HHS Public Access
Author manuscript
Inj Prev. Author manuscript; available in PMC 2022 April 01.

Published in final edited form as:
Inj Prev. 2021 April ; 27(2): 118–123. doi:10.1136/injuryprev-2020-043644.

Ridesharing and Motor Vehicle Crashes: A Spatial Ecological Case-Crossover Study of Trip-Level Data

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Abstract

Background.—Ridesharing services (e.g., Uber, Lyft) have facilitated over 11 billion trips worldwide since operations began in 2010, but the impacts of ridesharing on motor vehicle injury crashes are largely unknown.

Methods.—This spatial ecological case-cross over used highly spatially and temporally resolved trip-level rideshare data and incident-level injury crash data for New York City (NYC) for 2017 and 2018. The space-time units of analysis were NYC taxi zone polygons partitioned into hours. For each taxi zone-hour we calculated counts of rideshare trip origins and rideshare trip destinations. Case units were taxi zone-hours in which any motor vehicle injury crash occurred, and matched control units were the same taxi zone from one week before (−168 hours) and one week after (+168 hours) the case unit. Conditional logistic regression models estimated the odds of observing a crash (separated into all injury crashes, motorist injury crashes, pedestrian injury crashes, cyclist injury crashes) relative to rideshare trip counts. Models controlled for taxi trips and other theoretically relevant covariates (e.g., precipitation, holidays).

Results.—Each additional 100 rideshare trips originating within a taxi zone-hour was associated with 4.6% increased odds of observing any injury crash compared to the control taxi zone-hours (OR=1.046; 95%CI:1.032,1.060). Associations were detected for motorist injury and pedestrian injury crashes, but not cyclist injury crashes. Findings were substantively similar for analyses conducted using trip destinations as the exposure of interest.

Conclusions.—Ridesharing contributes to increased injury burden due to motor vehicle crashes, particularly for motorist and pedestrian injury crashes at trip nodes.

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Conflicts of Interest: None declared

Keywords

Ridesharing; Uber; Lyft; motor vehicle; road traffic; crash; distraction; motorist; pedestrian; cyclist

1. Introduction

Each year approximately 1.3 million lives [1] and 70 million disability adjusted life years [2] are lost in motor vehicle crashes worldwide. Reducing motor vehicle crash incidence has long been a global public health priority [3] and research identifies many primary prevention strategies that have strong empirical support, including speed management, improvements to infrastructure, vehicle safety standards, and law enforcement.[4] In addition to deliberate intervention to reduce the mortality and morbidity burden due to motor vehicle crashes, natural changes in human transportation systems can also greatly affect crash incidence. One such natural change is ridesharing, which has disrupted transportation markets across the US and globally, and which could have a marked impact on motor vehicle crash incidence.

Ridesharing is a mobile technology that enables prospective passengers to summon private owner-operator drivers to specific locations on demand. Ridesharing companies have facilitated more than 11 billion trips worldwide since operations began in 2010.[5,6] Initial Public Offerings in early 2019 for Uber, the world's largest ridesharing company, and Lyft, its largest US-based competitor, valued the companies at $82.4 billion [7] and $23 billion respectively.[8] At the same time, public transport trips have decreased by 6% in the US (9), taxi driver salaries have decreased by around 10% nationwide,[10] and the value of taxi medallions has fallen up to 50-fold in some cities.[11] Given the huge volume of ridesharing and the immense health burden due to motor vehicle crashes, even small relative associations between ridesharing and motor vehicle crash incidence could have substantial absolute impacts.

