing* effect plays a more significant role than the *demand-inducing* effect; whereas in the more compact areas where people are more likely to live in the neighborhood of public transit stations and have a shorter trip length, the *demand-inducing* effect balances out the *efficiency-enhancing* effect. Bearing the above in mind, we seek to address the following research questions: *What is the impact of Uber on traffic congestion? How does urban compactness moderate the impact of Uber on traffic congestion? What are plausible underlying mechanisms?*

We leveraged a quasi-natural experiment setting to quantify the impact of Uber entry on traffic congestion in different urban areas of the United States. This research design offers an important advantage: as Uber enters different urban areas at varying points of time, we are able to use a difference-in-differences (DID) approach to investigate whether Uber's entry into an urban area reduces traffic congestion, compared with urban areas that have not yet legalized

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Uber's operation. We construct a unique dataset, which combines monthly level congestion data for various metropolitan areas in the United States from 2012 to 2018 with the entry time of Uber into an urban area, from Uber's official website and major news outlets. In addition, we collected data on fuel cost, socioeconomic characteristics of urban areas, characteristics of road transport systems from the United States Census Bureau, and the Bureau of Economic Analysis to construct our key control variables. Based on the DID analyses, we found that the entry of Uber significantly increases traffic congestion in compact urban areas of the United States. Meanwhile, we find marginal evidence that the entry of Uber decreases traffic congestion in sprawling (less compact) areas. Moreover, to assess the robustness of the results, we performed further analysis, including the use of an alternative proxy measure for Uber penetration, relative time model, entry exogeneity test, and placebo tests (permutation). We also demonstrate circumstantial evidence for the underlying mechanisms by analyzing data on public transit and commuting characteristics. Uber substitutes public transit in compact areas where the average trip length is short, thus increasing traffic congestion; Uber complements public transit in sprawling areas and its effect on traffic congestion is only marginally significant. Furthermore, our results suggest that the introduction of Uber service influences individuals' choice of commuting mode.

This study makes several notable contributions. First, our study contributes to a deeper understanding of the societal impacts of ridesharing platforms (e.g., Uber). While prior OM studies on on-demand service platforms have examined the optimization problems regarding the service price (Bai et al., 2019, Besbes et al., 2021), market competition (Besbes et al., 2021, Yu et al., 2020) and the matching between supply and demand (Feng et al., 2020), our understanding of the societal impact (e.g., societal sustainability) of on-demand ridesharing services is limited. Among the first attempt to investigate the main effect and the vital moderating effect of urban compactness on the relationship between the uber entry and traffic congestion, we provide guidance on the design of operational strategies of on-demand ridesharing platforms and government to help reduce the negative effect of ridesharing platforms on traffic congestion and societal sustainability. Second, our study reveals a boundary condition under which on-demand ridesharing can help to alleviate the last mile problem and increase the demand for public transit services. The last mile problem is emerging as a major concern for urban logistics and operations management (e.g., Liu et al., 2020, Qi et al., 2018). Recent studies on vehicle sharing (e.g., Benjaafar and Hu 2020, He et al., 2017) suggest that the sharing economy has the potential to alleviate the last mile problem of public transit. Our study adds to this stream of literature by demonstrating that Uber entry increases the ridership of public transit in sprawling areas, whereas it decreases the ridership of public transit in compact areas. Our findings reveal that on-demand ridesharing could serve as a viable option for improving the demand for public transit in sprawling areas. This finding yields important insights for policymakers as they tackle the regulation and legality of these platforms. Third, our study highlights the importance of capturing urban compactness, which is critical to improving urban sustainability and the operation of the public transportation system in this arena. This study contributes to the literature of sustainable operations research (Bouchery et al., 2017, Kleindorfer et al., 2005) by providing empirical evidence for the context-dependent impact of ridesharing service on traffic congestion and public transit. The potential positive effect of ridesharing service on the smart-city movement and sustainability has been theoretically discussed (Qi and Shen 2019, Mak 2020) but not yet empirically validated. We find that regarding traffic congestion, ridesharing services may create a significant negative impact on the smart-city movement and sustainability in compact areas, whereas we also find marginal evidence that it may have a positive impact in sprawling areas. We suggest that city planners and policymakers consider urban compactness and design optimal policies for different cities.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on digital platforms and ridesharing. Based on the previous literature, we discuss two competing mechanisms, namely, *efficiency-enhancing* and *demand-inducing* effects, and develop hypotheses. Section 3 describes in detail the data and our econometric specifications. Section 4 presents our findings and the demonstration of underlying mechanisms. We conduct robustness checks and additional analyses in Section 5. In Section 6, we discuss our results, implications, and limitations.

## 2. Theoretical Background and Hypothesis Development

Information technology (IT) based platforms have had an increasing impact on OM, from new product development, supply chain management, to customer service (Gaimon et al., 2017). Specifically, ridesharing platforms, as a prime example of the sharing economy and on-demand service platforms, have the potential to play an important role in managing operations that support environmentally sustainable growth (Khuntia et al., 2018) and contribute to the

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development of the Smart City. Kleindorfer et al., (2005) identify multiple objectives of sustainability in a seminal OM paper. One of the key elements authors point out is strategies that can reduce the use of inputs (e.g., labor, material, energy) and the production of pollutants as outputs. The role of on-demand ridesharing platforms in affecting sustainability outcomes has been largely ignored in the literature. This research aims at addressing this question by documenting the impact of ridesharing on traffic congestion and public transit ridership, both of which are related to the sustainability of urban areas. Moreover, the potential positive effect of ridesharing platforms on the movement of Smart City has been theoretically discussed but not empirically validated. For instance, Qi and Shen (2019) propose to expand the OM literature to the Smart City scope by leveraging the data-driven modeling and decision-making methodologies. They suggest that ridesharing platforms, such as Uber, provide a promising OM research opportunity in particular regarding the smart-mobility empowered by the shared autonomous electric vehicles. Mak (2020) systematically discusses how OM research and the smart city movement can potentially benefit from each other and points out that crowd-based business models (e.g., ridesharing service) can improve the efficiency of urban operations and reduces the digital divide due to unequal citizens' accessibility to technologies. We position our work within this research area on the operational impact of the increased mobility provided by ridesharing service, wherein we study the impact of ridesharing platforms on traffic congestion and public transit.

The emergence of on-demand service platforms and sharing economy based on business model innovations pose operational challenges and creates new research opportunities (Roth et al., 2016). Most existing OM studies in this area focus on the optimal pricing of ridesharing service platforms and their impact on market competition. For instance, Bai et al., (2019) examine how to optimize the price and payout ratio (i.e., the ratio of wage over price) on on-demand ridesharing platforms where the supply and demand of ridesharing services are dynamically dependent on the price and payout ratio. Benjaafar and Hu (2020) also highlight the importance of optimally set service prices and wages to drivers and efficiently match heterogeneous demand and supply of ridesharing services. Besbes et al., (2021) further focus on the optimal surge pricing and ridesharing service supply by taking the spatial supply incentives and spatial pricing into consideration. With respect to market competition, Bernstein et al., (2020) investigate drivers' "multihoming" behavior and how this affects the competition between ridesharing platforms and the equilibrium price. Furthermore, ridesharing platforms do not just compete among themselves, but they compete with traditional industries (e.g., taxi) as well. As suggested by Yu et al., (2020), without the government regulation on the "maximum" number of registered Uber/DiDi drivers, ridesharing platforms have the potential to drive the taxi industry out of the market. While there are some OM papers investigating the operation problems of on-demand service platforms (Bai et al., 2019, Bernstein et al., 2020, Besbes et al., 2021, Yu et al., 2020) and providing a general discussion on the sharing economy (Benjaafar and Hu 2020, Hu 2020), our understanding of how on-demand ridesharing services platforms affect traffic congestion and the ridership of public transit across areas of different compactness levels is less well developed. In this study, we address this question by using an econometric model and analysis to reveal the underlying mechanisms.

We propose two mechanisms through which ridesharing platforms affect traffic congestion, namely, *efficiency-enhancing* and *demand-inducing* effects. On the one hand, ridesharing platforms could reduce traffic congestion by facilitating the use of public transit, which is a more environmentally sustainable mode. On the other hand, ridesharing services could also increase traffic congestion by inducing additional travel demand via ridesharing services switching from public transit.

### 2.1. The Efficiency-Enhancing Effect

Digital platforms enhance market efficiencies by facilitating the match between the supply side and the demand side (Bakos and Katsamakas 2008). In our context, efficiency in transportation means achieving transportation goals (e.g., enabling individuals to commute or goods to be delivered) with minimum vehicle miles. On-demand ridesharing services have the potential to increase the efficiency of the transportation system by facilitating the use of a more environmentally sustainable mode, which is public transit. Public transit is a more efficient mode that fulfills individuals' commuting needs with fewer vehicle miles. One of the disadvantages of public transportation, however, is its lack of flexibility for travelers because of the use of the preset routes, which only allow buses or trains to travel from station to station, taking on and letting off passengers at fixed stops (Haider 2013). This situation is the well-known last mile problem. In relation to this, many travelers need a "secondary mode" of transportation to arrive at their final destinations or will have to walk some distance between their homes or offices and the nearest station. Ridesharing platforms, offering efficient and convenient services at a more affordable price, can serve as a preferred "secondary mode," thereby increasing the reach and flexibility of the public transit systems. In other words, ridesharing services have the potential to complement public transit and alleviate the (first or) last mile problem. There is some preliminary evidence that people use Uber to address the (first or) last mile problem. For instance, according to a report from the Uber Policy Research Team, they find evidence that "*riders are intuitively using Uber to solve the first/last mile problem on their own.*"[6] They state that "*In some cases, 25% of trips in a region (or more) start or end near transit.*" Another survey conducted by Uber suggests that 62% of people address the (first or) last mile problem by taking Uber to other means of public transportation (train/bus).[7] The concentration of Uber pick-up and drop-off locations near public transit stations is also confirmed by another study by Rayle et al., (2016). Since on-demand ridesharing services can expand the service areas and accessibility of public transit by attracting individuals living outside of the neighborhood of public transit stations (Babar and Burtch 2020, Fahnenschreiber et al., 2016, Song and Huang 2020), they may help to alleviate the last mile problem and thus increase public transit ridership. In this way, on-demand ridesharing services can reduce traffic by diverting trips to public transit otherwise made in private, single-occupancy vehicles.

