Assessing the impact of a local community subsidized rideshare program on road traffic injuries: an evaluation of the Evesham Saves Lives Program

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Abstract

Background—Alcohol related vehicle crashes pose a significant challenge to public health in suburban communities. The Evesham Saves Lives program operated between late 2015 and 2018 in two townships (Evesham and Voorhees) in New Jersey. The program subsidized rideshare (e.g. Uber) trips from bars and restaurants between the hours of 9pm and 2am to prevent alcohol related traffic injuries.

Methods—This study used data from the New Jersey Department of Transportation to examine changes to rates of injury crashes between 2010 and 2018. We used an ecological difference-in-difference design with Bayesian conditional autoregressive (CAR) Poisson models to compare rates of injury crashes between participating municipalities (n=2) with non-participating municipalities (n=75). Sensitivity analyses included comparison with a weighted synthetic control series.

Results—The Evesham Saves Lives program was associated with 18% fewer injury crashes overall (Incidence Rate Ratio [IRR]= 0.82, 95% Credible Interval [CrI]: 0.76,0.88). Reductions in crashes were estimated to be greatest at night (IRR=0.62, 95% CrI: 0.48,0.79), with moderate reductions in the afternoon (IRR=0.80, 95% CrI: 0.72,0.88). We estimate that around three lives

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Contributors
DKH and CM conceived of the study, data collection was undertaken by all authors, analysis was led by CM, MDE and FGW. DKH and CM wrote the manuscript with significant contributions by MDE, FGW and MK. All authors read and edited the manuscript prior to submission.

Competing Interests
None declared

Conflicts of Interest: None declared

were saved (95%CrI: 2,5) and around 371 injuries were prevented (95% CrI: 204,625) potentially making considerable savings in terms of medical and economic expenses.

Conclusions—These findings support the claim that improving the convenience and reducing the costs of alternative night-time transportation can prevent road traffic injuries. Future studies should aim to replicate these analyses in programs that have been implemented in other suburban communities across the U.S.

Keywords

Rideshare; drink-driving; vehicle crashes; injuries; difference-in-difference analysis

1. Introduction

Motor vehicle crashes are a leading cause of fatal and non-fatal injuries in the United States (U.S.). Since the turn of the millennium there have been, on average, 39,000 motor vehicle deaths per year—equating to over 100 deaths per day.[1] According to the National Highway Traffic Safety Administration (NHTSA) approximately 29 percent of all motor vehicle fatalities in the U.S. are related to alcohol impairment, which is estimated to result in economic costs of around $44 billion, including lost productivity and medical costs, among others.[2,3] While aggregate rates of motor vehicle fatalities have decreased substantially during the last century, they remain one of the top contributors to premature mortality across all demographic groups.[4] Clear disparities are observable between communities, with rural and suburban communities experiencing higher fatality rates,[5] more problems with alcohol-impaired driving, and crashes of greater severity.[6]

The introduction of ridesharing services (e.g. Uber, Lyft, Didi.) has transformed traditional transportation systems across towns and major cities throughout the world.[7,8] In 2018 the US National Academies of Sciences, Engineering, and Medicine conducted a comprehensive review of strategies to reduce alcohol-involved crash deaths, identifying the use of smartphone-enabled ridesharing to provide alternative transportation as an area of great promise for reducing alcohol impaired driving fatalities.[6] Theoretically, access to subsidized ridesharing can help to prevent drunk driving and its consequences (i.e. crashing, injury or criminal penalties) by both: (a) reducing the financial costs of late-night private transportation (e.g. taxis); and (b) enhancing the convenience of private transportation through technological smartphone platforms that match demand with supply to provide a quick and convenient door-to-door transport solution.[9]