Very few empirical studies examine associations between ridesharing and motor vehicle crashes. Published analyses have mostly focused on alcohol-involved crashes and other related measures (such as DUI arrests) because of the potential for ridesharing to replace impaired driving.[12–15] These studies have yielded mixed results. For example, differences-in-differences analyses have detected associations between ridesharing and fewer alcohol-involved crashes in 540 California townships [12] and fewer impaired driving arrests and fatal crashes in 155 US cities.[13] However, a similar analysis conducted in the 100 most-populous US counties found no association between ridesharing and alcohol-involved road crash fatalities or all road crash fatalities.[14] A time-series analysis found evidence that ridesharing is associated with fewer alcohol-involved crashes in 2 of 4 US cities, but no concomitant change in all injury crashes.[15] This collective evidence suggests that ridesharing is associated with fewer alcohol-involved motor vehicle crashes in some locations; however, we know little about the effect of ridesharing on other injury crash types. Prior analyses have been uniformly limited because they use dichotomous measures for the presence or absence of ridesharing services within large space-time units (e.g. county-years). This imprecise approach limits the ability to assess dose-response relationships, ignores micro-geographic variation in the associations of interest, and may introduce aggregation bias, which increases the likelihood of false negative associations.[16]

The aim of the current study was to examine associations between ridesharing and motor vehicle crash incidence at high spatial and temporal resolution. We accessed highly spatially and temporally resolved trip-level rideshare data for New York City, which provides considerably greater precision compared to prior studies that have measured the presence or absence of ridesharing operations within space-time units using binary variables. Available outcome data enabled us to separate crash types according to the road users involved (i.e. motorists, pedestrians, cyclists). A major obstacle for spatial ecological studies of motor vehicle crashes is that vehicular traffic flow can confound associations of interest; however, researchers are rarely able to control statistically for vehicular traffic because complete and valid data (such as traffic counts) are often unavailable. Studies conducted using large space-time units (e.g. state-years) can approximate vehicular traffic using other variables (e.g. average annual daily traffic, number of licensed drivers), but this solution is not appropriate for studies conducted within small space-time units because proxy variables are unlikely to reflect variation in traffic. We addressed this denominator problem using a case-crossover design.

2. Method

2.1 Setting

The setting for this spatial ecological case-crossover study was New York City (NYC), which has a population of approximately 8.4 million and covers a land area over 302.7 square miles. The spatial units were 262 NYC taxi zones (excluding Newark Airport), which are administrative polygons that cover the extent of the city and which the NYC Taxi and Limousine Commission (the municipal authority responsible for ridesharing) uses for planning and reporting. These spatial units were partitioned into 17,520 hours from January 1, 2017, to December 31, 2018, providing a universe of 262 × 17,520 = 4,590,240 space-time units.

2.2 Data

Outcomes were injury crashes that occurred between January 1, 2017, and December 31, 2018. Per the National Highway Traffic Safety Administration's Model Minimum Uniform Crash Criteria (5th edition),[17] the New York Police Department (NYPD) maintains a registry of crashes involving death, personal injury, or property damage of $1,000. These crash-level data include the crash date, crash time, crash location (latitude, longitude), and the number of motorists, pedestrians, and cyclists killed or injured. We defined injury crashes as those in which a person was either killed or injured. In all, 98.7% of injury crashes had complete location data and could be spatially joined to the 262 taxi zones.

The primary exposure was rideshare trips. The Taxi and Limousine Commission has required since 2017 that rideshare companies submit complete trip-level data, including trip date, trip time, origin location, and destination location. NYC Council Local Law #11 of 2012 requires that NYC agencies make any comprehensively collected data publicly available,[18] and, accordingly, the Taxi and Limousine Commission releases these trip-level rideshare data on the NYC open data website.[19] Trip origins and trip destinations are masked within taxi zones to protect driver and passenger confidentiality.

In addition to the injury crash and rideshare trip data, we accessed publicly available data for other taxi trips, temperature, precipitation, government holidays, and school holidays. Taxi trip data are available in the same format as rideshare data through the Taxi and Limousine Commission, separated into yellow taxis (a general medallion) and green taxis (a restricted medallion). We calculated counts of taxi trip origins per taxi zone per hour. The National Centers of Environmental Information provided hourly temperature and precipitation data for the NYC Central Park Weather Station (99.8% of space-time units). Where these data were missing, we used data for the La Guardia International Airport Weather Station (0.2% of space-time units). School and government holiday days were measured using binary variables to reflect NYC Department of Education and NYC Office of Payroll Administration data.