### 2.2. The Demand-Inducing Effect

The demand-inducing effect means the increase in "*traffic choosing to use the road than would be the case*" when the transportation capacity is improved (Lee et al., 1999, *p.* 68). In the transportation literature, prior studies have focused on examining the demand-inducing effect caused by the improvement of transportation capacity from road investment (e.g., Cervero and Hansen 2002, Lee et al., 1999). In the context of on-demand ridesharing services, the demand-inducing effect here refers to the increase in traffic due to the improved transportation capacity from the elastic supply and the lower operational cost of on-demand ridesharing services. First, unlike the supply of public transit or taxi service that is relatively fixed in the short-term, the supply of ridesharing can scale relatively fast depending on demand (Qi et al., 2018), which leads to higher market efficiency and a higher travel demand fulfilled (Cullen and Farronato 2020). Before the introduction of the ridesharing service, some individuals with latent travel demand chose not to travel due to the low accessibility of public transit or taxi at certain times of the day or locations. However, the introduction of on-demand ridesharing services can help to fulfill the latent travel demand with a flexible workforce working on different schedules and from various locations. As such, on-demand ridesharing services are likely to increase people's trips for various purposes, for example, recreation, shopping, social activities (Dhanorkar and Burtch 2021, Rayle et al., 2016), thus increasing traffic congestion.

Meanwhile, the extant transportation literature suggests that the travel demand depends on some key factors, such as price, travel time, experience (e.g., Lee et al., 1999, Rayle et al., 2016). Since on-demand ridesharing services provide taxi-like services at more affordable prices and offer better user experiences, it could increase the demand for ride-hailing services and thus traffic congestion. Ordering a ride is convenient, as waiting time is shorter, quality and schedule uncertainty is lower, and service fees are paid automatically. In this sense, compared with traditional ridesharing services, convenience and flexibility have been improved significantly in on-demand ridesharing services. Moreover, people using public transit because of the high cost of the traditional cab service may switch to ridesharing due to its low cost and greater convenience. Those improvements of on-demand ridesharing services thus induce demand for this service. In other words, the demand for vehicles that had been latent because of low flexibility and convenience materializes as actual usage. On the whole, on-demand ridesharing services may increase the number of cars on the road by substituting public transit trips and thus increase traffic congestion.

As summarized in Table 1, the presence of plausible alternative mechanisms poses a compelling tension. The *efficiency-enhancing* effect suggests that on-demand ridesharing services could reduce traffic congestion, whereas the *demand-inducing* effect implies that on-demand ridesharing services can also increase traffic congestion.

### 2.3. The Moderating Role of Urban Compactness

With the above discussion of the two mechanisms in mind, both the necessity of leveraging on-demand ridesharing services to alleviate the last mile problem and the possibility of substituting public transit without major additional cost are related to the urban spatial feature. We herein propose that the urban spatial feature plays a moderating role in the relationship between on-demand ridesharing services and both mechanisms, that is, the efficiency-enhancing effect and the demand-inducing effect, and in extension, a moderating role between Uber and traffic congestion.

In particular, urban compactness is a widely used urban spatial feature (Ewing and Hamidi 2014, Ewing et al., 2002). By definition, urban compactness measures the concentration of land usage and activities in a specific area (Abdullahi et al., 2018). Low urban compactness means "*any development pattern in which related land uses have poor access to one another, leaving residents with no alternative to long distance trips by automobile*" (Ewing and Hamidi 2014, *p.* 11). In contrast, high compactness implies high connectivity among

**Table 1 Efficiency-enhancing Effect vs. Demand-inducing Effect and Implications on Traffic Congestion**

| Mechanism | Before Uber entry | After Uber entry | Expected effect on traffic congestion | Explanation |
|---|---|---|---|---|
| Enhancing efficiency | Private car or taxi | Public transit +Uber | − | Integrating ridesharing services with existing public transit can address the (first or) last mile problem (Qi et al., 2018), and thus expand the service areas and accessibility of public transit (Babar and Burtch 2020, Fahnenschreiber et al., 2016, Song and Huang 2020). This helps to reduce traffic congestion. |
| Inducing demand | No travel or public transit | Uber | + | Owing to the supply flexibility, ridesharing services can fulfill some latent travel demand for people who would not travel due to the low accessibility of public transit or taxi at certain times of the day or locations.<br>Ridesharing services can potentially substitute for public transit because they are more convenient, take less waiting time, and more affordable (Babar and Burtch 2020, Jin et al., 2019, Kong et al., 2020), which increases traffic congestion. |

locations within a given area and a short average trip distance. Accordingly, the efficiency-enhancing effect and the demand-inducing effect are likely dependent on the area-specific compactness.

First, we expect the efficiency-enhancing effect to be weaker in compact areas than in sprawling areas. Compared with compact areas, people in sprawling areas are faced with a more serious (first or) last mile problem (Qi et al., 2018) because of the absence of large traffic generating centers and large separation in land uses in sprawling areas. On-demand ridesharing services have a greater potential to be integrated with existing bus routes to address the (first or) last mile problem (Babar and Burtch 2020, Fahnenschreiber et al., 2016, Qi et al., 2018, Song and Huang 2020), and thus expand the service areas in sprawling areas. Accordingly, the effect of on-demand ridesharing services in expanding the service areas and accessibility of public transit is more pronounced in sprawling areas than in compact areas, suggesting a stronger efficiency-enhancing effect in sprawling areas.

Second, we expect the demand-inducing effect to be stronger in compact areas than in sprawling areas. As suggested by Ewing and Hamidi (2014), the average trip length is shorter in compact areas than in sprawling areas.[8] As the trip length decreases, people are more likely to substitute public transit trips with point-to-point on-demand ridesharing services trips because ridesharing services are more convenient, takes less waiting time, and faster (Babar and Burtch 2020, Kong et al., 2020). Further, since the cost per mile for ridesharing services is still higher than that for public transit, the shift from public transit trips to ridesharing services is more likely to occur for short-distance trips (Babar and Burtch 2020, Hall et al., 2018), which are more common in compact areas. Thus, ridesharing services may induce a high demand by substituting short-distance public transit trips in compact areas and thus increases traffic congestion.

Given the stronger (weaker) efficiency-enhancing effect and the weaker (stronger) the demand-inducing effect in sprawling (compact) areas, we draw the hypothesis as follows:

Hypothesis 1a. *Uber entry reduces traffic congestion in sprawling urban areas*

Hypothesis 1b. *Uber entry increases traffic congestion in compact urban areas*

## 3. Data and Methods

Given the large scale and scope of sharing economy platforms, our research focuses on one specific sharing economy platform, which is Uber—the largest on-demand ridesharing platform. Officially launched in San Francisco in 2011, Uber has become an international corporation with billions of dollars of valuation. By 2021, Uber was available in 63 countries and over 700 cities worldwide.[9] Uber's market share in the US ride-hailing market is estimated between 65% and 85%.[10] Uber's two-sided platform business model has made it possible for riders to tap their smartphones and have a vehicle arrive at their location in the minimum possible time. When a rider opens the Uber application, he/she can request a ride immediately or schedule one for the future. The Uber platform automatically assigns a driver to pick up the rider. Fares of a given ride may vary depending on the time of the day. If the demand for rides is higher than the supply of cars, the rider will face surge pricing and can decide whether to hail a ride at that time. During the ride, the rider could view the progress on the map and the current trip details, including the estimated time of arrival. After a ride is completed, the payment is automatically collected and the rider can rate the driver and provide optional feedback.

### 3.1. Data

Our main independent variable of interest is Uber entry. We obtained from Uber the list of Uber entry

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times into different cities covering around 251 cities.[11] We mapped those cities to metropolitan statistical areas (MSAs) in the US,[12] as most of the dependent and control variables are in the unit of MSA. For areas that were not in the data Uber shared, we manually searched for Uber launch time in the official Uber newsroom as well as the major news media to find out if and when Uber entered an urban area. Finally, we compiled an Uber entry list for 366 MSAs. Moreover, as data are reported publicly in the level of urban areas, we created a mapping from Uber entry cities to urban areas according to the center city and center state in the area data. Then, we created an Uber entry dummy variable according to the launch time in each area. Specifically, this dummy takes the value of 1 if in the current time period this area has Uber service and 0 otherwise. Meanwhile, we obtained our dependent variables from several archival data sources to measure traffic congestion and public transit ridership, as shown in Table 2.

