Ridesharing and Digital Resilience for Urban Anomalies: Evidence from NYC Taxi Market

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Urban anomalies bring uncertainties to society, urban transportation systems, and businesses. Some urban anomalies, such as no-notice and/or unpredictable terrorist attacks or other urban strikes, if not handled in timely ways, may result in loss of life or property and pose tremendous risks to public safety overall. Previous studies have focused on developing emergency-management technology but without in-depth analysis exploring how technology-mediated digital systems perform in reality. Besides, the recent literature has demonstrated significant interest in analyzing and comparing the traditional on-demand service (i.e., taxies) and ridesharing platforms (e.g., Uber). A majority of prior studies have focused on their complementary roles in determining environmental conditions. Little is known, however, regarding how and why the two types of platforms perform in contexts of uncertainty (e.g., under emergency situations). This paper aims to bridge this literature gap. Specifically, we consider different types of unexpected urban anomalies (including terrorist attacks, car crashes, and subway shutdowns) and collect large-scale trip data on taxi and ridesharing services. Empirically, we employ a difference-in-differences (DiD) econometric model to compare the platform-level performances (measured by the number of fulfilled trips) of a traditional taxi system and a ridesharing platform after urban anomaly shocks. We observe that the ridesharing platform significantly outperforms the traditional taxi platform in coping with the uncertainties brought about by unexpected anomalies. We conduct a set of robustness checks to verify our findings and propose multiple possibilities to explain them. We conclude, conservatively, that the technological effect, as well as the technology-enabled supply elasticity of the digital platforms, are the main factors determining the differences between the platforms during an urban anomaly. This work offers important insights into the design of platform strategies, especially for the stimulation of the labor supply and incentivization of the adoption and use of technology in urban transportation systems in response to anomalous urban upheavals.

Key words: Ridesharing; Urban Anomaly; Platform Utilization; Difference-in-Differences; Technological Effects

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1. Introduction

Urban anomalies, especially unpredictable and/or no-notice events, if not handled properly, could result in significant economic losses and societal crises (Manelici 2017, Moore 2007, Paizs 2013). Statistics show the total worldwide losses from both natural and man-made disasters reached 306 billion dollars in 2017 (McCarthy 2017). Manelici (2017) found that for cities, the 2005 London bombings led to a 6% fall in house prices, as “new firms,” for example, were “less likely to locate near major stations after the attacks.” Hence, major cities such as New York City (NYC) are required to respond efficiently to these urban anomalies. Emergency management has always been an important topic in both academia and practical fields. The literature, especially in computer science, has devoted significant attention to detecting and predicting urban anomalies (Fang et al. 2019, Xie et al. 2019, Zhang et al. 2020). Studies have conducted analyses with the aim of accurately detecting urban anomalous patterns/events using spatial-temporal data (Chawla et al. 2012, Pang et al. 2011). More recently, studies have demonstrated the power of technology in helping to predict anomalies and support management, specifically by developing IT-based systems based on, for example, artificial intelligence and remote sensors (Asadzadeh et al. 2020, Sinha et al. 2019).

Although previous studies have focused on developing and evaluating technology for emergency management, we lack solid empirical evidence regarding how technology-initiated digital systems actually perform in a realistic environment. This is difficult to predict accurately using simulation analyses because in many cases, technology’s performance relies on its stakeholders. Realized efficiency depends on how the public reacts to the technology as well as how the technology reshapes human behavior. The urban transportation system being a crucial component of urban emergency management, the present study aimed to understand how technology-equipped transportation services (i.e., ridesharing platforms) can potentially cope with uncertainty and help facilitate emergency relief.

It is well known that whereas the taxi industry played the dominant role in past decades, the emergence of ridesharing platforms has markedly reshaped urban transportation systems. Statistics show that during the first quarter of 2018, ridesharing platforms took "more than 70% of the worldwide transportation market for business travelers" (Goldstein 2018). Taxi companies are centralized with experienced drivers, while ridesharing platforms are a type of gig economy with self-employed drivers who are equipped with technology-based digital systems throughout the full working phases (e.g., searching for demands, picking up and locating passengers, and completing trips). The literature has shown tremendous interest in analyzing this newly emerging type of transportation service. On the one hand, prior studies have identified diverse patterns between taxies and ridesharing platforms. For example, schedule flexibility is an important factor among ridesharing drivers (Cramer and Krueger 2016, Hall and Krueger 2018), who are more likely to set up hourly than daily work targets. In contrast to this, taxi drivers might stop working when reaching their daily targets for the number of hours worked (Crawford and Meng 2011, Farber 2015). Meanwhile, findings are rich regarding the entry impacts of Uber/Lyft on reduced traffic congestion (Li et al. 2022), increased vehicle ownership (Gong et al. 2017), and reduced sexual assault (Martin-Buck 2017).

Most of the existing knowledge, however, focuses on normal conditions, few studies having explored irregular urban situations in-depth. The traditional taxi platform, unfortunately, demonstrates a limited capability to maintain efficiency during urban anomalies. As Camerer et al. (1997) pointed out, hailing a taxi on inclement-weather days is extremely difficult in large cities such as NYC. As the competitors of traditional taxi services, ridesharing platforms, though playing similar roles in urban transportation systems, present systematic differences, which in turn, might or might not help them to stay efficient in picking up passengers promptly during emergencies. For example, ridesharing drivers are equipped with embedded automatic navigation tools allowing them to better locate their assigned passengers and avoid actual or potential traffic jams, which are likely to arise during an urban anomaly. Albeit a technological advancement, ridesharing platforms may not always work as pleasantly, due to, for example, limitations in algorithms or over-reliance on the "automatic features" of technological applications. This can be problematic when facing unexpected situations, because computer algorithms might not have been trained for such situations, and thus, would not know how to react properly. For example, although surge pricing could be effective in allocating demand and supply, it might go to the extreme with algorithm failure. In specific, when demand suddenly peaks but supply cannot keep up, the algorithm-based prices might be unrealistic or even unaffordable. Uber has been accused of charging inflated prices and taking too long to turn off the "surge pricing" feature after the deadly terrorist attack in the heart of London on June 3, 2017. Users complained that they were being charged inflated prices on a Saturday night after a van plowed into pedestrians on London Bridge and three knife-wielding men attacked revelers in a nearby nightlife district. The backlash on social media was intense, whereas black cab drivers were praised for giving free rides to take people away from the surrounding area. Another significant difference between traditional and ridesharing platforms is the labor supply. Urban anomaly events often cause a temporary imbalance between demand and supply, leading to a price surge in the market. As Hall et al. (2018) pointed out, ridesharing drivers "respond to temporarily higher wages by working more hours, which has a business stealing effect." Thus, with unexpected urban situations, ridesharing drivers are more likely to adjust their working schedules and respond positively to potential income opportunities. Hence, the recent literature has offered burgeoning data and insight into transportation services' performance under normal situations or expected scenarios. A *key question* remains, however: How might unique designs regarding supply, demand, and technology equipment enable ridesharing platforms to facilitate or improve transportation service during no-notice and unpredictable urban anomalies, such as terrorist attacks, especially when compared with taxi companies?