2.3. Study Design

All injury crash, rideshare, taxi, and other data were aggregated within taxi zone-hours. These space-time units were dichotomized to indicate the presence or absence of a crash occurring within the spatial and temporal bounds. Rideshare trips and taxi trips were aggregated as counts of trip origins and counts of trip destinations. Temperature, precipitation, school holidays, and government holidays were spatially invariant across hours.

We addressed the problem of unknown vehicular traffic using a case-crossover design in which we compared taxi zone-hours where an injury crash occurred to the same taxi zone at the same time and day of week for different weeks. Cases were matched to controls at a ratio of 1:2, where controls were the same taxi zone at a time 168 hours (i.e., 1 week) before and 168 hours after the case. Thus, for example, an injury crash occurred in the 600 block of West 158th street at 8:55 pm on Monday, March 26, 2018. This street address is within taxi zone #244, so the space-time case unit was taxi zone #244 on Monday, March 26, 2018, from 8:00 pm to 8:59 pm, and the matched controls were taxi zone #244 from Monday, March 19, 2018, from 8:00 pm to 8:59 pm and taxi zone #244 from Monday, April 2, 2018, from 8:00 pm to 8:59 pm. This approach assumes that vehicular traffic flow is similar between matched space-time units and varies linearly within matched groups. Importantly, if one of the matched units was ineligible to be selected as a control because it contained an injury crash, controls were selected from the same taxi zone ± 336 hours. We continued this procedure for selecting matched controls in multiples of 168 hours until all case taxi zone-hours were matched to two control taxi zone-hours.

2.3 Statistical Analysis

Conditional logistic regression models estimated the odds of observing an injury crash relative to the number of rideshare trips within taxi zone-hours. Conditioning upon taxi zone ensured the statistical comparison was for temporal partitions within the spatial units. Separate models assessed associations for rideshare trip origins and rideshare trip destinations, because counts of trip origins and trip destinations were highly correlated across taxi zone-hours (r = 0.81) and these exposure variables could not be included in the same model. We first assessed associations for all injury crashes (Model 1), and then used stratified analyses to assess associations according to the road users who were injured (motorist [Model 2], pedestrian [Model 3], cyclist [Model 4]). We included taxi trips as a covariate in all models because taxi trips are likely to co-vary with vehicular traffic within taxi zone-hours and this variable therefore provides additional assurance that our results are not affected by unknown vehicular traffic. All models also controlled for temperature, precipitation, school holidays, and government holidays. A sensitivity analysis examined associations between injury crash outcomes and rideshare and taxi trip destinations as exposures.

Statistical analyses were conducted from July to September 2019 using SAS, version 9.4. This study involved no human subjects.

3. Results

A total of 83,753 injury crashes occurred between January 1, 2017, and December 31, 2018, including 54,530 that involved motorists, 20,629 that involved pedestrians, and 8,968 that involved cyclists. There were 421 fatalities. Crash counts increased slightly over the study period (Figure 1a). Rideshare companies facilitated a total of 372,957,845 rideshare trips and taxi companies provided a total of 232,230,256 taxi trips. Rideshare and taxi trip volume per week was about equal at the beginning of 2017, then rideshare trip volume approximately doubled during the study period while taxi trip volume decreased slightly (Figure 1b).

The space-time units of analysis for this study were taxi zone-hours, and from the universe of 4,590,240 taxi zone-hours, 81,716 (1.8%) contained any crash, including 53,525 (1.2%) that contained any motorist crash, 20,453 (0.4%) that contained any pedestrian crash, and 8,880 (0.2%) that contained any cyclist crash. Figure 2 shows the spatial distribution of injury crashes across the 262 taxi zones. There was a mean of 81.3 rideshare trip origins and 50.6 taxi trip origins per taxi zone-hour for all taxi zone hours during the study period (Figure 3). Within the taxi zone-hours included in the analyses, there was a mean of 113.6 rideshare trip origins in the case units (SD = 118.6) and 111.1 rideshare trip origins (SD = 115.7) in the control units ($p < 0.001$). Full descriptive statistics for the included case and control units are shown in Table 1.