To date, few empirical studies have examined the impact of ridesharing services on vehicle crashes and the findings from available studies is mixed. Several U.S. studies have taken advantage of the variation in the timing of the roll out of Uber or Lyft, which are the two main rideshare service providers in that country. These studies have identified significant reductions in aggregate rates of motor vehicle crashes,[10] reductions in alcohol-related driving deaths in California townships,[11] and considerable reductions in alcohol-related vehicle collisions in New York City.[12] Similarly, in a study capitalizing on abrupt breaks in Uber service in four US cities (Las Vegas, Reno, Portland and San Antonio), Morrison and colleagues found reductions in alcohol-involved vehicle crashes associated with the resumption of Uber services in some cities (e.g. Portland and San Antonio), but not in others (e.g. Reno).[13]

Conversely, other studies found that the introduction of rideshare services may be associated with adverse effects. For example, Barrios et al. found that the introduction of Uber and Lyft services in U.S. cities were associated with a 3% increase in total vehicle fatalities.[14] Analysis of event-level data from New York City by Morrison et al., found that increases in ridesharing were associated with increases motor vehicle and pedestrian crashes at pick up and drop off locations.[15] Brazil & Kirk found the deployment of Uber services in the 100 most populated metropolitan U.S. counties had no association with changes in general traffic fatalities or alcohol impaired driving fatalities, either during weekends or holiday periods.[16] Studies examining the introduction of rideshare services in non-U.S. contexts have increased in recent years, echoing the mixed nature of findings represented in the U.S. literature.[17–19]

Motor vehicle crashes that occur following public consumption of alcohol place a considerable burden on public health. It has been acknowledged that emerging technologies, such as rideshare services may be able to prevent alcohol-impaired driving by improving the convenience and reducing the costs of alternatives to personal transportation. Given this potential, the National Academies of Sciences, Engineering, and Medicine report emphasized that such services should be encouraged and incentivised in suburban and rural areas to boost alternative transportation.[6] On this basis, some communities have begun subsidizing rideshare platforms to provide safe night-time travel for local residents.[20,21] To our knowledge, no studies have evaluated the impact of such community programs on traffic safety. In this study we examine the effect of one of the first programs of this kind, the Evesham Saving Lives program, which operated in two New Jersey municipalities (the Townships of Evesham and Voorhees) between 2015 and 2018. We examine the association between the program and rates of motor vehicle-related injury crashes overall and stratified by time of day and county subgroup.

2. Method

2.1 Setting

The setting for this study was Burlington and Camden Counties in New Jersey, which have a combined land area of 1,047.3 square miles and which had a combined 2018 population of 952,462. New Jersey counties are divided geographically into municipalities. There are 40 municipalities in Burlington County, including Evesham Township (2018 population: 45,060), and 37 municipalities in Camden County, including Voorhees Township (2018 population: 29,239). We partitioned municipalities by calendar year from 2010 to 2018, thus our sample of space-time units was 693 municipality-years (77 municipalities; 9 years).

2.2. Intervention

The Evesham Saving Lives program began in September 2015 as a shuttle service from bars and taverns in Evesham Township.[22,23] With funding from local philanthropic organizations, the program provided travel home from the municipality's 19 licensed on-premise alcohol outlets upon presentation of proof of residence. In October 2015, the Mayor of Evesham, Randy Brown, announced that service had expanded to include the adjacent municipality of Voorhees, and that the Townships had partnered with Uber to make the service available via the ridesharing app.[24] Residents could access a subsidized trip up to $30 from a bar or tavern within Evesham or Voorhees to their home within these Townships between the hours of 9pm and 2am. In September 2017, Mayor Brown announced that the service had provided between 5,000 and 6,000 rides at a cost of approximately $10,000.[25,26]

2.3. Data

The outcome of interest was motor vehicle injury crashes that occurred between January 1, 2010, and December 31, 2018. In accordance with the National Highway Traffic Safety Administration's Model Minimum Uniform Crash Criteria (5th edition),[27] the New Jersey Department of Transportation maintains a registry of crashes involving death, personal injury, or property damage of $1,000. These crash-level data are publicly available online.[28] We defined injury crashes as those in which a person was either killed or injured and calculated counts of injury crashes per municipality-year. We also calculated counts of injury crashes within time of day categories (morning: 5am-12:59pm; afternoon: 1pm-8:59pm; and night: 9pm-4:59am). The night time subgroup included the hours during which the intervention was active (9pm-2am), plus additional time to account for journeys that occurred while drivers remained impaired.