We conducted our study in NYC, where we collected taxi and for-hire-vehicle (FHV) trip records from January 2015 to December 2017. We considered multiple types of urban anomalies, including terrorist attacks, subway shutdowns, and car crashes. Given that those events are no-notice and unpredictable, we employed a difference-in-differences (DiD) econometric model to quantify the effects on the platform-level utilization of taxi and ridesharing platforms. Specifically, we measured platform-level utilization based on the hourly number of served trips. Interestingly, we observed that ridesharing platforms (Uber as an example) performed better than taxi companies after an urban anomaly. For example, we identified, after two well-known terrorist attacks (the Manhattan bombing on September 17, 2016; the truck attack on October 31, 2017), a significantly decreasing trend in the utilization of both the taxi and ridesharing platforms post-terrorist-attack. The ridesharing platforms, in general, showed a statistically significantly smaller utilization decline than the taxi platforms. We also conducted a sequence of robustness checks, all of which were consistent with our main findings. Based on our empirical data, we propose multiple possibilities to explain the better performance of ridesharing platforms. Specifically, we consider the technological effect, passengers' preference changes (from the demand side), and supply elasticity. Based on our empirical evidence, we conclude conservatively that the technological effect, as well as supply elasticity, are the main factors explaining the differences between the platforms during an urban anomaly. Moreover, to offer more insightful implications in terms of the design and adjustment of preparation or response strategies regarding urban strikes, we extended our analyses by considering heterogeneous treatment effects. Two main patterns emerged. First, locations with higher densities are affected less by urban anomalies. Second, from the temporal perspective, the decrease in taxi utilization is smaller during rush hours or in the evening relative to the two other slots (i.e., midnight and daytime). In contrast to this fluctuation in taxi utilization, daily ridesharing platform utilization is relatively stable.

2. Literature Review

2.1. Two-sided Platforms and Ridesharing Service

One of the key design-side differences between the taxi and ridesharing platforms is that ridesharing imposes a two-sided market component (Gong et al. 2017, Hu and Zhou 2015). The literature is rich on two-sided markets under different contexts (Parker and Van Alstyne 2005, Rochet and Tirole 2004). Both sides of the two-sided market benefit from platform design, including network effects and price discrimination (Parker and Van Alstyne 2005, Rochet and Tirole 2003). As Cohen and Sundararajan (2015) pointed out, platforms such as Airbnb and Uber serve as third-party intermediaries and offer solutions to potential market failure using digital technologies to reduce information asymmetries. With proper designs, platform intermediaries can improve consumer welfare as well as profits (Parker and Van Alstyne 2005). However, Bai et al. (2019) noted that in the specific ridesharing domain, on-demand platforms (e.g., Uber and Lyft) differ from product-sharing platforms like Airbnb, where consumers reserve the service in advance. And work participation of independent providers is primarily driven by earnings. Since the introduction of technology-enabled ridesharing platforms, the literature has drawn considerable attention to this sharing economy. Broadly speaking, our paper is related to two ridesharing-based literature streams: (1) entry impacts of the sharing economy and (2) platform design and mechanism as compared with incumbent industries. First, the results are equally rich when considering the (entry) impacts of ridesharing platforms (Babar and Burtch 2017, Cohen et al. 2016, Greenwood and Wattal 2017, Lam and Liu 2017, Li et al. 2022, Wallsten 2015). Two main issues have been investigated within this stream. The first is the entry effects of ridesharing platforms on incumbent industries or systems; the second regards the spillover effects on society. Babar and Burtch (2017), for example, scrutinized the impact of the Uber platform and found a significant reduction in the utilization of city buses, but an increase in the usage of subways and commuter rails. Alternatively, the literature also highlighted the societal impacts of these technology-enabled platforms in increasing vehicle ownership (Gong et al. 2017), minimizing sexual assault (Martin-Buck 2017), and reducing lower-quality entrepreneurial activity (Burtch et al. 2018).

The second stream is more closely related to the present study. Although ridesharing drivers perform similar functions, their supply mechanisms and information systems are different from those of taxi drivers (Castillo et al. 2017, Chen and Sheldon 2016, Cohen et al. 2016, Cramer and Krueger 2016, Hall and Krueger 2018). Flexibility is an important characteristic of ridesharing platforms' driver-partners when compared to the traditional taxi companies' taxi drivers (Cramer and Krueger 2016, Hall and Krueger 2018). Their unique relationship with the Uber platform allows drivers to have more flexible working schedules, which in turn, gains higher utilization rates for them relative to taxi drivers. Alarmingly, unlike street-hail taxies, ridesharing drivers might have to be dispatched by a technology-based matching system to pick up a rider at a distant location. This leads to a Wild Goose Chase (WGC) problem, wherein the available supply might be lower in times of high demand. The surge pricing mechanism provides a good way to solve this problem (Castillo et al. 2017). This WGC problem and related surge pricing are noteworthy differences between taxi and ridesharing drivers. Recent studies also have pointed out that this surge pricing mechanism on ridesharing platforms like Uber significantly increased labor supply and brought a substantial consumer surplus to the transportation service market (Chen and Sheldon 2016, Hall and Krueger 2018).

Our study extends this stream of literature by exploiting the systematic differences between platforms under *abnormal* and *unexpected* scenarios, which would help us to better design and regulate urban transportation systems, especially in terms of the maintenance of stability and efficiency.

2.2. Urban Anomalies

It is well-recognized that understanding and being well-prepared for urban anomalies are important practical imperatives for both city planners and service providers. The literature, especially in the field of computer science, has made significant efforts to understand and predict urban anomalies (Fang et al. 2019, Xie et al. 2019, Zhang et al. 2018). Generally speaking, there are two directions in this specific area. The first one focuses on prediction analyses aiming to accurately detect or forecast urban anomalous patterns/events using different sources of data, including spatial-temporal data (Pang et al. 2011, Chawla et al. 2012, Kuang et al. 2015, Zhou et al. 2016, Zhang et al. 2018). For example, Kuang et al. (2015) presented a new method to leverage taxi GPS data to detect traffic anomalies, and their experimental results demonstrated that such a method could identify more than 70% anomalies. Another direction is to study the impacts of urban anomalies (Fang et al. 2019, Xie et al. 2019). For example, Fang et al. (2019) studied the effects of both expected (e.g., concerts) and unexpected (e.g., subway delays, accidents, and facility malfunction) events on travel time. Specifically, they compared taxies, buses, subways, and private vehicles. They found that unexpected anomalies had a larger impact on travel time than did expected events, and that taxies tended to have a lower delay in travel time compared with private vehicles. Studies in this stream of literature have investigated multiple types of urban anomalies. As summarized by Zhang et al. (2020), prior studies focused on "traffic anomaly, unexpected crowds, environment anomaly, and individual anomaly". This study takes a close eye on the traffic anomaly and unexpected crowds.

Among the different types of urban anomalies, terrorist attacks strike a community without notice (Sayyady and Eksioglu 2010). Studies have shown the significant economic effects of terrorism (Manelici 2017, Moore 2007, Paizs 2013). For example, Manelici (2017) found that the 2005 London bombings led to a 6% fall in house prices, and that "new firms [were] less likely to locate near major stations after the attacks." Therefore, urban planning, especially transportation planning or response, becomes essential for such urban upheavals (Sayyady and Eksioglu 2010, Wolshon et al. 2005). Prior studies have put more emphasis on the macro and long-term effects of terrorism (e.g., the September 11 terrorist attack) on urban design, or the specific practices regarding evacuation orders. The present study, contrastingly, targets the micro perspective. Although studies like Fang et al. (2019) explored the travel time distribution in different urban transportation systems, little is yet known about how ridesharing platforms might perform after no-notice terrorist attacks, especially as compared with taxi platforms. Moreover, prior studies have focused more on exploring statistical phenomena related to urban anomalies. This study adds to the literature on urban anomalies by decomposing the underlying mechanisms to explain, both theoretically and empirically, the trends of urban riding platforms during anomalies. Such in-depth analyses provide more insights into the design of urban transportation systems and strategies for their response to such no-notice urban anomalies. And it is worth noting that such empirical evidence is rare in prior studies and simulation results might not be sufficient. This is because the realized performance relies on not only technology efficiency, but also the public's reactions toward technology during urban anomalies.