**3.1.1. Monthly Traffic Data from the Federal Highway Administration.** We obtained the monthly traffic data from the Federal Highway Administration (FHWA), an agency within the U.S. Department of Transportation. The FHWA produces the monthly Urban Congestion Report, which characterizes the most recent traffic congestion and reliability trends at the MSA level. The dataset has 52 MSAs from January 2012 to August 2018. We adopted the *Planning Time Index* 95 from the data as the main congestion measure. PTI95 is the ratio of the 95th percentile peak travel time to the free-flow travel time. In a nutshell, the higher the index, the worse the traffic. PTI95 is a well-established measure of traffic congestion,[13] and it has been used in a large body of work related to traffic congestion (e.g., Bhouri et al., 2013, Mathew and Pulugurtha 2020). We further collected multiple control variables that have been shown to influence traffic congestion in the prior literature, including the percent of people who worked within the county of residence, the number of workers aged 16 years above, total miles of all roads, total miles of freeway lanes, and daily vehicle miles traveled (DVMT). We also included two variables to represent the supply of the public transit of each area, that is, the number of active fleets of all public transit agencies in this area and the total funds this area receives yearly for public transit operation and development. We collected the monthly gasoline prices for each Petroleum Administration of Defense District (PADD), defined as regions of the United States that comprise multiple states from the U.S. Energy Information Administration (EIA). Furthermore, we controlled for additional time-varying variables, including population size and socioeconomic status of an MSA (e.g., GDP and median income, unemployment rate). Several variables displayed excessive skewness, thus, we performed log-transformation of these variables before conducting the analysis. The definition of all variables, summary statistics, and the correlation matrix are reported in Appendix A. Note that we provided additional robustness checks using annual level congestion data from a different source in Appendix G.

**Table 2 Independent Variable and Dependent Variables in This Research**

| Independent variable | Uber entry | |
|---|---|---|
| Dependent Variables | Traffic Congestion | PTI95 |
| | Public transit ridership | ln(UPT_Total) |
| | | ln(UPT_Bus) |
| | | ln(UPT_Rail) |

*Note*: PTI stands for the Planning Time Index and UPT stands for the Unlinked Passenger Trips.

**3.1.2. Public Transit Ridership Data from National Transit Database.** To further test the underlying mechanisms, we obtained public transit data from the National Transit Database (NTD). The Federal Transit Administration records the financial, operating, and asset conditions of transit systems in this database. The data included monthly ridership data and transit system profile data. This database is the main source for data and statistics on the public transit systems of the United States. Data are generated by self-reporting statistics from agencies who receive funding from the Urbanized Area Formula Program. Most of the areas have only one agency that provides multiple modes of transportation, whereas other areas have many. We first looked into the overall transit ridership for each area without differentiating modes and agencies. The unit of analysis is area-month with the time span of January 2012 to August 2018. Next, we analyzed the ridership for different modes. According to the NTD summary report,[14] the majority of public transit trips come from bus and rail services. Specifically, we consider three related transit modes, namely, Bus (MB), Heavy Rail (HR), and Light Rail (LR). However, because the heavy rail is only available in a few compact areas, examining the heterogeneous effect on the ridership of heavy rail across sprawling and compact areas has limited practical value. Thus, we use the ridership of Light Rail (LR) as the measure of the ridership of rail services.[15] In this data set, the unit of analysis is mode-month with the time span of January 2012 to August 2018. The 2018 NTD agency monthly report contains values from 386 urbanized areas (UZA). Among all the variables provided by NTD, the Unlinked Passenger Trips (UPT), that is, the number of passengers who board public transportation vehicles, is a widely used measure of the ridership of public transit (e.g., Babar and Burtch

2020). We use UPT as the main dependent variable. We collected and controlled for agency-level statistics (e.g., Fare Revenues and Total Operating Expenses from NTD) and a set of similar socioeconomic factors from various data sources. The definition and summary statistics of all variables are reported in Appendix A.

**3.1.3. Urban Compactness.** As discussed previously, we expect that the urban spatial feature may play a moderating role in both mechanisms, that is, the efficiency-enhancing effect and the demand-inducing effect, and thereby also between Uber and traffic congestion. In particular, urban compactness is the widely used urban spatial feature measure (Ewing and Hamidi 2014, Ewing et al., 2002). The urban compactness data were collected from the Geographic Information Systems Data Sources of the National Cancer Institute. The compactness measure is generated based on four related factors including (a) density factor (i.e., the gross density of urban and suburban census tracts and percentage of the population living at high urban densities); (b) land use mix factor (i.e., job-population balance, the mixture of jobs in different sectors, walkability); 3) centering factor (i.e., the concentration of population and employment in the center of the business district (CBD) or certain census block groups); 4) street factor (i.e., average block length and size, percentage of blocks that are less than the typical size of an urban block, the intersection density and percentage of multiple-way intersections) (Ewing and Hamidi 2014, Ewing et al., 2002). Table B1 is the correlation matrix between *Compactness* and its four constituent factors, which suggests that *Compactness* is highly correlated with all the four constituent factors.

$$Compactness = 0.25{*}DensityFactor + 0.25{*}MixFactor + 0.25{*}CenteringFactor + 0.25{*}StreetFactor \quad (1)$$

As shown in Equation 1, Ewing and Hamidi (2014) calculate the composite urban compactness score by assigning equal weight to each factor and further transform the urban compactness score into an index with a mean of 100 and a standard deviation of 25. The larger *Compactness* is, the municipality is more compact (less sprawling). For illustration purposes, in our data, MSAs with high compactness include "New York City-Newark-Jersey City, NY-NJ-PA MSA", "San Francisco-Oakland-Hayward, CA MSA", and "Los Angeles-Long Beach-Anaheim, CA MSA". MSAs with low compactness include "Atlanta, GA MSA", "Nashville, TN MSA", and "Rochester, NY MSA".

To investigate the impact of the Uber entry on traffic congestion across compact and sprawling MSAs, we merged the Uber entry data, the monthly traffic data from FHWA, and the MSA-level urban compactness measure (Ewing et al., 2002) together. Out of the 366 MSAs in our Uber entry list, monthly traffic congestion data were available for 52 MSAs.[16] Within the 52 MSAs, 2 MSAs were dropped due to their missing compactness values and 11 MSAs were dropped due to missing time-varying control variables (e.g., total funding for public transit and total active fleets).[17]

## 3.2. Empirical Model and Specification

As discussed earlier, Uber enters different MSAs (urban areas) at different points of time. This naturally-occurring variation allows the use of an entry model for econometric identification (Chan and Ghose 2013, Greenwood and Wattal 2017). Specifically, by repeatedly observing the congestion level in each MSA (urban area) over time, we could employ a DID framework to examine the differences in congestion before and after Uber entry across multiple areas. The DID estimation is a popular way to estimate causal relationships (Bertrand et al., 2004). DID is appropriate when one wants to compare the differences in outcomes before and after the intervention for the treated groups to the same differences for the untreated groups.[18] To control for the existing time-invariant differences among the heterogeneous geographical areas, we included area fixed effects in our model. We included time fixed effects to control for the common temporal shocks. Our model specification for the traffic congestion analysis is given by:

$$Congestion_{it} = \alpha + \delta UberEntry_{it} + \lambda Cs_{it} + \theta_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where $UberEntry_{it}$ is a dummy variable equals 1 if MSA (urban area) $i$ has Uber service in time period $t$, and 0 otherwise; $Cs_{it}$ represents the control variables for MSA (urban area) $i$ in period $t$; and $\alpha$ is the grand mean congestion level. In addition, parameters $\delta$ and $\lambda$ are the coefficients; $\theta_i$ and $\gamma_t$ represent area and time fixed effects, respectively; and $\varepsilon_{it}$ denotes the error term. We used robust standard errors clustered at the MSA (urban area) level to deal with potential issues of heteroscedasticity.

To investigate the potential heterogeneous effect of Uber entry, we leverage the variation in *Compactness* across areas and include an interaction term of Uber entry dummy multiplied with *Compactness* ($C_i$) of area $i$. Since the *Compactness* measure is stable over time, the main effect of *Compactness* is absorbed into the area fixed effect and thus cannot be explicitly estimated.[19] The coefficients $\beta$ and $\delta$ together can capture the actual Uber effect and the conditional effect.

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$$Congestion_{it} = \alpha + \delta UberEntry_{it} + \beta UberEntry_{it} {*} C_i + \lambda Cs_{it} + \theta_i + \gamma_t + \varepsilon_{it} \quad (3)$$

To verify the underlying mechanism, we also apply the DID model to the NTD public transit ridership data. The econometric models are shown below with slight modifications.

$$PublicTransit_{it} = \alpha + \delta UberEntry_{it} + \lambda Cs_{it} + \theta_i + \gamma_t + \varepsilon_{it} \quad (4)$$

$$PublicTransit_{it} = \alpha + \delta UberEntry_{it} + \beta UberEntry_{it} {*} C_i + \lambda Cs_{it} + \theta_i + \gamma_t + \varepsilon_{it} \quad (5)$$

The dependent variable in Models (4) and (5) is the log of the measure of public transit ridership of area $i$ at time $t$. Specifically, we consider a set of public transit ridership measures in area $i$ at time $t$: (1) the total public transit ridership (i.e., $UPT\_Total_{it}$); (2) the public transit ridership of bus (i.e., $UPT\_Bus_{it}$) and that of rail (i.e., $UPT\_Rail_{it}$). We expect that the ridership for bus and rail service varies given the different characteristics of each transit mode. The control variables in the vector of $Cs_{it}$ involves socioeconomic factors: percent of people who worked within the county of residence, the number of workers aged 16 and over, median income, gas price, and unemployment rate; public transit supply-side information: total funding and number of fleets; agency characteristics: fare revenues earned by agency, operating expenses by the agency, and area-specific time trend. The coefficients $\delta$ and $\beta$ together determine the overall Uber impact on public transit ridership in area $i$. For example, a positive $\delta$ and a negative $\beta$ suggest that Uber has a positive effect on the public transit ridership in sprawling areas but the effect may turn into negative in compact areas. The unit of analysis here is UZA- month. The dependent variables include ridership for the bus and for rail in area $i$ at time $t$.