American Community Survey 5-year estimates for 2010–2018 provided time-varying population characteristics for the included municipality-years. Theoretically relevant characteristics that could confound associations between the intervention and injury crashes were population size, median age, percent male, percent of workers who commute by motor vehicle, median household income, and composition by racial and ethnic background (non-Hispanic White, non-Hispanic Black, Hispanic, Asian, and other). We also calculated a composite index of concentrated disadvantage by standardizing the sum of the percent of the population with access to a motor vehicle, percent of the population living below the poverty line, percent of the population aged ≥ 16 years that is unemployed, percent of households that were female headed, and percent of households that are renters ($\alpha = 0.66$). This approach is consistent with other studies that use census data to generate indices of concentrated disadvantage within small areas composed of variables that are theoretically relevant to the local context (cite). A TIGER line file from the US Census Bureau provided a count of roadway meters per municipality. There were no funds available for patient and public involvement in this study and therefore we were unable to involve patients.

2.4 Design

We used a spatial ecological difference-in-difference design. A spatially-defined dichotomous variable identified Evesham and Voorhees Townships as intervention municipalities and the remaining 75 municipalities as controls. A temporally-defined dichotomous variable identified 2010–2015 as pre-intervention years and 2016–2018 as post-intervention years. A difference-in-difference term was the product of the spatially-defined and temporally-defined variables, such that Evesham and Vorhees were coded 1 for 2016–2018 (n = 6) and all other municipality years were coded 0 (n = 687).

Bayesian conditional autoregressive (CAR) Poisson models related injury crash counts to the spatially-defined intervention variable, the temporally-defined intervention variable, and the difference-in-difference term. Models adjusted for 2018 population and time-varying demographic characteristics, and included a fixed effect for year (to account for linear trends over time in injury crashes) and a fixed effect for Camden County (to account for differences between counties). Total roadway miles per municipality was entered as a time-invariant offset variable to derive injury crash rates per miles. The main model assessed associations for rates of all injury crashes. Additional analyses stratified by time of day categories and county subgroups. Bayesian posteriors estimated absolute impacts within the 6 municipality-years affected by the intervention by subtracting the linear combination of the fixed effects and the CAR random effects for these space-time units with the difference-in-difference term specified as the observed value of 1, from the linear combination with the difference-in-difference term set to a value of 0. Sensitivity analyses used different pre-intervention years (2013–2015) and included an indicator variable to identify municipalities adjacent to Evesham and Voorhees Townships (n = 9).

Spatially autocorrelated errors can artificially reduce standard errors, leading to possible Type I error.[29] We accounted for spatial autocorrelation using a conditional autoregressive random effect specified using queen's contiguity for municipality boundaries. This approach controls for over-dispersion of the count outcomes and for the small area problem by "borrowing strength" from surrounding areas.[30] In WinBUGS v14, two MCMC chains stabilized over 50,000 iterations before a further 50,000 iterations provided the median estimate and 95% credible intervals.[31]

We included an additional synthetic control analysis as a robustness check.[32] The synthetic control analysis served to guard against selection bias by using a data-driven technique to identify the best data fitting control series and address the parallel trends assumption.[33] We derived a weighted control series for rates of all injury crashes per 100kms for the intervention municipalities (Evesham and Voorhees [averaged]) between 2010 and 2018. The weights for the synthetic control series were identified using mean squared prediction errors (MSPE) to minimize systematic differences between pre-intervention trends (2010 to 2015) in rates of injury crashes per 100kms, as well as theoretically relevant area-level characteristics (see above for the full list of confounders and Table S4). The donor pool consisted of 75 control municipalities that did not implement the Evesham Saving Lives program (see Figure 1). Synthetic control analyses were run in R (version 3.5.2) using the "Synth" package.[34]