2.3. Technology and Emergency Management

Considering the potential scale of critical threats to cities, emergency management has always been an important area in both academia and practical fields. Extensive research has examined the use of technology in disasters as well as under other emergency conditions (Jefferson 2006, Pine 2017). Prior studies have demonstrated the power of technology in disaster management by developing diverse technology-based systems to help predict and support management throughout all phases (Fiedrich and Burghardt 2007, Sinha et al. 2019). Recently, with the outbreaks of COVID-19, studies have explored how IT-based systems (including artificial intelligence and remote-sensing sensors) help to control spreads (Asadzadeh et al. 2020) and how related technologies (e.g., collaborative tools) develop and cope with environmental changes (e.g., remote working) brought about by the COVID-19 outbreaks (Fatimah et al. 2021, Raza et al. 2021). In the area of urban transportation, although studies have explored the development and effects of technological systems in dealing with future disasters and hazards (Jia and Du 2020, Korkmaz 2017), little in-depth has been done on the existing commuting services (e.g., technology-initiated ridesharing services) in helping individual passengers to cope with unexpected urban anomalies. This study aimed to bridge this gap.

3. Context and Data

We conducted this study in NYC. Our research context was the taxi industry and ridesharing platforms (e.g., Uber and Lyft) there. As shown in the 2019 annual report released by the NYC Taxi and Limousine Commission (TLC),[1] in NYC, there were approximately 197,000 taxi drivers and over 130,000 licensed for-hire vehicles, the majority of which were connected with Uber and Lyft. According to the trip data provided by the TLC, over the past 4 years, ridesharing-based trips have grown from 0 to 15 million per month, while the number of taxi trips per month has decreased by around 5 million. In NYC, taxies are operated by multiple private companies and licensed by the TLC. Taxi fares are pre-determined by the TLC.[2] Most taxi drivers lease their taxi medallions (a required permit allowing a taxi driver to operate[3]) from different private companies/owners (Liu et al. 2021). Therefore, in addition to certain fixed annual costs (including the TLC licensing and training fees), taxi drivers pay a certain percentage of their gross fares or a fixed daily/weekly/monthly rental fee to the taxi cab companies.[4] To find an accessible ride, a passenger can call the dispatch center directly, use an E-hail app, or hail on the street. The TLC handles compliments and complaints from passengers and regulates the operations of taxi drivers. On the other hand, on ridesharing platforms such as Uber Technologies Inc., Uber fares are affected dynamically by real-time factors like traffic, and Uber drivers pay a service fee for each trip to the Uber platform.[5] All Uber trips are matched by the platform through the Uber App.

[1] https://www1.nyc.gov/assets/tlc/downloads/pdf/annual_report_2019.pdf

[2] https://www1.nyc.gov/site/tlc/passengers/taxi-fare.page

[3] https://www1.nyc.gov/site/tlc/businesses/medallion-owners-and-agents.page

[4] https://careertrend.com/how-2090790-become-taxi-driver-new-york.html

[5] https://www.uber.com/us/en/marketplace/pricing/service-fee/

Geographically, NYC is divided by the TLC into 263 taxi zones, 69 of which are located in the Manhattan borough. We treat the taxi zones as our mega geographical units of analysis.

3.1. Observational Data of Trip Records

We first collected taxi trip records and for-hire vehicle (FHV hereafter) trip data from the TLC website.[6] Our panel data cover the time window from January 2015 to December 2017. The taxi trip records include fields capturing pick-up and drop-off time stamps, pick-up and drop-off locations,[7] trip distances, trip fares, payment information, and driver-reported passenger counts.[8] Note that the taxies in NYC are generally classified into 2 types: yellow and green. The yellow cabs can pick up passengers in all boroughs of NYC, while the green ones are allowed to pick up passengers only within restricted locations (e.g., upper Manhattan, Queens excluding LaGuardia Airport and JFK Airport). Our empirical analyses focused mainly on the Manhattan area. This would also help us alleviate potential biases brought by different geographical features (e.g., financial or government areas with high-security service vs. civilian districts). For consistency, we considered yellow cabs only in this study.

NYC has four classes of FHV service, including community cars, traditional black cars, luxury limousines, and high-volume for-hire services (e.g., Uber and Lyft). TLC regulations require that for-hire service must be arranged through a TLC-licensed base and be performed by TLC-licensed drivers in TLC-licensed vehicles. A single company may have multiple bases through which it dispatches trips. In the data, we could identify only two Lyft bases, while the Uber platform covered 28 bases. The FHV trip records include fields capturing dispatched base numbers, pick-up locations (i.e., taxi zone ID), and time stamps. Starting from July 2017, TLC provides information

[6] https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

[7] Before July 2016, the TLC offered coordinate information (i.e., latitude and longitude) or each pick-up/drop-off location. Since July 2016, the TLC has provided only taxi zone information. For consistency concerns, we treat the taxi zones as the mega units in all of our analyses.

[8] From 2013, taxi trip data cannot track individual trajectories, due to the lack of information on driver IDs.

Table 1 Descriptive Statistics of Raw Data

	Variables	Mean	Std. Dev	Min	Max	N
Taxi	# Trips/day	356,420.23	59,514.36	78,133	515,540	1096
	Trip fare	12.9859	11.2102	0.01	999.99	390,636,573
	Trip distance	2.9792	3.6957	0.01	199.7	390,636,573
FHV	# Uber trips/day	189,836.57	90,503.37	21,974	497,204	
	# Lyft trips/day	37,026.29	30,040.45	0	146,605	1096
	#s FHV trips/day	284,658.48	164,763.48	29,124	822,770	

on drop-off locations as well. We identified Uber and Lyft trips based on the dispatching base information.[9]

In total, we collected 390,636,573 taxi trip records and 282,628,256 FHV trip records. Table 1 summarizes the descriptive statistics of those records.

3.2. Information on Urban Anomalies

In this study, our initial focus was on unexpected types of urban anomalies.[10] On the one hand, efficient and effective responses to these uncertain urban anomalies are of prime importance to any urban services, especially to urban transportation systems. Second, given that they are unpredictable, we could treat them empirically as exogenous shocks wherein the taxi and ridesharing platforms would respond to completely unexpected incidents. This, in turn, allowed us to identify the causal impacts and disentangle the potential underlying mechanisms. Specifically, we considered terrorist attacks, subway shutdowns, and car accidents. First, we considered two widely-known terrorist attacks that occurred during the same period as our panel trip data (January 2015 to December 2017) in NYC. Both attacks had dramatic social impacts. The first is the Manhattan bombing at 8:31 pm on September 17, 2016. This terrorist attack took place in a crowded space on West 23rd Street between Sixth Avenue and Seventh Avenue, causing 31 injuries. The second is the truck attack on October 31, 2017. This terrorist attack took place in Lower Manhattan, causing 8 deaths and 15 injuries. Although terrorist attacks are highly unpredictable, they occur rarely

[9] https://www1.nyc.gov/assets/tlc/downloads/pdf/exception_approved_bases.pdf

[10] Appendix C in the online supplementary materials includes the expected types of urban anomalies to deepen our understanding of the response efficiencies of the two platforms.

and involve certain confounders such as political interventions. To further validate our analyses as well as to explore in a more comprehensive way the different patterns between ridesharing and taxi services, we considered two additional types of urban anomalies: the Times Square car crash of May 18, 2017, and the subway train derailment of June 27, 2017. The Times Square car crash caused one death and 20 injuries, and the subway train derailment led to some mechanical issues, causing delays and suspensions on multiple train lines. Appendix A in the online supplementary materials provides detailed descriptions of all the above anomalies, which brought non-neglected impacts to the NYC transportation systems.

3.3. Definitions of Key Variables

We parsed the trip data and extracted the following features for our empirical analyses.