Table 2 presents the results of the conditional logistic regression models. Model 1 shows that an increase of 100 rideshare trip origins (approximately double compared to the mean within taxi zone-hours) was associated with 4.6% increased odds of observing any injury crash within a taxi zone-hour (OR = 1.046; 95%CI: 1.032, 1.060). We detected no association between taxi trips and all injury crashes (OR = 0.994; 95%CI: 0.977, 1.011). In the stratified analyses, rideshare trips were associated with increased odds of observing motorist crashes (Model 2: OR = 1.044; 95%CI: 1.025, 1.062) and pedestrian crashes (Model 3: OR = 1.061; 95%CI: 1.035, 1.087), but there was no association for cyclist crashes (Model 4: OR =

1.016; 95%CI: 0.983, 1.050). Results for rideshare trip destinations were substantively similar compared to the results for rideshare trip origins (Supplementary Table S1).

4. Discussion

Ridesharing is a mobile technology that has altered public and private transportation markets worldwide. Prior studies suggest the availability of rideshare services is associated with fewer alcohol-involved crashes, but little is known regarding the effect of ridesharing on other motor vehicle crash types. This spatial ecological case-crossover study identified that ridesharing trips are associated with increased incidence of motor vehicle injury crashes at trip origins and trip destinations, and that associations were detectable for injury crashes involving motorists and pedestrians but not cyclists.

These findings help explain the mixed results in previous studies of ridesharing and motor vehicle crashes. Some prior studies find ridesharing is associated with fewer alcohol-involved crashes,[12–14] but associations differ across geographic contexts and are not observed for all injury crashes (i.e. combining alcohol-involved and non-alcohol-involved crashes).[15] These studies were critically limited because authors aggregated data within large spatial and temporal units and used dichotomous measures for the presence or absence of ridesharing services. By contrast, we used spatially and temporally specific trip-level data for New York City and separated crashes according to victim type. Our main finding—that ridesharing was associated with increased crash incidence for motorists and pedestrians at trip origins and destinations—suggests that any benefits of ridesharing to reduce alcohol-involved crashes may be offset by increases in motorist and pedestrian crashes at trip nodes. Studies aggregating data within large space-time units may not detect these associations due to aggregation bias. Studies combining alcohol-involved and non-alcohol involved crashes may yield null results due to the simultaneous opposing effects.

Two main mechanisms may explain for our findings. First, ridesharing produces net increases in vehicular traffic [9,10,20] which will raise the number of interactions between motor vehicles and other road users [21] and will produce additional expected crashes. This increased vehicular traffic is due to rideshare drivers travelling between passengers, and to ridesharing replacing public transit, cycling, and walking for some trips. Although this mechanism may apply, it does not explain why we observed additional crash incidence relative to rideshare trips but not taxi trips. Second, rideshare companies connect drivers and prospective passengers through mobile applications, and imbedded GPS tracking provides live continuous updates regarding driver and passenger locations. Both the driver and the passenger must monitor the GPS signal in order to meet, and distraction due to cell phones is associated with increased crash risks for motorists [22–25] and pedestrians.[26,27] Thus, the additional motorist and passenger crashes may be due to distracted driving and walking. Similarly, rideshare companies have recently begun sending messages imploring passengers to look out for cyclists when exiting vehicles, in order to reduce crashes between cyclists and open vehicle doors.[28] Our results indicate this crash type is no more common for rideshare vehicles than taxis or other vehicles in New York City.