As discussed, we included area fixed effects to control for unobserved time-invariant factors that may influence Uber's entry into different areas. Moreover, the common temporal shocks are controlled by time fixed effects. In addition, we included a rich set of control variables from socioeconomic factors, transportation-related factors, and geographic factors to public transit agency characteristics. However, some existing time-variant factors may affect Uber entry and our dependent variables simultaneously. After reporting the main results in the next session, we take further steps to address the endogeneity issue in section 5.

# 4. Results

## 4.1. Main Results

In this section, we report the main results with the DID specifications on the monthly traffic data. The dependent variable used here is PTI95. As shown in Column 1 of Table 3, we do not find any significant net impact. However, after interacting the Uber entry dummy with the area-specific compactness, we observe a significant heterogeneous effect as shown in Column 2 of Table 3, supporting that urban compactness significantly moderates the impact of Uber on traffic congestion. While the negative moderating effect of compactness is pronounced, the actual range of effect of Uber entry is still highly contingent on the sample or the modeling approach.

Specifically, based on the marginal effect estimated with the Delta method (Figure 1), after Uber enters a sprawling urban area with a compactness index of 41 (the minimum compactness in our data set), the congestion index decreases by approximately 9.96% ($p$-value = 0.120).[20] In contrast, after Uber enters a compact urban area with a compactness index of 203 (the maximum compactness in the data set), the congestion index increases by approximately 20.2% ($p$-value = 0.032). Overall, we find that Uber entry significantly increases traffic congestion only in compact areas. By comparison, we find marginal evidence that Uber entry decreases traffic congestion in sprawling urban areas. Therefore, Hypotheses 1a is weakly supported and H1b is fully supported. Note that for the control variables, the traffic tends to get worse as the median income in an urban area increases. This outcome is consistent with the finding of existing literature that traffic conditions in a city are associated with its overall economic activities.

## 4.2. Underlying Mechanisms

**4.2.1. Total Public Transit Ridership.** Guided by the two potential mechanisms (i.e., the efficiency-enhancing effect and the demand-inducing effect) which describe how the Uber entry affects traffic congestion by influencing the public transit ridership, we further investigate the effect of the Uber entry on the total public transit ridership and the mode-specific (bus vs. rail) public transit ridership as well.

Based on the total public transit ridership measure from NTD (i.e., *InUPT_Total*), we find there is no significant average effect of the Uber entry on the public transit ridership (Column 1 of Table 4). After interacting the Uber entry dummy with the area-specific compactness, we find that the Uber entry has a significant heterogeneous impact on the total public transit ridership across compact and sprawling areas. Specifically, as Figure 2 shows, the Uber entry to a sprawling urban area with a compactness index of 41 (the minimum compactness in our data set) can lead to a 7.2% ($p$-value = 0.024) increase in the total public transit ridership. In contrast, the Uber entry to a compact urban area with a compactness index of 203 (the maximum compactness in the data set) remarkably

**Table 3 Main Results and Interaction Effect of Uber Entry on Traffic Congestion**

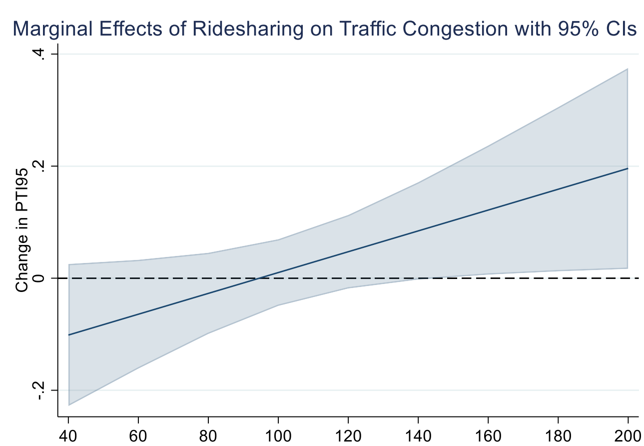
| Dependent Variable | (1) PTI95 | | (2) PTI95 | |
|---|---|---|---|---|
| UberEntry | −0.002 | (0.031) | −0.176* | (0.098) |
| UberEntry * Compactness | | | 0.002** | (0.001) |
| ln(Income) | 5.554*** | (1.213) | 5.483*** | (1.204) |
| ln(TotalWorkers16+) | 1.136* | (0.612) | 1.138* | (0.628) |
| ln(WorkedInCounty) | 0.783 | (1.073) | 0.712 | (1.050) |
| ln(TotalRoadMiles) | −0.252 | (0.353) | −0.222 | (0.349) |
| ln(FreewayLaneMiles) | −0.162 | (0.385) | −0.169 | (0.387) |
| ln(GDP) | −0.877 | (0.781) | −0.879 | (0.769) |
| UnemploymentRate | −0.055 | (0.037) | −0.056 | (0.037) |
| ln(CivilianLaborForce) | −1.070 | (1.348) | −1.274 | (1.327) |
| ln(DVMT) | 1.044* | (0.534) | 1.053* | (0.528) |
| ln(Population) | −0.359** | (0.152) | −0.359** | (0.148) |
| ln(GasPrice) | −0.273*** | (0.061) | −0.266*** | (0.060) |
| ln(ActiveFleet) | −0.255 | (0.213) | −0.272 | (0.198) |
| ln(TotalFunds) | 0.049 | (0.083) | 0.049 | (0.083) |
| Observations | 2,808 | | 2,808 | |
| R-squared | 0.880 | | 0.880 | |
| Number of MSAs | 39 | | 39 | |
| MSA FE | Yes | | Yes | |
| Time FE | Yes | | Yes | |

*Notes*: Robust standard errors clustered by MSA reported in parentheses; the MSA-specific time trend is included.
$^{***}p < 0.01$,
$^{**}p < 0.05$,
$^{*}p < 0.1$.

decreases the total public transit ridership by 17.0% ($p$-value = 0.011). Since the decrease in public transit ridership is very likely to translate to Uber trips, this can help to explain the increase in traffic congestion in compact areas following the Uber entry.

According to our theoretical discussion on the efficiency-enhancing effect and the demand-inducing effect, the efficiency-enhancing effect should be stronger for long-distance trips and the demand-inducing effect should be stronger for short-distance trips. To further lend support to the underlying mechanisms we proposed and examine the expected moderating effect of the average length of public transit trips in a given area. Consistent with the substitution between Uber trips and bus trips in compact areas, our additional analysis reported in Appendix C validates that the Uber entry significantly reduces the ridership of public transit in areas with a short average trip length and increase the ridership of public transit in areas with a long average trip length.

**Figure 1 Marginal Effect of Uber Entry on Traffic Congestion [Color figure can be viewed at wileyonlinelibrary.com]**




**4.2.2. Bus vs. Rail Transit Ridership.** As suggested by Babar and Burtch (2020), Uber entry may have different effects on bus and rail ridership. Next, we investigate the average and heterogeneous effect of Uber entry on the bus ridership and rail ridership, respectively. Similar to what we found in the total public transit, the average effects of Uber entry on bus ridership and rail ridership are insignificant (Columns 1 and 3 of Table 5). That said, there is a significant heterogeneous effect of Uber entry on the bus ridership across compact and sprawling areas.

For the ease of interpretation of the actual range of effects of Uber entry, we estimate the marginal effect of Uber entry on the bus ridership and rail ridership with the Delta method and plot the marginal effect of Uber entry in Figure 3. With regard to the bus ridership, the Uber entry to a sprawling urban area with a compactness index of 41 (the minimum compactness in our data set) can lead to an 8.4% increase ($p$-value = 0.010), whereas the Uber entry to a compact urban area with a compactness index of 203 (the