Dependent Variable: $ln(\texttt{NumTrips}_{lt})$ is the natural log of hourly numbers of taxi (or ridesharing-based) trips picked up in taxi zone l at time t. Inspired by Cramer and Krueger (2016) and Haggag et al. (2017), we considered the observed number of trips as a measure of platform utilization, which is our main variable of interest in this paper.[11] Specifically, the number of fulfilled trips captures the throughput of the platform (or, say, the efficiency in providing a specific type of mobility service). It can be affected by both demand- and supply-side factors. Moreover, the design of a platform itself also affects the total number of fulfilled trips per hour. Thus, instead of extracting factors that measure the efficiency of the demand or supply sides separately, we used the total number of fulfilled trips as a proxy for overall platform utilization. We visualized the trends in Online Appendix B.

Independent Variables: $\texttt{Geoproximity}_l$ measures the closeness between the anomaly location zone l_e and any location l. Specifically, we applied the inverse value of the distances (unit: miles) between the centroid points of two taxi zones. Besides, to capture the time stamp of terrorist

[11] Unfortunately, the TLC does not provide information on the number of unique drivers on either the taxi or ridesharing platform. Thus, we could not measure per capita utilization. Instead, we considered utilization at the platform/company level, which captured the overall performance of the two platforms.

Table 2 Summary Statistics of Sampled Key Variables

Variables	Definitions	Mean	Std. Dev	Min	Max
`taxiTrip`	Hourly # of taxi trips per zone	177.6342	207.3753	0	3108
`uberTrip`	Hourly # of Uber trips per zone	85.1811	89.6846	0	1245
`lyftTrip`	Hourly # of Lyft trips per zone	16.8844	19.8800	0	453
`fhvTrip`	Hourly # of for-hire-vehicle trips per zone	122.1151	125.4147	0	1864
`Geoproximity`	Inverse value of distances to event zone	0.3066	0.1825	0.0735	1
`Pick2005`	Log # of pick-ups in 2015 per hour	13.0169	3.2704	0	15.4334
`Drop2015`	Log # of drop-offs in 2015 per hour	13.3373	2.9375	0	15.5064

Notes: The above statistics are based on a sample size that covers 2 weeks before and 1 week after the two terrorist attacks. Thus, the number of observations is 69552 (21 days, 24 hours/day, 69 zones, and 2 attacks).

attacks, we introduced $\texttt{AfterAnomaly}_t$ as an indicator of whether time t is after a certain urban anomaly.

Other controls: For each taxi zone, we also extracted several spatial features for measuring the density or popularity of the given zone. Specifically, we considered the average hourly number of taxi pick-ups and drop-offs before the occurrence of those urban anomalies (i.e., in 2015). All of the unexpected urban anomalies described above occurred in Manhattan. Thus, our analysis considered only the Manhattan borough.

4. Empirical Strategies and Results

4.1. Econometric Model and Identification Strategy

To estimate the urban transportation services' efficiency in handling urban anomaly situations, we used a difference-in-differences (DiD) model (Angrist and Pischke 2008, Bertrand et al. 2004). All of the events we considered (i.e., terrorist attacks, subway shutdown, and car crashes) were unlikely to be predicted in advance, and thus, we considered this type of anomaly event to be an exogenous treatment. The idea was to compare platform utilization changes between the incident location and other locations that were not affected. The DiD model is an increasingly popular approach to the quantification of causal effects, and proceeds by comparing outcome differences before and after an exogenous shock of a treatment group to that of a control group unaffected by the same exogenous shock. Our unit of analysis was the (taxi-)zone-hour. We specified our DiD model as follows:

$$ln(\texttt{NumTrips}_{lt}) = \gamma_l + \texttt{PERIOD}_t + \beta_1 \texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l + \texttt{Controls} + \varepsilon_{lt}, \quad (1)$$

where $ln(\texttt{NumTrips}_{lt})$ is the log value of hourly numbers of taxi (or ridesharing) trips within location zone l at time t, γ_l captures the zone-fixed effects, and $\texttt{PERIOD}_t$ denotes the time-fixed effects (we included both the daily effect and time-of-day effect). As noted earlier, $\texttt{AfterAnomaly}_t$ is a dummy variable (1 for yes, 0 otherwise) denoting whether time t is before or after the treatment (i.e., the specific urban anomaly).

Our key variable of interest was the interaction term $\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$, the coefficient of which encapsulates the effects of urban anomalies on the outcome measure. Note that when an urban anomaly occurs in a city, the potential effect is likely to have a ripple aspect that expands to the vicinity of the incident location. Hence, following Danaher and Smith (2014), our main identification strategy is based on the difference in the treatment effects across locations with different geographic distances to the center location of the anomaly event. The intuition is that a closer location might be affected more by urban anomalies.[12] Thus, the coefficient of the interaction term can identify the average treatment effects. Take terrorist attacks as an example. It is possible that terrorists might choose locations based on particular features (e.g., higher traffic density), rather than randomly. But our DiD empirical strategy, using the differences between the control and treated groups, would eliminate this concern. On the other hand, if the event location has some short-term variations (e.g., some particular festivals), our estimates might underestimate the effects, because in most cases, terrorists would choose a targeted location of higher popularity,

[12] There are at least two possibilities to explain how distances affect rides. First, it takes time for the information to be communicated to other areas via different approaches, such as word-of-mouth, radio, and online news reporting. Second, the level of closeness to the attached area also brings a diverse sense of shock to individual drivers. Besides, our DiD model captures an average effect and the identification assumption states that locations with a closer distance to the event area would be affected more on average. This assumption holds unless the districts with the same distances are the same types of buildings, which we believe is less likely to happen in Manhattan.

which in turn, would have a potentially higher traffic demand/supply in the short run. However, based on the parallel trends and multiple robustness tests, as we will discuss later, we did not find evidence for the latter case. Empirically, we introduced $\texttt{GeoProximity}_l$, the inverse distance (unit: miles) from taxi zone l to incident taxi zone l_e. To capture the common time trend specific to each location zone, we included an interaction term between location-specific features (i.e., location density proxies with traffic density measures, numbers of pick-ups or drop-offs, in previous years)[13] and temporal factors. And the inclusion of location-specific features, to some degree, implies the change of taxi/Uber supply. We clustered the standard errors at the zone level.

To further quantify the differences between the taxies and ridesharing platforms, we applied a difference-in-difference-in-difference (DDD) model. The key idea is to jointly estimate the effects of the urban anomaly events on both platforms while controlling for the differences in pre-treatment trends between them:

$$\begin{aligned} ln(\texttt{NumTrips}_{ljt}) = &\alpha_j + \gamma_l + \texttt{PERIOD}_t + \beta_1 \texttt{AfterAnomaly}_t \times \texttt{TaxiInd}_j \times \texttt{GeoProximity}_l \\ &+ \beta_2 \texttt{TaxiInd}_j \times \texttt{GeoProximity}_l + \beta_3 \texttt{AfterAnomaly}_t \times \texttt{TaxiInd}_j \\ &+ \beta_4 \texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l + \texttt{Controls} + \varepsilon_{ljt}, \end{aligned} \tag{2}$$

where $ln(\texttt{NumTrips}_{ljt})$ is the log value of the hourly numbers of trips completed by platform j within location zone l at time t, α_j captures the platform-fixed effects, and $\texttt{TaxiInd}_j$ is a dummy variable denoting whether it is a taxi platform (1 if yes, 0 otherwise). Our key variable of interest was the interactive term $\texttt{AfterAnomaly}_t \times \texttt{TaxiInd}_j \times \texttt{GeoProximity}_l$, which captures the differences of the anomaly effects between the transportation service platforms. We also included all lower-order interactive terms. Additionally, α_j captures the platform-fixed effects. The rest of the variables remain the same definitions as those in Equation (1).

[13] Because the additional spatial features are highly correlated, we present only the estimates after including controls of previous drop-offs. We also tried pick-ups and average taxi fares as additional controls, and the results are consistent.