This study has many strengths. It is the first to use highly resolved spatial and temporal data for rideshare trips and motor vehicle crashes. These data enabled us to assess dose-response relationships and assess differential associations according to injury crash type. Further, our study design almost wholly excludes the possibility that ridesharing marks for increased overall vehicular traffic within the small space-time units, meaning that observed increases in crash incidence were likely due to an association specific to ridesharing rather than an association that applies generally to all road users. Our case-crossover design compares taxi zone-hours to the same taxi zone from prior and subsequent hours on the same day of the week, thereby accounting methodologically for routine vehicular traffic flow. We further controlled for taxi trips because these vehicles do not use GPS monitoring to connect drivers and passengers and taxi traffic is likely to co-vary with vehicular traffic. That we detected no association between taxi trips and injury crashes suggests our study design fully accounted for vehicular traffic, and that the association between ridesharing and injury crashes is unlikely to be confounded by traffic flow.

We also acknowledge important limitations. Although taxi zone-hours are far smaller space-time units than those used in previous studies, our results may still be affected by aggregation bias. We cannot be certain that rideshare trips and injury crashes were co-located, only that they tended to occur in the same taxi zone and during the same hour. We also lacked data regarding the involvement of rideshare vehicles in crashes, which would facilitate individual-level confirmation of these ecological associations. The high correlation between rideshare trip origins and rideshare trip destinations limits our ability to fully assess differential associations for these trip nodes. For example, it is possible that bicycle crash incidence is greater at trip destinations but not trip origins, and the effect for the latter attenuates the parameter estimates. We were also unable to assess motor vehicle crash incidence along the route path between rideshare trip origins and rideshare trip destinations, and where crashes occurred on taxi zone boundaries we relied on small random noise in the precise geocodes to join crash points to taxi zones. Future studies could use spatial interpolation (e.g. kernel density methods) to estimate trip routes and continuous trip densities. Finally, our results may not generalize beyond the study region. Private motor vehicle use is uncommon in NYC compared to other US cities, and the overall impacts of ridesharing on mobility and on crash incidence may differ between locations and impede external validity.

Ridesharing has had a remarkable impact on urban transportation in just a few short years since operations began. Continued linear growth means the technology could substantially impact human movement, with potential implications for the global injury burden due to motor vehicle crashes. This research indicates that ridesharing is associated with increased incidence of motor vehicle and pedestrian crash incidence at trip origins and trip destinations in NYC. Future research should assess these associations in different geographic contexts, such as in cities with less public transit availability, more private motor vehicle use, and different roadway configuration.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Funding Sources:

This study was funded by the National Institute for Alcohol Abuse and Alcoholism (K01AA026327) and the Centers for Disease Control and Prevention (R49-CE003094).