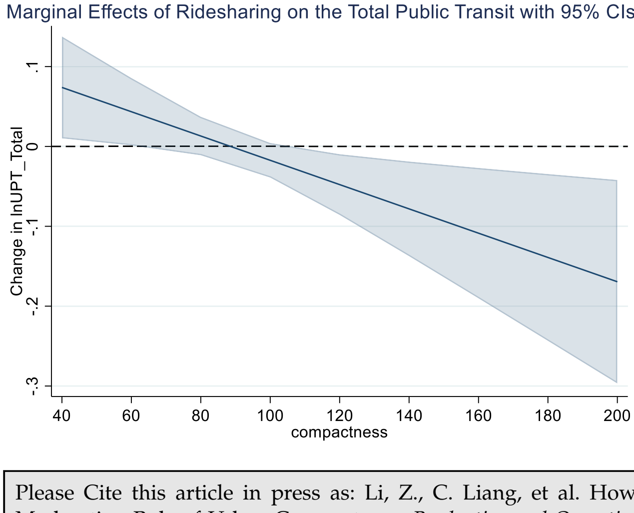
**Table 4 Main Effect and the Interaction Effect of Uber Entry on Total Public Transit Ridership**

| Dependent Variable | (1) ln(UPT_Total) | | (2) ln(UPT_Total) | |
|---|---|---|---|---|
| UberEntry | −0.015 | (0.010) | 0.133** | (0.055) |
| UberEntry * Compactness | | | −0.001** | (0.001) |
| ln(Fares) | 0.132** | (0.051) | 0.130** | (0.051) |
| ln(Expense) | 0.144** | (0.056) | 0.136** | (0.054) |
| ln(Income) | 0.212 | (0.198) | 0.237 | (0.191) |
| ln(TotalWorkers16+) | −0.057 | (0.247) | −0.070 | (0.244) |
| ln(WorkedInCounty) | −0.043 | (0.295) | −0.036 | (0.294) |
| UnemploymentRate | 0.026*** | (0.009) | 0.026*** | (0.009) |
| ln(GasPrice) | −0.104*** | (0.022) | −0.102*** | (0.022) |
| ln(ActiveFleet) | 0.097* | (0.058) | 0.105* | (0.058) |
| ln(TotalFunds) | 0.018 | (0.043) | 0.017 | (0.042) |
| Observations | 9,627 | | 9,627 | |
| R-squared | 0.994 | | 0.994 | |
| Number of UZAs | 139 | | 139 | |
| UZA FE | Yes | | Yes | |
| Time FE | Yes | | Yes | |

*Note*: Robust standard errors clustered by UZA reported in parentheses; the UZA-specific time trend is included.
$^{***}p < 0.01$,
$^{**}p < 0.05$,
$^{*}p < 0.1$.

maximum compactness in the data set) can result in a 15.9% decrease ($p$-value = 0.009). On the contrary, the marginal effect of Uber entry on rail ridership tends to increase with the area-specific compactness (although insignificant).[21] Moreover, the slope of the marginal effect on the rail ridership is relatively flatter and has a wider CI than that of bus ridership. For instance, Uber entry into a compact urban area with a compactness index of 203 (the maximum compactness in the data set) can lead to a 3.6% decrease ($p$-value = 0.751). Taken together, we find that the impact of Uber entry on the rail ridership is not only less statically significant but also less economically significant than the impact on the bus ridership in compact areas, which may explain why the Uber entry has a significant negative effect on the total public transit ridership and a significant positive effect on the traffic congestion in compact areas. This suggests the important role of the demand-inducing effect of Uber (i.e., substituting bus trips with Uber trips) in explaining the increased traffic congestion in compact areas.

**Figure 2 Marginal Effect of Uber Entry for Total Public Transit Ridership [Color figure can be viewed at wileyonlinelibrary.com]**




### 4.3. Summary and Discussion

Table 6 summarizes our main empirical results on the impact of Uber entry on public transit ridership and traffic congestion. We find that the Uber entry decreases the ridership of public transit (especially bus trips) in compact areas, whereas it increases the ridership of public transit in sprawling areas.

Meanwhile, we find that Uber entry significantly increases the traffic congestion in compact areas while its effect on the traffic congestion in sprawling areas is marginally significant. The results lend support for the two competing mechanisms we proposed based on the prior literature on ridesharing and public transit: (a) the stronger demand-inducing effect in the compact areas where Uber trips substitute short-distance public transit trips; (b) the weaker efficiency-enhancing effect in the compact areas where Uber can be potentially integrated with existing bus routes to address the (first or) last mile problem (Babar and Burtch 2020, Fahnenschreiber et al., 2016, Qi et al., 2018, Song and Huang 2020), and thus expand the service areas and accessibility of public transit. Based on the area-specific compactness, we calculate the expected marginal effect of the Uber entry on the traffic congestion and public transit ridership for each area and list some example locations to demonstrate the heterogeneous treatment effects of the Uber entry in Table 7.

There are potentially other mechanisms that may contribute to the increased traffic congestion in compact areas that are not captured by the above two

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**Table 5 Main Effect and the Interaction Effect of Uber Entry on Bus and Rail Ridership**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variables | ln(UPT_Bus) | ln(UPT_Bus) | ln(UPT_Rail) | ln(UPT_Rail) |
| UberEntry | −0.003 (0.009) | 0.145*** (0.055) | −0.027 (0.024) | −0.109 (0.104) |
| UberEntry*Compactness | | −0.001*** (0.001) | | 0.001 (0.001) |
| ln(Fares) | 0.052 (0.040) | 0.054 (0.041) | 0.273* (0.129) | 0.271* (0.130) |
| ln(Expense) | 0.133** (0.053) | 0.128** (0.051) | 0.072*** (0.014) | 0.076*** (0.016) |
| ln(Income) | 0.129 (0.202) | 0.144 (0.195) | −0.531 (0.381) | −0.563 (0.380) |
| ln(TotalWorkers16+) | −0.049 (0.237) | −0.070 (0.234) | 0.140 (0.526) | 0.174 (0.535) |
| ln(WorkedInCounty) | 0.074 (0.282) | 0.085 (0.278) | −2.027** (0.875) | −1.986** (0.889) |
| UnemploymentRate | 0.025*** (0.009) | 0.025*** (0.009) | 0.005 (0.017) | 0.003 (0.018) |
| ln(GasPrice) | −0.102*** (0.023) | −0.099*** (0.023) | −0.081** (0.036) | −0.082** (0.035) |
| ln(ActiveFleet) | 0.268*** (0.075) | 0.273*** (0.073) | 0.126*** (0.041) | 0.128*** (0.040) |
| ln(TotalFunds) | −0.001 (0.035) | −0.002 (0.035) | 0.046 (0.086) | 0.049 (0.085) |
| Observations | 9,411 | 9,411 | 1,296 | 1,296 |
| R-squared | 0.992 | 0.992 | 0.987 | 0.987 |
| Number of UZAs | 135 | 135 | 18 | 18 |
| UZA FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |

*Note*: Robust standard errors clustered by UZA reported in parentheses; the UZA-specific time trend is included.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

mechanicals focusing on public transit, such as the change in commuting behavior other than public transit (e.g., driving or taking a taxi) and drivers' roaming around waiting to pick up passengers. First, to complement our analysis on public transit, we examine the impact of Uber entry on those commuting behaviors other than public transit (i.e., driving alone, carpooling, taking a taxi or other modes, riding a bicycle, and walking) based on the commuting behavior data from the American Community Survey (ACS). As shown in Appendix D, we find that the Uber entry significantly decreases people's use of private vehicles (e.g., driving alone) and increases people's other non-public transit ridership (e.g., taxi, Uber, and others) in compact areas, which may contribute to the increased traffic congestion in compact areas. Second, based on the limited data regarding the number of active Uber drivers in different municipalities from Hall et al., (2018),[22] we find that the number of active Uber drivers is positively correlated with the area compactness (correlation coefficient = 0.353, $p$-value = 0.000), suggesting that there are more active drivers in compact areas. As such, drivers' roaming around waiting for fares is more likely to happen in compact areas than in sprawling areas, which further lends support to the increased traffic congestion in compact areas. However, since we do not have data on drivers' roaming behaviors, we cannot formally test this potential mechanism. Future studies can be done to examine this effect on traffic congestion if such data is available.

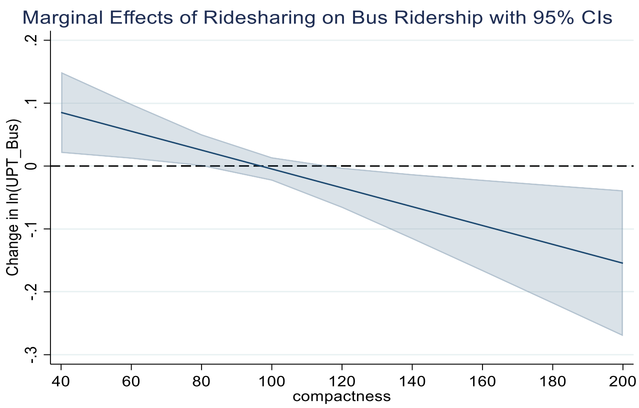
Overall, apart from the two main mechanisms we proposed from the public transit perspective (i.e., the demand-inducing effect and the efficiency-enhancing effect), other changes associated with the Uber entry (e.g., the decrease in private vehicle use, the increase in non-public transit ridership, and potential Uber drivers' roaming behavior) may also contribute to the increased traffic congestion in compact areas. We note that it is difficult to quantify the contribution of each specific mechanism to the observed change in traffic congestion. Nevertheless, although the demand-inducing effect and the efficiency-enhancing effect may not be the only mechanisms responsible for the effect of Uber on traffic congestion, the DID estimates of the effects of Uber entry on traffic congestion and public transit ridership still have causal interpretations and strong managerial implications.