4.2. Effects of Urban Anomalies on Taxies and Ridesharing Services

Table 3 reports the estimation results of our main model (Equation (1)) for the two types of mobility service (i.e., taxi and Uber), respectively. We considered only Uber trips in our main results because, in NYC, the Uber platform has most of the ridesharing market share. The time window we considered here extended from one week before the incident to two days after the incident. Our results with alternative time windows (e.g., two weeks before or one day after the anomalies) remained highly consistent. As seen, the coefficients of the key interactive term $\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$ in Columns (2)-(5) are significantly negative for both taxi and Uber trips, suggesting a decline in utilization on both platforms. Although an urban anomaly might bring abnormal movements of crowds, leading to a significant increase in the need for evacuation, it does not necessarily result in a decrease in the utilization of either platform. For example, the supply side might decrease due to an uncertain traffic and safety situation, and traffic chaos might also prevent efficient matching between passengers and drivers. However, when we examined the other two types of urban anomalies (i.e., Columns 6-9), we noticed diverse patterns. The unexpected subway shutdown brought a significant increase in demand needs but potentially worsened the road traffic conditions. We observed that the utilization of taxi services stayed constant while Uber achieved a significant increase in utilization. Meanwhile, the car crash in Times Square decreased the performance of taxi services significantly while Uber's performance stayed constant. Taking all things together, although different types of urban anomalies might affect platform utilization in different directions, a consistent pattern was observed in that ridesharing platforms, compared to taxies, present better platform utilization and thus, are more likely to fulfill fluctuating demand in a more efficient way.

The ridesharing platforms' better performance after an urban anomaly is confirmed in Table 4, in which we report the estimates of Equation (2) for all four scenarios. For example, when we compared the taxi companies with the largest ridesharing platform, Uber Inc., we observed an

Table 3 Main Analysis I: A Difference-in-Difference Model

Variables	2 Terrorist attacks		Truck attack		Subway Shutdown		Time Square Car Crash	
	Taxi	Uber	Taxi	Uber	Taxi	Uber	Taxi	Uber
$\texttt{AfterAnomaly}_t \times$	-0.3062***	-0.2600***	-0.1946**	-0.1608***	0.0973	0.2191**	-0.1689***	0.0235
$\texttt{GeoProximity}_l$	(0.0542)	(0.0437)	(0.0758)	(0.0393)	(0.1047)	(0.0960)	(0.0634)	(0.0515)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. Observations	29,808	29,808	14,904	14,904	14,904	14,904	14,904	14,904
R-square	0.4558	0.4867	0.4872	0.5632	0.4972	0.5345	0.4945	0.5668

***p<0.01; **p<0.05; *p<0.10; Standard errors are shown in parentheses; We include both the zone- and time-specific fixed effects.

Table 4 Main Analysis II: Differences in the Anomaly Effects among Platforms

Variables	Manhattan Bombing	Truck Attack	Subway Shutdown	Time Square Car Crash
$\texttt{AfterAnomaly}_t \times \texttt{TaxiInd}_j \times \texttt{GeoProximity}_l$	-0.2658***	-0.2022***	-0.4611***	-0.1367**
	(0.0603)	(0.0394)	(0.0914)	(0.0712)
$\texttt{AfterAnomaly}_t \times \texttt{TaxiInd}_j$	0.0863***	0.1809***	0.1797***	0.1016***
	(0.0189)	(0.0139)	(0.0195)	(0.0277)
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	-0.1547**	-0.1511***	0.2930***	-0.0407
	(0.0621)	(0.0436)	(0.1015)	(0.0445)
$\texttt{TaxiInd}_j \times \texttt{GeoProximity}_l$	2.1342***	0.9648	-1.8799***	3.0892***
	(0.5487)	(0.5975)	(0.3608)	(0.6683)
Fixed effects	Yes	Yes	Yes	Yes
Num. Observations	29,808	29,808	29,808	29,808
R-square	0.4819	0.3685	0.3919	0.4725

***p<0.01; **p<0.05; *p<0.10; Standard errors are shown in parentheses; We include both the zone- and time-specific fixed effects.

18.31% ($e^{-0.2022} - 1$) more decrease in taxies' numbers of served trips per hour after the truck attack, with one unit change in $\texttt{GeoProximity}_l$. We also considered comparisons with different types of ridesharing services (e.g., Lyft) and present consistent results in Table D1 in the online appendices.

4.3. Robustness Checks

To validate our empirical findings, we implemented an extensive set of analyses to support the robustness of our results. We elaborated our robustness checks using the truck attack as an example.[14]

[14] As described before, the TLC provides the drop-off information on each trip only after July 2017. Thus, we could obtain only the drop-off information when analyzing the truck attack. For the purpose of consistency, we present only the robustness checks (and also the mechanism tests and heterogeneity tests) using the truck attack as an example. Regarding the other three urban anomalies, we validated our findings with the available data. All of the findings are consistent and the results are available upon request. We also present alternative robustness checks, such as a placebo test and alternative outcome measures, in Online Appendix F.

4.3.1 Parallel Pre-Treatment Trends

The validity of the DiD approach (shown in Equation (1)) relies on a critical assumption of pre-treatment parallel trends. That is, the control and treated groups (i.e., location zones) should have parallel trends in their number of trips before the treatment (i.e., the urban anomaly) (Angrist and Pischke 2008, Bertrand et al. 2004). In other words, the parallel trends guarantee that the differences in the trends between the control and treated groups would not exist before the treatment. To validate the parallel pre-treatment trend assumption, we applied the relative time model with the inclusion of both the leads and lags in the periods (Autor 2003, Greenwood et al. 2016). Following previous studies, we executed the leads and lags model by creating new time dummies indicating the relative chronological distance between time t and event time t_e. Theoretically speaking, if we observed a significant estimate of the time dummy before treatment, it was considered to imply the existence of a pre-treatment gap between the control and treated groups. Otherwise, our data met the requirement of a parallel pre-treatment trend assumption. Mathematically, this analysis estimated the equation:

$$ln(\texttt{NumTrips}_{lt}) = \gamma_l + \texttt{PERIOD}_t + \sum_k \gamma_k \texttt{PreAnomaly}_{lt}(k) + \sum_m \gamma_m \texttt{PostAnomaly}_{lt}(m) + \varepsilon_{lt}, \quad (3)$$

where $\sum_k \gamma_k \texttt{PreAnomaly}_{lt}(k)$ allows us to examine potential false significant treatment effects prior to the urban anomalies. Specifically, $\texttt{PreAnomaly}_{lt}(k)$ equals 1 if period t is k periods prior to the event and location l is in the treated group. Similarly, $\texttt{PostAnomaly}_{lt}(m)$ is m periods after time t. Therefore, the coefficient set γ_k for $k = -J, -J-1, ..., -1, 0$ captures the pre-treatment trend of the effects. If γ_k is negative and significant, it implies that the trend of worse performance of taxi drivers than ridesharing drivers, relative to the control groups, already existed prior to the terrorist attacks. The coefficient set γ_m capture the post-treatment trend of the effects.[15] We present the estimated

[15] Note that to better interpret our estimated results, instead of using the continuous variable $\texttt{GeoProximity}_l$, we divided all locations into the treated/control groups using a binary variable: the treated group includes locations adjacent to the exact event area. In Section 4.3.2, we show that such an alternative definition yields results that are consistent with our main findings based on continuous $\texttt{GeoProximity}_l$.

results, with different specifications, in Appendix E in the online supplementary materials. The coefficients of pre-treatment indicators are statistically insignificant. This insignificance suggests that no decreasing trends existed prior to the terrorist attacks between the treated and control location zones. In other words, the observed changes in both platforms' utilization was unlikely to have been driven by a false trend starting prior to the urban anomaly.

4.3.2 Alternative Verification of Identification Strategy

We identified the causal effects of urban anomalies using the differences in the treatment effects across locations with different geographic distances. To further validate this, we conducted multiple robustness checks covering both alternative definitions of the treated/control groups and the application of an alternative data source.