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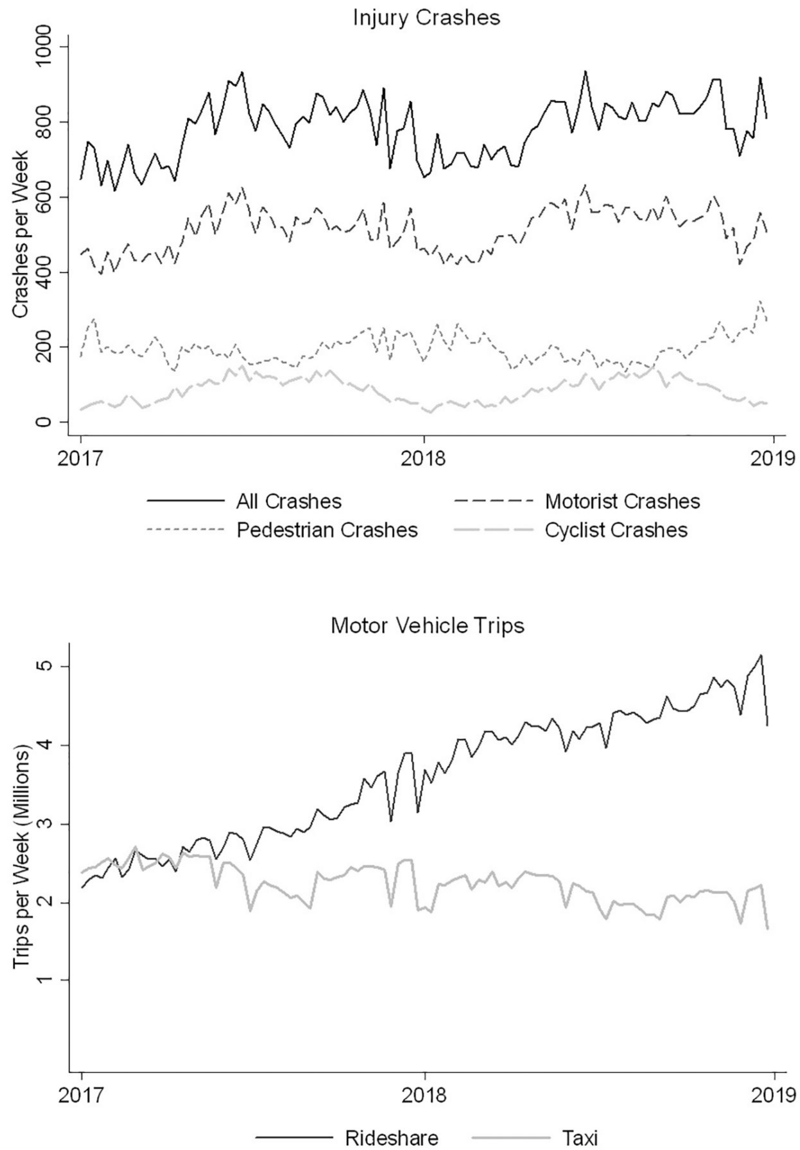