## 5. Robustness Checks and Additional Analysis

### 5.1. Alternative Measures for Uber Entry

Thus far, we used Uber entry time to proxy for the availability of Uber service. This approach is extensively used in the entry model literature (Burtch et al., 2018, Greenwood and Agarwal 2016), but Uber entry may not fully capture the intricacies of the actual

**Figure 3 Marginal Effect of Uber Entry for Bus and Rail Ridership [Color figure can be viewed at wileyonlinelibrary.com]**



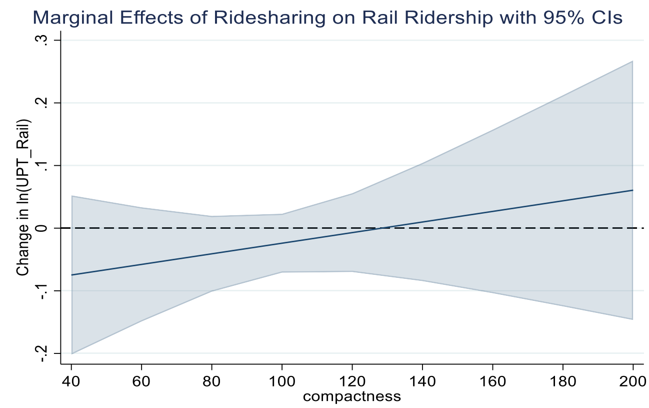




**Table 6 Summary of Empirical Results**

| Compactness | Bus | Rail | Public transit | Traffic congestion | Summary |
|---|---|---|---|---|---|
| H | – | (+) | – | + | The Uber entry decreases the ridership of public transit (especially bus trips) in compact areas by inducing demand for Uber trips, and further increases traffic congestion. |
| L | + | (–) | + | (–) | The Uber entry increases the ridership of public transit in sprawling areas by addressing the last mile problem and enhancing the efficiency of public transit. |

*Note*: Those signs in the parentheses suggest that they are *not* statistically significant.

**Table 7 Example Locations Classified by the Marginal Effect of the Uber Entry**

| Example MSAs in which Uber significantly increases traffic congestion | Example MSAs in which Uber has an insignificant effect on traffic congestion |
|---|---|
| New York-Newark-Jersey City, NY-NJ-PA; San Francisco-Oakland-Hayward, CA; Los Angeles-Long Beach-Anaheim, CA; Miami-Fort Lauderdale, FL | Atlanta, GA; Dallas-Fort Worth, TX; Denver-Boulder-Greeley, CO; Hartford, CT; Nashville, TN; Phoenix-Mesa, AZ |
| **Example UZAs in which Uber decreases public transit ridership** | **Example UZAs in which Uber increases public transit ridership** |
| New York-Newark, NY-NJ-CT; San Francisco-Oakland, CA; Los Angeles-Long Beach-Anaheim, CA; Miami, FL | Atlanta, GA; Nashville-Davidson, TN; Clarksville, TN-KY; Green Bay, WI |
| **Example UZAs in which Uber reduces bus ridership** | **Example UZAs in which Uber increases bus ridership** |
| New York-Newark, NY-NJ-CT; San Francisco-Oakland, CA; Los Angeles-Long Beach-Anaheim, CA; Miami, FL | Atlanta, GA; Nashville-Davidson, TN; Clarksville, TN-KY; Green Bay, WI; Rochester, NY |

usage of Uber services. To complement the Uber entry analysis, we consider an alternative continuous measure of the penetration of Uber service in urban areas, namely, the number of Uber searches in an urban area on Google Trends.

Google Trends is a publicly available web application of Google based on Google Search. It provides an index of the popularity of search terms. It has been previously demonstrated to measure the levels of economic activities (e.g., automotive sales and travel) in real time (Choi and Varian 2012). As confirmed by Hall et al., (2018), the Google search volume index for "Uber " is strongly correlated with the number of active drivers per capita in each market and their correlation coefficient is as high as 0.948. Following Hall et al., (2018), we use the Google Trends search history of the keyword "Uber" in different areas to measure the popularity and the usage level of Uber in an urban area in each time period. Figure E1 in Appendix E plots the search history of Uber service in some example cities along with the corresponding actual Uber entry times. As expected, the correlation between Uber's entry time and the Google search volume is significantly positive. However, a potential issue with using Google search volume as a measure for Uber usage is that, the search volume generally exists for most urban areas, even before Uber entered such areas. A non-zero search volume could represent

**Table 8 Results of Impacts of Uber Entry Using Google Trend as a Proxy**

| Dependent Variable | (1) PTI95 | | (2) PTI95 | |
|---|---|---|---|---|
| lnUberUsage | 0.002 | (0.003) | −0.018 | (0.011) |
| lnUberUsage * Compactness | | | 0.000** | (0.000) |
| ln(Income) | 5.567*** | (1.272) | 5.523*** | (1.261) |
| ln(TotalWorkers16+) | 1.129* | (0.644) | 1.116 | (0.672) |
| ln(WorkedInCounty) | 1.183 | (1.031) | 1.107 | (1.006) |
| ln(TotalRoadMiles) | −0.392 | (0.378) | −0.361 | (0.370) |
| ln(FreewayLaneMiles) | −0.221 | (0.387) | −0.227 | (0.394) |
| ln(GDP) | −0.771 | (0.757) | −0.799 | (0.750) |
| UnemploymentRate | −0.056 | (0.043) | −0.058 | (0.042) |
| ln(CivilianLaborForce) | −2.435 | (1.898) | −2.788 | (1.828) |
| ln(DVMT) | 1.137* | (0.584) | 1.175* | (0.586) |
| ln(Population) | −0.270* | (0.149) | −0.254* | (0.138) |
| ln(GasPrice) | −0.274*** | (0.066) | −0.264*** | (0.066) |
| ln(ActiveFleet) | −0.237 | (0.213) | −0.256 | (0.198) |
| ln(TotalFunds) | 0.004 | (0.068) | −0.003 | (0.065) |
| Observations | 2,714 | | 2,714 | |
| R-squared | 0.885 | | 0.885 | |
| Number of MSAs | 39 | | 39 | |
| MSA FE | Yes | | Yes | |
| Time FE | Yes | | Yes | |

*Note*: Robust standard errors clustered by MSA reported in parentheses; the MSA-specific time trend is included.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

expectations and curiosity but not the actual usage of the Uber service. We address this problem by multiplying the log-transformed Google Trend search index with the Uber entry dummy variable to create a new variable: *lnUberUsage*. Table 8 reports the result of our analysis with *lnUberUsage* as our main independent variable. Consistently, we find that the Uber usage significantly increases the traffic congestion in compact areas, suggesting that our estimates are robust to this alternative treatment measure.

### 5.2. Entry Exogeneity Test

A common threat to the staggered DID design is that the entry time of Uber may be endogenous and affected by an unobserved trend in traffic congestion. Instead of controlling for a series of time-varying variables regarding the economic development and transportation infrastructure, we perform a robustness check to formally test what factors can predict the Uber entry.

Specifically, we employ a Weibull hazard model with the expected time for Uber to enter an MSA as the dependent variable. As results summarized in Table 9, neither the lagged term of traffic congestion nor the area compactness significantly affects the Uber entry time. Only the lagged term of percent of people who worked within the county of residence can significantly accelerate the Uber entry. Since we control for the effect of the percent of people who worked within the county of residence in all models, this should not be a concern to our main analysis regarding the impact of Uber entry on traffic congestion. Overall, the survival analysis lends support to the causal impact of Uber entry on traffic congestion.

### 5.3. Parallel Trend Assumption

According to Angrist and Pischke (2008), a key assumption of the DID model is the parallel trend assumption, which means that in absence of the treatment (Uber entry in this context), the dependent variable of both the treatment and the control groups should exhibit the same trend. To test the parallel trend assumption, we conducted two robustness checks. First, using the subsample that consisted only of pre-treatment observations, we created a pseudo-Uber entry time variable (*Placebo_UberEntry*) based on the middle of the pre-treatment period and reran the DID model. If the observed heterogeneous treatment effects of Uber on traffic congestion are driven by a pre-treatment trend, *Pseudo_UberEntry* and *Pseudo_UberEntry* $\times$ *Compactness* should be significant as well. As Table F1 shows, there are no significant effects on traffic congestion before the actual Uber entry. Second, we applied the relative time model to alleviate the concern regarding a potential pre-treatment trend and estimate the dynamics of the impact after the Uber entry. As Table F2 shows, there are no significant impacts before the Uber entry but after the Uber entry there exist significant heterogeneous effects across sprawling and compact areas.

**Table 9 Survival Analysis of the Entry Time of Uber**

| Dependent Variable | (1) UberEntry | | (2) UberEntry | | (3) UberEntry | |
|---|---|---|---|---|---|---|
| lag_ln(UPT_Total) | −0.163 | (0.123) | −0.178 | (0.258) | −0.213 | (0.264) |
| lag_PTI95 | −0.219 | (0.245) | 0.110 | (0.437) | 0.071 | (0.456) |
| Compactness | | | | | 0.005 | (0.007) |
| lag_ln(Income) | | | −1.520 | (1.860) | −2.039 | (2.070) |
| lag_ln(TotalWorkers16+) | | | −1.425 | (3.460) | −1.568 | (3.802) |
| lag_ln(WorkedInCounty) | | | 1.478** | (0.594) | 1.433** | (0.638) |
| lag_ln(TotalRoadMiles) | | | 0.513 | (1.377) | 0.660 | (1.578) |
| lag_ln(FreewayLaneMiles) | | | 0.034 | (0.635) | 0.136 | (0.565) |
| lag_ln(GDP) | | | −0.402 | (1.151) | −0.066 | (1.079) |
| lag_UnemploymentRate | | | 0.005 | (0.119) | 0.025 | (0.115) |
| lag_ln(CivilianLaborForce) | | | 3.755 | (4.744) | 4.235 | (5.410) |
| lag_ln(DVMT) | | | −1.594 | (1.701) | −1.788 | (1.954) |
| lag_ln(Population) | | | 0.547 | (0.466) | 0.388 | (0.516) |
| lag_ln(GasPrice) | | | −0.616 | (0.796) | −0.815 | (0.871) |
| lag_ln(ActiveFleet) | | | −0.119 | (0.429) | −0.077 | (0.494) |
| lag_ln(TotalFunds) | | | −0.032 | (0.293) | −0.063 | (0.353) |
| Constant | 6.202*** | (1.646) | −4.391 | (7.838) | −3.937 | (8.160) |
| Observations | 1,078 | | 829 | | 829 | |
| LogLik | −39.04 | | −17.26 | | −16.97 | |
| AIC | 82.07 | | 64.52 | | 65.94 | |
| BIC | 92.04 | | 135.3 | | 141.5 | |

*Note:*: Robust standard errors clustered by MSA reported in parentheses.
***$p < 0.01$,
**$p < 0.05$,
*$p < 0.1$.