First, in the above discussions, $\texttt{GeoProximity}_l$ was defined as a continuous variable, which is different from the traditional DiD framework with its clear 0/1 treatment definition. To better interpret the results, we redefined this location feature as a binary variable using different thresholds. First, we classified a taxi zone into the treated group if the distance between this zone to the event zone was smaller than the average distance across all zones within the Manhattan borough. As shown in Columns 2 and 3 in Table 5, the estimates suggest consistent findings, with observations of declines in both platforms' utilization. Next, to further test whether the treatment effects would be limited to locations close to the event area, we included only the adjacent taxi zones as the treated group. Columns 4 and 5 in Table 5 report the estimates under this threshold. Again, the results are qualitatively consistent with our main findings. Furthermore, to alleviate the potential concern that the areas with a distance around the thresholds might bias our findings, we also examined cases where the treated and control taxi zones were separate from each other. Besides, given that our identification strategy was not a standard presentation of the DiD model, it is possible that the treatment effect would disproportionately spill over to other units, which, in turn, would violate the Stable Unit Treatment Value Assumption (SUTVA). To alleviate this concern, we excluded taxi zones that were neither adjacent to nor far away from the urban anomalies. Nonetheless, we observed qualitatively consistent results, as shown in Columns 6 and 7. Interestingly, we observed a larger decline in the separate areas when compared with the adjacent areas. This was expected, because changes in traffic and demand flows might spread to adjacent areas. That is to say, the effects of the urban anomalies might spill over to locations adjacent to the exact event area. Statistically, if we included adjacent areas as control groups, the difference between the treated and control areas could be smaller. Moreover, one might be concerned that if there existed a demand or supply flow from the attack area to the adjacent areas, it could shift the utilization changes in the "control" areas. To alleviate this concern, we shortened the time window to 2 hours after the attack and reran the analyses using the above three definitions. This assumed that within a limited time, the areas far away from the attack location had not been affected by the attack via demand/supply flows or any related policies. The results (in the last two columns) support the robustness.

Table 5 Robustness Check I: Alternative Definitions of Treatment

Variables	Mean Distance		Adjacent Areas		Separate Areas		Limited Time	
	Taxi	**Uber**	**Taxi**	**Uber**	**Taxi**	**Uber**	**Taxi**	**Uber**
$\texttt{AfterAnomaly}_t \times$	-0.0744***	-0.0689***	-0.1289**	-0.0815**	-0.1565**	-0.1052***	-0.3443**	-0.1775***
$\texttt{GeoProximity}_l$	(0.0211)	(0.0183)	(0.0507)	(0.0344)	(0.0522)	(0.0352)	(0.1471)	(0.0149)
Constant	3.6543***	3.7088***	3.6294***	3.6859***	3.2734***	3.5841***	3.6410***	3.6945***
	(0.4444)	(0.0920)	(0.1046)	(0.0878)	(0.1755)	(0.2131)	(0.1051)	(0.0875)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. Observations	14904	14904	14904	14904	9720	9720	7650	7650
R-square	0.4872	0.5633	0.4872	0.5631	0.5565	0.6063	0.5383	0.5941

***p<0.01; **p<0.05; *p<0.10; Standard errors are shown in parentheses; FE includes time- and zone-fixed effects.

Furthermore, we collected an additional dataset from the Chicago Data Portal.[16] When an urban anomaly occurs in NYC, it is impossible to have an immediate impact on the Chicago

[16] Data Source: https://data.cityofchicago.org/Transportation/Taxi-Trips/wrvz-psew. We did not include this dataset in our main analyses because it only offers taxi trip data while the ridesharing trip data is only available from 2018.

transportation system thereafter. Thus, we could construct an ideal control group using the relevant Chicago information. If the observed pattern when comparing NYC and Chicago was similar to our main findings, we could conservatively conclude that our treatment/control group design did not deviate from the direction. Specifically, we collected individual taxi trip records during the truck attack (i.e., October and November 2017) and applied the same data processing strategy as for our main analyses. In total, we obtained 4,049,194 trip records and aggregated them to a (census) track-hour level. The Chicago dataset includes information on the census track, which is similar to the taxi zones in the NYC dataset. As presented in Table 6, we observed a highly consistent and decreasing trend right after the terrorist attack, which implies that our identification strategy did not alter the direction of the actual effects.

Table 6 **Robustness Check II: Additional Identification Strategy Validation**

Variables	Taxi Case
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	-0.1589*** (0.0262)
Zone and Time-sepcific Fixed-effects	Yes
Num. Observations	17,782
R-square	0.1549

***p<0.01; **p<0.05; *p<0.10; Standard errors are shown in parentheses.

4.3.3 Inclusion of MTA Information

NYC has well-developed public transportation involving both subways and buses. In 2018, the average weekday subway ridership was more than 5.4 million.[17] To further examine how public transportation networks are stressed and affect private mobile services (i.e., taxies and ridesharing platforms) during times of urban upheaval, we collected an additional dataset from the Metropolitan Transportation Authority (MTA hereafter).[18] The dataset records the entry/exit register values for each turnstile in NYC. Specifically, each record includes the station address, timestamp (at a

[17] http://web.mta.info/nyct/facts/ridership/.

[18] http://web.mta.info/developers/turnstile.html.

4-hour level), and cumulative entry and exit counts. We first geocoded the addresses using Google Map API and then assigned the addresses to the closest taxi zones using the latitude and longitude information. Because the MTA data is collected at a 4-hour level, we aggregated the number of trips to the same time window. Based on this dataset, we conducted two extra analyses: (1) MTA as the outcome, to examine how the public transportation service was stressed, and (2) MTA as an additional control, to examine whether and how the MTA data affected our main results. Table 7 presents the estimates of the above two analyses. First, we observe no changes in either the entry or exit counts of the NYC subway stations. And, our main findings remained consistent after adding the MTA data as additional controls. This indicates the robustness of our main findings and also implies that the public transportation service was relatively stable after the urban anomaly.

Table 7 Robustness Check III: Inclusion of MTA Information

Variables	**MTA Outcome**		**Trips**			
	Entry	Exit	Taxi Trips		Uber Trips	
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	0.0108	-0.0930	-0.2867***	-0.2984***	-0.1282***	-0.1389***
	(0.0861)	(0.0713)	(0.0551)	(0.0531)	(0.44)	(0.0418)
`MTAEntry`				0.0661*		0.0748**
				(0.0338)		(0.0327)
`MTAExit`				-0.0506		-0.0678**
				(0.0325)		(0.0279)
Constant	4.8905***	4.7044***	5.0238***	4.9369***	4.3700***	4.3218***
	(0.0744)	(0.0793)	(0.0747)	(0.1567)	(0.0562)	(0.1381)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Num. Observations	3,726	3,726	3,726	3,726	3,726	3,726
R-square	0.4423	0.4117	0.4264	0.4297	0.5648	0.5693

Notes: ***p<0.01; **p<0.05; *p<0.10; Standard errors clustered at the zone level in parentheses; FE includes time- and zone-fixed effects; MTA entry and exit are measured with the log value; The analysis is conducted at a 4-hour level.

4.3.4 Inclusion of Traffic Information

For safety purposes, after urban anomaly events (especially the terrorist attacks), the police temporarily shut off vehicular traffic on the streets around the site, which meant that the streets could have been congested due to evacuating traffic. There was a concern that the changes in traffic conditions, rather than the terrorist attack itself, might have driven the decreasing trends and performance divergence that are recorded in our main findings. To alleviate this concern, we collect an additional dataset to control for the traffic condition and re-estimated the model accordingly. Specifically, we used the National Performance Management Research Data Set (NPMRDS) Version 2.[19] The dataset contains average hourly speed data aggregated to each road segment. In total, it contains more than 1.5 billion traffic records within our data period. We averaged the speed value across all of the road segments within each taxi zone as a control of the traffic condition at the hourly level. The results, shown in Table 8, were consistent with our main analyses. In particular, we again observed a smaller decline in Uber's utilization rate after controlling for the traffic condition (i.e., ruling out potential congestion factors).