Figure 1.
Injury crashes and motor vehicle trips per week; 2017–2018

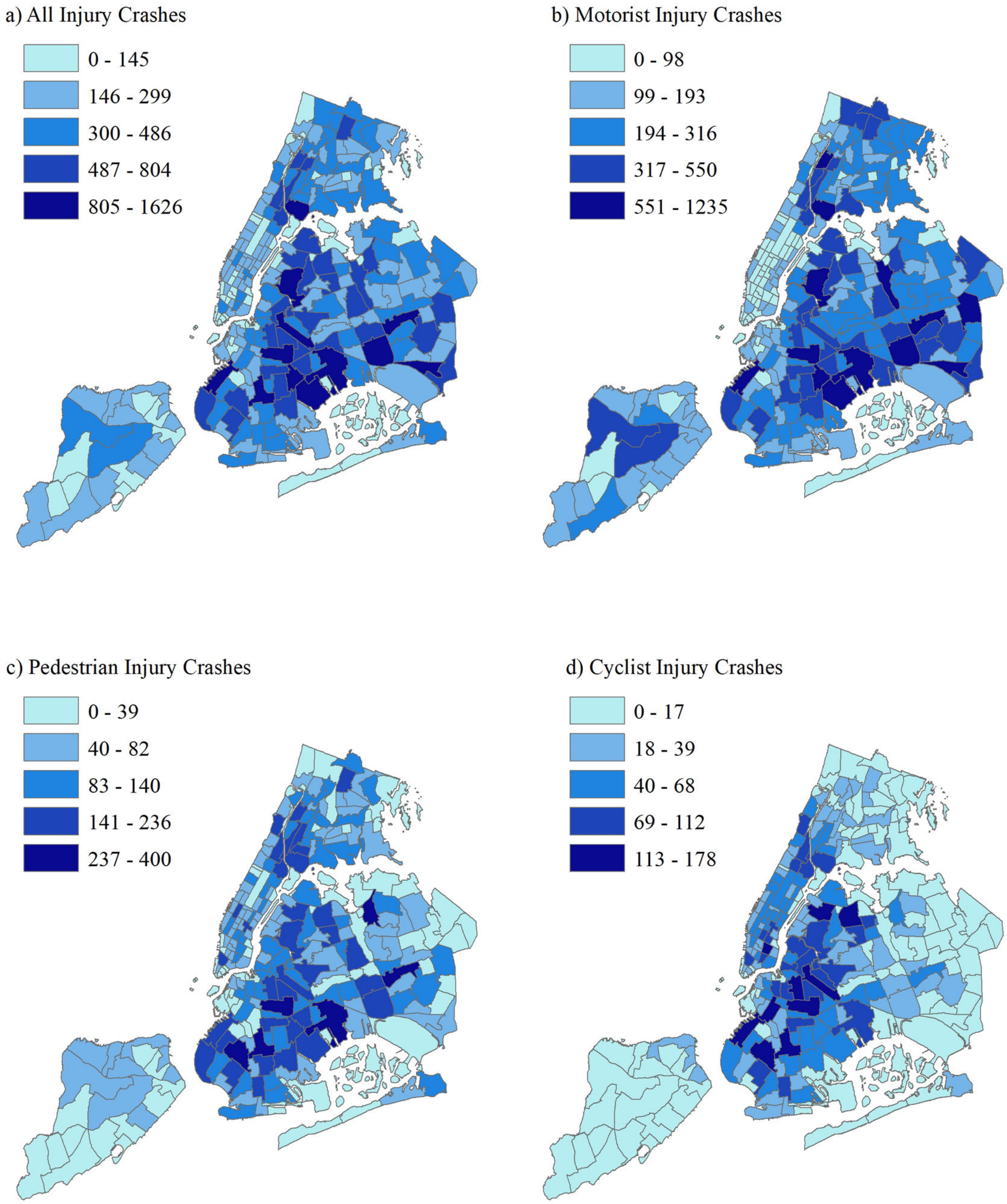

Figure 2.
Injury crashes per taxi zone; 2017–2018

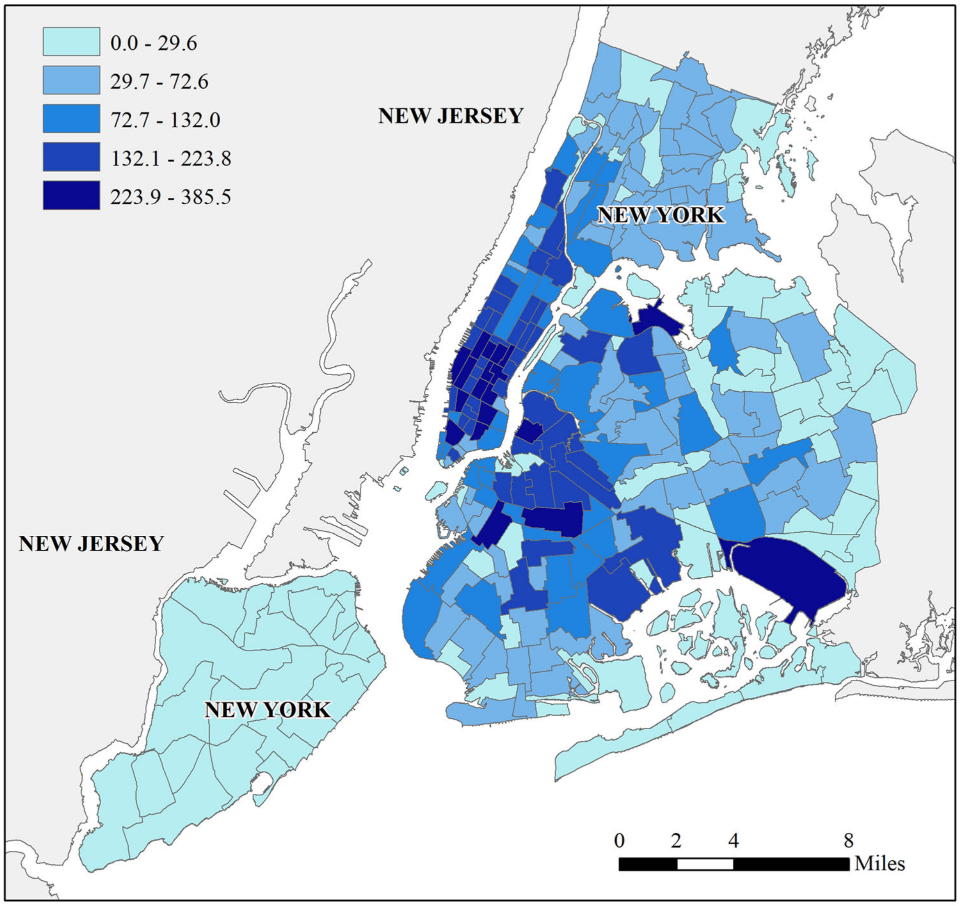

Figure 3.
Mean rideshare trips per hour; NYC taxi zones, 2017–2018

Table 1.

Descriptive statistics for case taxi zone-hours in which any injury crash occurred and 2 matched control taxi zone-hours; January 2017- December 2018.

	Case (n=81,716)		Control (n=163,432)		p-value
	mean	***(SD)***	***mean***	***(SD)***	
Rideshare trips (origins)	113.56	(118.61)	111.09	(115.74)	<0.001
Rideshare trips (destinations)	97.94	(119.68)	96.45	(117.82)	0.003
Taxi trips (origins)	47.55	(126.44)	46.79	(124.55)	0.155
Taxi trips (destinations)	48.59	(115.62)	47.99	(114.32)	0.223
Temperature (degrees Farenheit)	58.19	(17.66)	57.85	(17.79)	<0.001
Precipitation (inches)	0.01	(0.03)	0.00	(0.03)	<0.001
	n	**%**	**n**	**%**	
Any holiday	2724	3.3	6318	3.9	<0.001
School not in session, not holiday	4620	5.7	10035	6.1	<0.001

Table 2.