3. Results

In total, 63,103 injury crashes occurred in Burlington and Camden counties from 2010–2018, including 733 (1.1%) fatalities. Table 1 presents descriptive statistics for the 18 municipality-years for Evesham and Voorhees and the 675 municipality-years for the control locations. There were no differences in the crude crash incidence per 100 roadway kilometers between the intervention and control municipalities. Figure 2 shows that the trends for crash incidence per 100 roadway kilometers were approximately parallel during the pre-intervention period, after which time crash incidence in Evesham and Voorhees decreased markedly compared to the control locations.

In the Bayesian Poisson models (Figure 3), the parameter estimate for the difference-in-difference term indicated that the intervention was associated with 18 percent fewer injury crashes overall in Evesham and Voorhees compared to non-intervention municipalities (IRR = 0.82, 95%CrI: 0.76, 0.88) (Figure 3). Associations were strongest at night, with 38 percent fewer crashes estimated between 9pm-4:49am (IRR = 0.62, 95%CrI: 0.48, 0.79), but also estimated reductions of 11 percent in the morning (IRR = 0.89, 95%CrI: 0.79, 1.01) and 20 percent in the afternoon (IRR = 0.80, 95%CrI: 0.72, 0.88). Results were similar for the subgroup analysis within only Burlington County and for the sensitivity analyses (Table S2, Supplementary Materials). A total of 1,190 injury crashes occurred in the 6 municipality-years of Evesham and Voorhees from 2016–2018, and the main Bayesian model predicted a total of precisely 1,190 injury crashes (95%CrI: 842, 1,704). Our analysis estimates that the Evesham Saving Lives initiative prevented around 268 injury crashes (95% CrI: 147, 451) and, on the basis that 1.1% of injury crashes in Burlington and Camden during the study period were fatal and that injury crashes, on average, result in 1.38 person injuries per crash, we estimate that around three lives (95% CI: 2, 5) were saved and around 371 injuries prevented (95% CI: 204, 625).

The synthetic control analyses replicated these findings. The synthetic control showed good pre-intervention fit, more closely representing the intervention municipalities (see Table S4) and improving the parallel trends during the pre-intervention period (Figure S1). Rates of injury from crash incidence per 100 roadway kilometers in the synthetic control series mirrored the mean of the control series—following an upward trend after 2016—while the intervention units also follow a sharp decrease relative to the synthetic control after 2016 (Figure S2). In summary, the results from the synthetic control analyses supplement and support the main findings and help to rule out selection bias and non-parallel trends as plausible alternative explanations for the observed reduction in injury crashes in Evesham and Voorhees following the introduction of the program.

4. Discussion

The Evesham Saves Lives program was a low-cost intervention utilizing a $10,000 investment from local businesses aimed at subsidizing safe trips from local bars and restaurants using smartphone rideshare technologies. We estimated that the program prevented 371 injury crashes, including 3 fatal crashes, with the largest effects appearing to occur at night-time, when most alcohol impaired driving typically occurs. Our results suggest that the intervention has had a substantial effect on injuries, which may have resulted in significant savings to the local economy. To our knowledge, this is the first study to examine the effects of rideshare services in a non-urban context and the first study to examine a community funded program to subsidise rideshare trips to residents frequenting local alcohol outlets.