Table 8 Robustness Check IV: Inclusion of Traffic Conditions

Variables	Taxi Case	Uber Case
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	-0.2132*** (0.0509)	-0.1828*** (0.048)
Speed Value	-0.0311*** (0.0089)	-0.0207*** (0.0071)
Fixed-effects	Yes	Yes
Num. Observations	14,904	14,904
R-square	0.5202	0.5948

***p<0.01; **p<0.05; *p<0.10; Standard errors clustered at the zone level in parentheses; FE includes time- and zone-fixed effects.

4.4. Discussion of Underlying Mechanisms

We discuss in this section the potential explanations for our main findings. It is worth noting that though the different types of urban anomalies had diverse effects on either the taxies or ridesharing platforms, we focus herein on the comparisons between platforms (i.e., better utilization of the ridesharing platforms compared with the taxi companies) and discuss the underlying mechanisms.

The first and also the most important factor is the technological effect. Most ridesharing platforms are built on technological advantages. One such technology is its efficient driver-passenger

[19] https://ops.fhwa.dot.gov/perf_measurement/

matching system (Cramer and Krueger 2016). On the one hand, ridesharing platforms offer real-time updates on the availability of demand to ridesharing drivers via Uber's surge pricing maps or heat maps with Lyft Prime Time information. When an urban anomaly event occurs, it can dramatically shuffle the distributions and flows of demand calling for mobility services (Castillo et al. 2017, Bimpikis et al. 2019, Hall et al. 2015). Such real-time information allows ridesharing drivers to more efficiently respond to sudden demand changes, which likely leads to more efficient decisions than in the case of taxi drivers. The latter tend to follow similar daily routines and are not able to access real-time demand information. On the other hand, even though E-hail apps are available for taxi trips, most of them are completed by traditional methods, like calling the dispatch center or hailing on the street. As Guse (2020) pointed out, whereas New Yorkers can use Curb and Arro to hail yellow cabs, they are not very popular.

Another technological affordance is embedded navigation technology, which is widely accepted on ridesharing platforms. In some cases, platforms might even penalize drivers if they deviate from the suggested routes. Navigation technology could help ridesharing drivers better adjust their routes and avoid potential traffic jams due to an urban anomaly, which in turn, allows ridesharing platforms to perform more efficiently than taxi companies where drivers rely more on experience and intuition. This is also supported in Liu et al. (2021), who pointed out that the technology could reduce drivers' moral hazard and increase efficiency correspondingly. In sum, potentially, the technological advancements in ridesharing platforms strengthen the capability of ridesharing drivers not only to quickly cope with immediate demand changes and locate their assigned passengers but also to efficiently avoid street closures and traffic congestion caused by any unpredictable urban anomalies.

Apart from the technological advantages, the supply or demand elasticity due to ridesharing platforms' decentralized system could also explain why they outperform the alternative after an urban anomaly. From the supply-side perspective, as gig-economy workers, ridesharing drivers tend to have a relatively more flexible working schedule than do drivers in a traditional taxi company (Hall et al. 2018). Thus, the ridesharing platforms, as a digital peer-to-peer type of service, could have a highly elastic supply (Cullen and Farronato 2021). With unexpected urban situations, ridesharing drivers are more likely to adjust their working schedules and respond positively to observed demand inflation and potential income opportunities. From the demand side, compared with taxies, ridesharing passengers might perceive ridesharing options as a safer option, because it usually allows passengers to check drivers' backgrounds before getting into the car.[20] This preference might stand out during an urban anomaly.

We conducted multiple analyses (in Online Appendix G) to empirically identify the proposed explanations. Based on our available dataset, we concluded conservatively that the technological effect (with a focus on the dynamic matching system) and supply elasticity are the main factors behind the platforms' differences.

5. Empirical Extensions

We explore the heterogeneous treatment effects with both spatial and temporal factors. Online Appendix H presents additional extensions regarding how the presence of police stations and media coverage moderated the observed effects.

5.1. Heterogeneous Effects by Spatial Features

With the distance indicator $\texttt{GeoProximity}_l$ in our main analysis, we showed that a location zone closer to the event area was affected more by the terrorist attack. But even among location zones with similar distances to an event area, anomaly effects might vary with different spatial features. For example, a popular location might attract a higher mobile density, which leads to potentially unexpected demand after an urban anomaly event. On the other hand, a popular location tends to

[20] https://www.haffnerlawyers.com/is-uber-lyft-really-safer-than-a-taxi/

have worse traffic conditions, especially when the local area falls into disorder. In this case, fewer trips would be completed within a given time period. Thus, to further test how the treatment effects vary with spatial features, we explored the heterogeneous effects by adding the additional spatial features:

$$\begin{aligned} ln(\texttt{NumTrips}_{lt}) = & \gamma_l + \texttt{PERIOD}_t + \beta_1 \texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{Density}_l + \beta_2 \texttt{AfterAnomaly}_t \\ & \times \texttt{GeoProximity}_l + \beta_3 \texttt{AfterAnomaly}_t \times \texttt{Density}_l + \varepsilon_{lt}, \end{aligned} \tag{4}$$

where $\texttt{Density}_l$ is a proxy of the popularity/population density of location l and was measured according to the numbers of pick-ups (or drop-offs) in 2015 (before the times of the two terrorist attacks considered in this study). Table 9 reports the estimation results. Interestingly, we observed a general trend on both platforms, which is, that locations of higher popularity are affected slightly less. In other words, leaving everything else constant, the percentage changes (i.e., decrease) in platform-level utilization would be smaller in higher-population locations than in others. One potential causal factor behind this is that a popular area might attract more taxies/Uber cars to cruise around, which might bridge the gap between supply and demand after urban anomaly events.

Table 9 Heterogeneous Effects by Spatial Features

Variables	Taxi Trips	Uber Trips
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{Density}_l$	0.0044* (0.0020)	0.0072** (0.0036)
$\texttt{AfterAnomaly}_t \times \texttt{Density}_l$	0.0024 (0.0015)	0.0061** (0.0028)
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	-0.4104*** (0.0876)	-0.3653*** (0.0943)
Constant	3.8805*** (0.0524)	3.8259*** (0.0347)
Fixed effects	Yes	Yes
Num. Observations	14,904	14,904
R-square	0.4558	0.4870

***p<0.01; **p<0.05; *p<0.10; Standard errors clustered at the zone level in parentheses; FE includes time- and zone-fixed effects.

5.2. Heterogeneous Effects by Temporal Factors

In NYC, traffic conditions and demand/supply flows are time-sensitive, which leads to another important question about whether effects would be heterogeneous at different times of the day. To examine such time-varying characteristics, we divided one day into four slots:[21] midnight (12-6:30 am), rush hours (6:30-9:30 am, 3:30-8 pm), daytime (9:30 am-3:30 pm), and evening (8 pm-12 am). Then, we decomposed the main analysis by adding the following indicators of those different time-of-day slots:

$$\begin{aligned}
ln(\texttt{NumTrips}_{lt}) &= \gamma_l + \texttt{PERIOD}_t + \beta_{11}\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{RushHour}_t \\
&+ \beta_{12}\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{DayTime}_t + \beta_{13}\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{Evening}_t \\
&+ \beta_2\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l + \beta_{31}\texttt{AfterAnomaly}_t \times \texttt{RushHour}_t + \beta_{32}\texttt{AfterAnomaly}_t \times \texttt{DayTime}_t \\
&+ \beta_{33}\texttt{AfterAnomaly}_t \times \texttt{Evening}_t + \varepsilon_{lt},
\end{aligned} \tag{5}$$

where $\texttt{RushHour}_t$, $\texttt{DayTime}_t$, and $\texttt{Evening}_t$ are indicators of rush hours, daytime, and evening slots, respectively. We treated the midnight slot as the baseline. We present the estimates in Table 10 for the separate taxi and Uber cases. First, the average trends (i.e., coefficient of $\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$) remained consistent with our main findings. Interestingly, we observed that the effects were heterogeneous concerning taxi trips: the decrease in taxi utilization was smaller during rush hours or in the evening when compared with the other two slots (i.e., midnight and daytime). Unlike such a fluctuating change in taxies' utilization, the ridesharing platform was relatively stable within a single day. Probably the flexible working schedules of ridesharing drivers and the surging price mechanisms that encourage a relatively stable performance in terms of platform utilization are the explanations.