### 5.4. Placebo Tests

To further validate the relationship between the Uber entry and the change in traffic congestion is causal, we conduct a systematic placebo test of our results using a permutation approach suggested by Abadie et al., (2010). Specifically, we use the 39 MSAs that remained in Equation (2) and randomly reassign the treatment variable $UberEntry_{it}$. Furthermore, we re-estimate the DID model using the shuffled treatment time and save the coefficient estimates for both the entry dummy and the interaction term (Greenwood and Wattal 2017). We repeat this process 1000 times and obtain the distribution of the placebo heterogeneous effect of Uber entry on traffic congestion. Table 10 summarizes the results of the placebo test. We find that, if the treatment time is randomly assigned, the observed coefficient of $UberEntry_{it}$ and that of the interaction term ($UberEntry_{it}$*$Comopactness_i$) are close to zero. Moreover, the probability of observing the actual Uber effect purely by chance is statistically impossible ($p < 0.001$), thereby suggesting that it is the Uber entry that drives the increase in traffic congestion of compact areas. This helps to alleviate the concern that the observed treatment of Uber entry is due to the spurious relationship between Uber entry time and traffic congestion.

We also conduct a series of other additional analyses to assess the robustness of the observed effect of Uber on traffic congestion. First, instead of using the composite compactness measure, we include the four constituent factors of compactness as moderators and rerun the DID model (Appendix B). We find that the heterogeneous effect of Uber on traffic congestion across sprawling and compact areas is more related to the centering factor (i.e., concentration of population and employment in the center of business) and the street factor (the intersection density and percentage of multiple-way intersections). Second, to further lend support to the two mechanisms we proposed (i.e., the efficiency-enhancing effect and the demand-inducing effect), we use the average trip length of an area as a moderator and find a consistent heterogeneous effect of Uber on the ridership of public transit (Appendix C). In particular, Uber substitutes public transit for short-distance trips but complements

**Table 10 Results of the Placebo (Permutation) Test**

| Estimate | Actual Estimated Effect | Average Placebo Effect | Z-score ($H_0$: placebo = actual effect) | *P*-value |
|---|---|---|---|---|
| Coefficient of $UberEntry_{it}$ | −0.176 | 0.001 | −4.169 | 0.000 |
| Coefficient of $UberEntry_{it}$*$Comopactness_i$ | 0.002 | −0.000 | 4.338 | 0.000 |

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public transit for long-distance trips. Given that the trip length is negatively associated with compactness, our additional analysis reinforces our theoretical arguments regarding the mechanism for the impact of Uber on traffic congestion. Third, instead of using PTI95 as the measure of traffic congestion, we use the Travel Time Index (TTI), that is, the ratio of the travel time in the average peak period to that of free-flow conditions, as the dependent variable (Appendix G). We find consistent results that Uber increases traffic congestion in compact areas and its effect is insignificant in sprawling areas. Fourth, we investigated the impact of Uber's largest competitor in the US (i.e., Lyft) on traffic congestion by running the DID model based on the staggered Lyft entry time (Appendix H). We find that the coefficients for the Lyft entry dummy and the interaction term are consistent with the analysis for Uber in terms of the value sign, both are not significant, suggesting that the effect of ridesharing services on traffic congestion primarily comes from Uber.

## 6. Discussion

As the sharing economy grows, its increasing impact and implications on OM should be more thoroughly examined (Ba and Nault 2017, Roth et al., 2016). This paper studies one of many important operational issues associated with on-demand ridesharing platforms-their impact on sustainability. Specifically, we empirically examine how the entry of a major on-demand ridesharing platform into major urban areas in the United States influences traffic congestion. An interesting tension arises when one considers this question from two different theoretical angles. Specifically, the introduction of Uber services into an urban area might either increase traffic congestion by inducing demand for Uber trips or decrease traffic congestion by expanding the service areas and accessibility of public transit service, thereby increasing the efficiency of the public transit system. Leveraging a quasi-natural experiment setting wherein Uber's ridesharing services enter different urban areas in the United States at different points in time, we compare the differences in congestion before and after Uber enters an urban area against the difference in congestion for urban areas without Uber service. More importantly, we investigate the moderating effect of urban spatial feature (i.e., compactness) on this relationship. We find that Uber's entry into urban areas in the United States significantly increases traffic congestion in compact areas. Meanwhile, we find weak evidence that Uber's entry reduces traffic congestion in sprawling urban areas. We also verify the underlying mechanism whereby Uber tends to decrease public transit ridership in compact areas and increase public transit ridership in sprawling areas. We performed further analyses and robustness checks to validate these results. Our findings are consistent and robust to these extensions.

The results reveal that both *efficiency-enhancing* and *demand-inducing* effects exist and that their net effect is contingent on the urban spatial feature. We emphasize the necessity of considering the heterogeneity of Uber's impact on traffic congestion depending on urban spatial features. Urban compactness could explain the inconsistency of the previous findings on the impact of ridesharing services on traffic congestion. We also reveal that individuals change their public transit ridership in the presence of a ridesharing service.

This study makes several important contributions to the literature and introduces new perspectives and opportunities for future research. First, this paper examines the impact of the on-demand ride-sharing platform on sustainability and reveals that it significantly reduces traffic congestion in the more sprawling urban areas yet increases traffic congestion in the more compact urban areas. Although numerous scholars call for papers on how information systems and technology could contribute to environmental sustainability (Jenkin et al., 2011, Malhotra et al., 2013, Watson et al., 2010), few empirical studies examine the sustainability impact of this new platform-based economy. We contribute to this research area and showcase the importance of investigating the sustainability impact of ridesharing platforms and illustrate how they influence traffic congestion. And in extension, we would expect the entry of ridesharing platforms could either reduce or increase emissions or pollutions.

Second, this study provides empirical evidence that adds to the ongoing debate on whether and how sharing economy platforms affect society and sustainability (Alexander and González 2015, Burtch et al., 2018, Greenwood and Agarwal 2016), with a specific focus on traffic congestion (Goodwin 1996, Merrill and Coote 2017). This question has generated heated discussions in the press and academia. Information technology can have a significant influence on sustainable operations (Melville 2010). Researchers in production and operations management have pointed out that it is important to understand the role of IT as a sustainability solution (Bowen et al., 2001, Linton et al., 2007, Singhal and Singhal 2002). However, the impact of the new IT-based economy on sustainability is not clear. As sharing economy companies (e.g., Uber and Airbnb) further expand, they face strong resistance not only from the traditional industries they are disrupting but also social and political pressures that intend to protect the public. Our results suggest that,

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in some areas, these innovative platform-based services could be a solution to a broader set of societal issues (e.g., traffic), thus offering insights for policymakers who are currently debating on the legality of services like Uber. Policymakers must balance the positive effects against the unintended negative consequences of these platforms to make informed decisions. Furthermore, the heterogeneous effect also warns against making broad policy prescriptions regarding Uber. The alteration in the public transit system from city to city changes the effects of Uber itself, eventually leading to variations in the optimal policy response as we move from one city to another.

Third, this work contributes to the research on the sustainability impact of sharing economy platforms not only by providing additional empirical evidence but also by highlighting the necessity of considering the heterogeneity of the impacts in terms of urban spatial structures. We demonstrate that the net effect varies with focal MSAs' urban compactness. Ignoring this important moderator may lead to misleading policies. For policy implications, it is important to not just understand the overall impact of such platforms but also the underlying mechanism. Following the urban economics literature, we use the urban compactness measure as well as trip distance as moderator and demonstrate that the effect of Uber is dependent on the urban spatial feature. We believe these notions could be extended to other contexts wherein the impact is varied along the length of daily commuting trips. This also provides an alternative for city planners and policymakers who may not have access to fine-grained data to design optimal responses and policies. This research also contributes to the broader literature on the societal impact of digital infrastructures and platforms (e.g., Chan and Ghose 2013). Such economic and societal effects are worthy of further research efforts. As information technology improves, new business models and platforms will emerge. In the beginning, the uncertainty is going to continue to stifle innovation. Understanding their impacts is crucial for policymakers and practitioners in better managing those platforms.

Fourth, this paper contributes to expanding OM to a smart-city scope with a specific focus on shared mobility. Qi and Shen (2019) have pointed out the timeliness and relevance of doing research at the smart-city scope. Our study is likely to generate more discussions on whether and how digital platforms (such as Uber) can affect transportation, city infrastructure planning, and urban development. We believe that the landscape of on-demand ridesharing will change dramatically in the years to come. Two major trends are currently emerging in the auto industry: automation and the shared use of vehicles. Before long, we shall witness the shared use of driverless cars. More studies are thus needed to help inform the public and the decision-makers.