These findings offer further support for the claim that both reducing the financial costs and improving the convenience of alternative transport can impact on rates of vehicle crashes potentially related to alcohol consumption,[9] which is consistent with some other studies of rideshare services and vehicle crashes.[10–13] Unlike previous studies, this study was set in a suburban context where the potential impact of the intervention on the hypothesised theoretical mechanisms (i.e. cost and convenience) may be stronger than urban contexts. Research has found that around 73% of motor vehicle crash fatalities take place in suburban areas, where the public transportation network maybe unreliable and where residents are highly dependent on personal vehicular transportation.[35] Furthermore, such environments may present greater dangers in terms of more hazardous road conditions (e.g. narrow curves, absence of medians, etc) and higher maximum speeds, which may make controlling vehicles under the influence of alcohol more challenging.[36,37] As a consequence, initiatives that can jointly improve the convenience and accessibility (i.e. through new technologies) of transportation, while also limiting financial disincentives (i.e through local subsidies) may have the potential to make substantial practical difference to the convenience of night-time travel in non-urban locations.[6]

This study has a number of important limitations. Firstly, we lacked access to trip level data to assess whether changes in rideshare trips mediated associations between the Evesham Saving Lives and crash incidence, which could be important for understanding why patterns of injury crashes fluctuate from year to year in the post-intervention period. Second, the crash data used here did not allow us to determine the fraction of injury crashes attributable to alcohol. Third, this independent evaluation was conducted without input from the mayoral offices of the Townships of Evesham and Voorhees, therefore we were unable to draw conclusions about the financial sustainability or practical challenges there may have been. Attempts by email and telephone to contact these offices were unsuccessful, so we relied on media reports regarding implementation and funding of the initiative. As a result, we were forced to make assumptions about the extent to which the initiative was implemented as planned. Fourth, we found associations between the intervention and reduced crash rates in the target areas at all times of the day, which could be indicative of either spill over effects on transport-related behaviours to times of the day when the intervention was not operating (i.e. interrupting patterns of daytime drink-driving, where delayed drinking may have occurred in order to meet the eligibility times after 9pm), or the presence of an unknown confounder impacting on outcomes (day-time injury crashes) not hypothesised to be affected by the Evesham Saves Lives intervention.

Our analytical design aimed to address some of the limitations inherent in these methods by using conditional autoregressive random effect terms to adjust for spatial autocorrelation and by incorporating synthetic control techniques to assess the robustness of our comparison units to selection bias and non-parallel trends. However, these analyses may still be subject to other biases, including measurement bias in the police reports of injury crashes and unmeasured confounding.[38] Future research should formally examine the cost-effectiveness of these programs using rigorous designs. While our analyses focus on the benefits of subsidising rideshare trips, we were unable to examine any potential adverse effects that could emerge from such an intervention.[39] For example, the intervention could inadvertently promote increased alcohol consumption in the local population, which could impact on a range of other outcomes (e.g. violence, domestic abuse, drug use, etc).[40]

Conclusion

The Evesham Saves Lives program was an intervention utilising smartphone enabled ridesharing services that were subsidized from philanthropic donations to two suburban New Jersey townships between 2015 and 2019. The program was designed to prevent local residents drinking and driving home from local bars and restaurants. The results of this study found that this service was associated with significant post-intervention reductions in night-time injury crashes and suggests that the modest investment by the local community may have had considerable cost savings in terms of the medical and economic costs. These findings extend the literature studying the impact of ridesharing services on road traffic crashes, suggesting that these services may also be useful in supplementing transport alternatives for suburban communities in which public transportation is often lacking.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors would like to acknowledge Madison Little (University of Oxford) who helped with some of the initial data collection.

Funding Sources:

This study received funding from the Centers for Disease Control and Prevention (R49-CE003094) and the National Institute for Alcohol Abuse and Alcoholism (K01AA026327).

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What is already known on this subject

- The absence of public transportation in suburban and rural communities is a potential risk factor for drink driving
- There is some evidence to suggest that the introduction of rideshare technologies can prevent vehicle crashes by providing a cheaper and more convenient alternative to some forms of alternative late-night transportation.

What this study adds

- This study provides evidence that fully subsidized transportation in suburban communities using rideshare technologies is associated with reductions in rates of injury from vehicle crashes.
- Rideshare technologies can be utilized by local officials to supplement provisions for late-night transportation from bars and taverns in settings where alternatives to driving are lacking.