6. Conclusions

To sum up, anomalies have become critical threats to the stability of urban transportation systems. Whether the technology-equipped ridesharing platforms can efficiently respond to urban anomalies

[21] http://web.mta.info/nyct/subway/howto_sub.htm

Table 10 Heterogeneous Effects by Time-of-day

Variables	Taxi Trips	Uber Trips
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{RushHour}_t$	0.3482*** (0.1238)	0.1434 (0.1050)
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{DayTime}_t$	0.0259 (0.0870)	-0.0659 (0.0698)
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l \times \texttt{Evening}_t$	0.3443*** (0.0691)	0.0717 (0.0721)
$\texttt{AfterAnomaly}_t \times \texttt{GeoProximity}_l$	-0.4124*** (0.0376)	-0.2237*** (0.0556)
$\texttt{GeoProximity}_l \times \texttt{RushHour}_t$	-0.2192 (0.5425)	-0.3649 (0.3318)
$\texttt{GeoProximity}_l \times \texttt{DayTime}_t$	0.3515 (0.5230)	-0.1403 (0.2904)
$\texttt{GeoProximity}_l \times \texttt{Evening}_t$	0.6493** (0.2709)	0.1669 (0.1791)
Constant	3.7228*** (0.0655)	3.6918*** (0.0391)
Fixed effects	Yes	Yes
Num. Observations	14,904	14,904
R-square	0.4925	0.5656

***p<0.01; **p<0.05; *p<0.10; Standard errors clustered at the zone level in parentheses; FE includes time- and zone-fixed effects.

is an essential concern that has gained even more attention recently. In the present study, we leveraged the natural experimental setup of multiple types of urban anomalies to investigate the responding behavior of taxi and ridesharing platforms. Specifically, we focused on platform-level utilization changes, which were measured as the changes in the number of served trips. We applied a DiD econometric model to a large-scale dataset with fine-grained trip information. We showed that the Uber platform, in general, performed better than the traditional taxi companies after no-notice and unpredictable urban anomalies. We herein discuss multiple possibilities to explain the underlying mechanisms.

Several contributions stem from this work. *First*, we contribute to the literature streams on the understanding of urban anomalies and technology/emergency management. We noticed that prior studies emphasized the detection and forecast of urban anomalies with diverse data sources and algorithms, while our study started from a distinguished angle by investigating how the existing transportation services respond to urban anomalies. Meanwhile, although this research is burgeoning in its contributions to the development and improvement of technology-based systems to cope with abnormal scenarios, the present study, as far as we know, is the first to provide robust empirical evidence of relative transportation platform utilizations in response to urban anomalies. This sheds light on how the technology supports emergency management as well as how the public reacts to the adoption of technology during an urban anomaly. *Second*, we add to the streams of literature on both urban transportation and two-sided markets by comparing the platform-level performance between the traditional on-demand service market (i.e., taxi companies) and the emerging ridesharing platforms under unpredictable urban anomalies. Although prior studies have explored in-depth the differences between the two types of transportation systems (Bai et al. 2019, Cachon et al. 2017, Gong et al. 2017) under normal scenarios, or within a certain equilibrium, it remains under-explored in the literature how and why taxies and ridesharing platforms perform when a no-notice urban anomaly occurs. Furthermore, we decompose and empirically test the potential mechanisms leading to the above differences. Supplementary to prior studies (Caillaud and Jullien 2003, Cohen and Sundararajan 2015, Liu et al. 2021) that have emphasized the importance of technological advantages adopted by emerging industries when compared with traditional firms, our empirical findings suggest that the supply-side imbalance is one of the main causes of the better performance of ridesharing platforms under abnormal conditions. The above understanding allows us to offer practical implications for the design and adjustment of strategies for dealing with urban anomalies.

The present study yields the following notable policy implications. *First*, we notice that between the types of urban anomalies explored in this study, taxi companies are less capable of fulfilling passengers' needs, as we observed either larger decreases or no change in platform utilization (relative to Uber's smaller decreases or even increases after the subway shutdown). Such criticism urges both service providers and city planners to re-evaluate and improve their systems. For example, in order to stimulate the labor supply during an urban anomaly, taxi companies could design and adjust their subsidy strategies to encourage drivers to stay at work or re-allocate the supply across locations in a more efficient way. Meanwhile, considering the superior role of technology identified from our mechanism detection, city planners could try to incentivize cooperation between the two platforms, because the ridesharing platform is an important element in the urban transportation ecosystem and may complement the taxi system in various ways, especially when accommodating uncertainty with multiple advanced techniques such as real-time information presentations of supply/demand flows. For example, city planners could encourage sharing of information and technological systems during an urban anomaly. *Second*, our empirical findings suggest that passengers' preferences between the different types of transportation systems remain stable even after terrorism. In order to compensate for the decreasing trend due to a lower supply or technological deficiency, service providers might need to consider changes in either the demand or platform design during an emergency. For example, service providers could encourage drivers to take more passengers on trips. And city planners could set up certain emergency pick-up areas so that drivers outside the exact event area could have better access to the event location while avoiding potential traffic jams or road closures. *Third*, from the passenger perspective, and in light of the current design of ridesharing platforms, we noticed that Uber, in general, maintains a relatively stable utilization level. Based on this empirical finding, we suggest conservatively that passengers who have urgent needs could seek a ridesharing service first, given its relatively stable supply and technological support.

Our study is subject to several limitations that yet offer fruitful avenues for potential future research. First, our empirical analysis focused on platform-level utilization, measured as the number of served trips. This could be generalized to other dimensions, provided that more data were available. For example, future research may decompose overall platform utilization into a finer-grained level, such as utilization per capita. Second, our data allowed us only to examine successfully fulfilled trips, whereas requested but unfulfilled trips were out of our scope. This might not be problematic for our current research design, as we specifically aimed to investigate the differences between different platforms with respect to the success of evacuating users during urban anomalies.

Future studies working with additional available data could further explore how platforms allocate resources in fulfilling passengers' requests, which would provide insights into platform system designs. Third, although we conducted multiple robustness checks to verify our empirical identification strategy, we acknowledge that our main analyses might suffer from multiple potential confounders, such as reallocation of traffic (especially given that we could conduct only a taxi-zone-level analysis) or redistribution of drivers. For example, if drivers were redistributed to areas far away from the attack rather than quit the market, our estimated effect of the urban anomalies on a single platform could have been underestimated. To address this issue, future research could consider using finer-grained information. Besides, when comparing directly the efficiency between ridesharing platforms and taxis, we employed a DDD empirical model. Considering that the two types are substitutions in normal scenarios, the correlations of demand changes between the two might bias our results because the increase in one's demand might directly lead to a decrease in the other's. Though the main conclusions of our findings could not be affected (as shown in the DiD analyses), future studies could leverage some exogenous shocks applied to one platform only to address this empirical issue. Fourth, due to data limitations, we could not fully tease out all of the alternative possibilities and empirically identify additional causal factors explaining the main findings. Future research, with proper experimental designs, could improve our mechanism tests and offer more concrete practical implications for emergency management thereby.

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