Finally, this paper has important practical implications by informing regulators, policymakers, and platform owners, and helping them make decisions. Deciding on how to regulate these companies presents a challenge for governments, in part because of the poor understanding of the actual economic effects of ridesharing companies. The findings of this paper indicate that on-demand ridesharing platforms facilitate and increase the use of public transit in sprawling urban areas. However, in compact urban areas, ridesharing platforms attract commuters away from more environmentally sustainable modes and increase traffic congestion. Proper guidance and intervention can mitigate the negative impact and magnify the positive impact. In sprawling areas where Uber increases the efficiency of the transportation system, policymakers can strategically encourage the use of ridesharing services, such as by allocating dedicated parking spaces throughout the city or subsidizing Uber trips for people living far away from public transit stations. Furthermore, regulators should encourage the collaboration between public transit agencies and on-demand ridesharing companies to take advantage of the complementarity and incentivize people to use public transit more. From another perspective, ridesharing platform operators, such as Uber and Lyft, must be aware that ridesharing platforms have provided unintended positive externalities to society. As such, they should help find ways to design the platforms effectively to enable the technological affordance that would enhance these positive externalities. For example, they can partner with public transit by incorporating public transit information into their apps[23] and even allowing people to buy train tickets from their apps.[24]

This study has several limitations. First, although we highlighted a few mechanisms through which Uber decreases traffic congestion, data limitations prevented us from directly testing those mechanisms in this paper. Thus, we call for future studies to empirically examine the mechanisms that drive our main results. Second, due to the limited availability of monthly traffic congestion data, we are not able to examine the heterogeneous effect of the Uber entry on traffic congestion for all the MSAs in our Uber entry list. When the traffic congestion data is available on larger scales (e.g., more granular area level or more areas), future research could check if our findings still hold and further examine the heterogeneous effect of Uber entry on traffic congestion by granular neighborhood characteristics (e.g., racial composition). Third, regarding the generalizability of our findings, our results are based on traffic patterns in the United States. Therefore, they cannot be directly generalized

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to other countries without further rigorous empirical analysis. Other contextual factors, such as public acceptance of ridesharing, culture, and existing government policies, should be considered to make a sound conclusion. Fourth, because the sharing economy is a relatively new phenomenon, we are unable to examine the long-term consequences of Uber's entry on traffic congestion. Future work using longer panel data is worth pursuing. Finally, as a robustness check, we use a standard entry model approach (Chan and Ghose 2013, Greenwood and Wattal 2017) to estimate the effect of Uber entry to further assess the validity of the findings. We conduct the entry exogeneity test to rule out the possibility that the Uber entry time is affected by the area-specific trend in traffic congestion or urban compactness. We believe that we have leveraged a standard approach of research design established in the extant literature, and future research may also consider other identification strategies to check the robustness of our findings. In addition, further research can examine how regulatory hurdles affect the effect of Uber on traffic congestion. Some cities considered imposing various regulatory hurdles on Uber. For instance, Seattle introduced an additional tax on Uber ride to fund the city's public transportation infrastructure projects.[25] Chicago approved a congestion tax on downtown peak-hour Uber trips.[26] New York City imposed a limit on the time drivers roaming or waiting to pick up new passengers.[27] These regulatory hurdles tend to weaken the efficiency-enhancing effect and the induced-demand effect at the same time. The fact that we find significant results indicates that the true results would be even stronger if there were no regulatory hurdles. Overall, we hope that our study will become one of the pioneering studies that will attract researchers and practitioners to engage in meaningful open discussions about this exciting domain of on-demand ridesharing.

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### Notes

[1]For example, Mark Warner, Senator from the Commonwealth of Virginia, has proposed several initiatives related to sharing economy. https://www.warner.senate.gov/public/index.cfm/gig-economy (accessed on August 19, 2020).

[2]https://www.pwc.fr/fr/assets/files/pdf/2015/05/pwc_etude_sharing_economy.pdf (accessed on August 19, 2020).

[3]https://www.uber.com/newsroom/semi-automated-science-using-an-ai-simulation-framework/ (accessed on August 19, 2020).

[4]http://www.nytimes.com/2015/07/28/upshot/blame-uber-for-congestion-in-manhattan-not-so-fast.html (accessed on January 26, 2021).

[5]http://www.nytimes.com/2016/01/16/nyregion/uber-not-to-blame-for-rise-in-manhattan-traffic-congestion-report-says.html (accessed on January 26, 2021).

[6]https://medium.com/uber-under-the-hood/diving-deeper-on- how-uber-improves-access-to-transit-574d3af18d7b (accessed on January 9, 2021).

[7]https://www.uber.com/blog/new-england/uber-and-public-transit-working-hand-in-hand-in-connecticut/ (accessed on January 9, 2021).

[8]We also confirm this based on the trip length data from NTD. As shown in Appendix C, there is a strong negative relationship between compactness and trip length. As the compactness increases, the average trip length in an area tends to decrease.

[9]https://www.uber.com/newsroom/company-info/ (accessed on May 20, 2021).

[10]http://www.businessofapps.com/data/uber-statistics/ (accessed on May 20, 2021).

[11]We thank Dr. Jonathan Hall, Chief Economist of Uber, for sharing the data with us. Note that "cities" used in the data are spaces defined by Uber and not actual cities. San Francisco, for example, is actually a wide swath of the Bay Area, extending from the far North Bay to Gilroy. This information poses a challenge for us to map those cities to the MSAs. Thus, one of the authors and two research assistants verified Uber entry information area by area by searching the news articles related to Uber entering into different areas.

[12]The United States Office of Management and Budget (OMB) defined 383 MSAs for the United States and 7 for Puerto Rico. For areas that are not in the data Uber shared with us, we searched the entry data by ourselves.

[13]Another traffic congestion measure is Travel Time Index (TTI), the ratio of the travel time in the average peak period to that of free-flow conditions (FHWA 2018). PTI95 is a proxy of traffic conditions during congestion, whereas TTI is a proxy of average traffic conditions. To investigate the traffic condition during congestion, we adopted PTI95 as our dependent variable. Results are consistent if we use TTI as the dependent variable (See Appendix G).

[14]https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/ntd/66011/2016-ntst.pdf (accessed on January 10, 2021).

[15]All results regarding the ridership of rail are qualitatively consistent if we use the ridership of heavy rail (HR) as the dependent variable.

[16]Our sample includes all the MSAs whose traffic congestion data was provided by the Federal Highway Administration (FHWA). We believe that the sample of the traffic congestion data from FHWA is representative. According to the FHWA's website, in order to study the current state

of congestion and reliability on the National Highway System (NHS), FHWA routinely measures the traffic congestion status for 52 of the largest metropolitan areas in the United States (source: https://ops.fhwa.dot.gov/publications/fhwahop20012/index.htm, accessed on May 15, 2021).

[17]With the above said, we do find that our results are highly consistent when we use the sample of 50 MSAs whose MSA-level compactness is known (the results are available upon request). In particular, for both the sample of 50 MSAs and our main sample of 39 MSAs, we consistently find that Uber entry significantly increases traffic congestion only in compact areas. This lends further credibility to the robustness of the findings we reported.

[18]It's possible that Uber's decision to enter an urban area could be endogenous. We further alleviate this concern by conducting the entry exogeneity test, as presented in section 5.2.

[19]According to Ewing and Hamidi (2014), they only published two versions of the urban compactness measure, that is, the 2000 version and the 2010 version. Given that our observation window is between 2012 and 2018, we do not have any variation in the compactness measure within each area. Additionally, as validated by Ewing and Hamidi (2014), the compactness measure does not change dramatically over a 10-year period. Therefore, we expect that the urban compactness does not change dramatically during our observation window.

[20]Unfortunately, the PTI95 measure is not available to all MSAs, which limits the number of observations in our model. The estimated marginal effect may have a smaller standard error and become significant if the traffic congestion data of more areas or a longer observation window is available.

[21]We need to be cautious when concluding the heterogeneous effect of Uber entry on rail ridership across compact and sprawling areas. Given the limited areas have the rail service and Uber service, the standard error of the interaction term between *UberEnty* and *Compactness* is relatively large. If more observations are available, the interaction effect can become significant. We find that the interaction term between *UberEnty* and *Compactness* is significantly positive on the ridership of commuter rail when we expand the observation window to 2011-2018.

[22]A driver is active if they complete at least four trips in a given month.

[23]https://www.uber.com/us/en/community/supporting-cities/transit/ (accessed on January 15, 2021).

[24]https://www.nytimes.com/2019/08/07/technology/uber-train-bus-public-transit.html (accessed on January 15, 2021).

[25]https://www.geekwire.com/2019/seattle-passes-minimum-wage-uber-lyft-drivers-raising-fees-rides/ (accessed on January 15, 2021).

[26]https://chi.streetsblog.org/2019/11/26/once-again-chicago-leads-the-way-passing-a-ride-hail-tax-to-help-get-uber-and-lyft-under-control/ (accessed on January 15, 2021).

[27]https://www.reuters.com/article/us-uber-new-york/uber-to-limit-drivers-app-access-to-comply-with-nyc-regulation-idUSKBN1W12OV (accessed on January 15, 2021).

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## Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supplementary Material