Conditional logistic regression models for taxi zone-hours in which any injury crash occurred compared to 2 matched control taxi zone-hours; January 2017- December 2018. Outcomes are all injury crashes (Model 1; n = 245,148 taxi zone-hours), motorist crashes (Model 2; n = 159,756 taxi zone-hours), pedestrian crashes (Model 3; n = 61,359 taxi zone-hours), and cyclist crashes (Model 4; n = 26,640 taxi zone-hours). Exposure of interest is rideshare trip origins.

	Model 1: All injury crashes			**Model 2: Motorist crashes**			**Model 3: Pedestrian crashes**			**Model 4: Cyclist crashes**		
	OR	**95%**	**CI**	**OR**	**95%**	**CI**	**OR**	**95%**	**CI**	**OR**	**95%**	**CI**
Rideshare trips (per 100 increase)	1.046	(1.032,	1.060)	1.044	(1.025,	1.062)	1.061	(1.035,	1.087)	1.016	(0.983,	1.050)
Taxi trips (per 100 increase)	0.994	(0.977,	1.011)	0.986	(0.962,	1.011)	0.989	(0.960,	1.019)	1.032	(0.989,	1.077)
Temperature (per 10 degree increase)	1.010	(1.006,	1.015)	1.008	(1.002,	1.014)	1.010	(1.000,	1.020)	1.039	(1.023,	1.056)
Precipitation (per 0.1 inch increase)	1.155	(1.121,	1.190)	1.069	(1.032,	1.108)	1.633	(1.523,	1.751)	0.869	(0.771,	0.980)
Any holiday	0.872	(0.833,	0.913)	0.906	(0.857,	0.958)	0.789	(0.718,	0.866)	0.844	(0.727,	0.980)
School not in session, not holiday	0.933	(0.900,	0.967)	0.940	(0.899,	0.983)	0.866	(0.807,	0.930)	1.049	(0.936,	1.175)