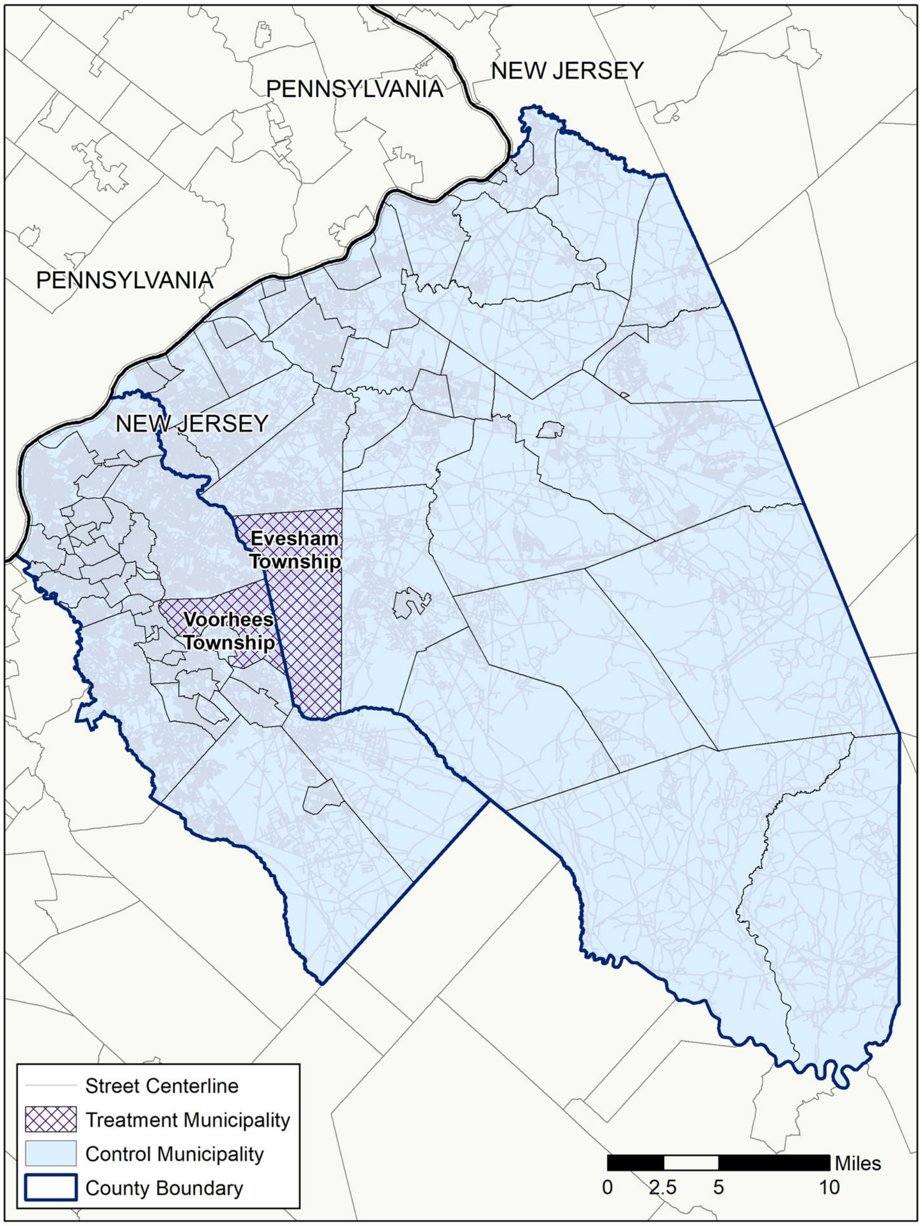

Figure 1.
Study region, New Jersey counties and municipalities 2010–2018 (n = 693 municipality-years).

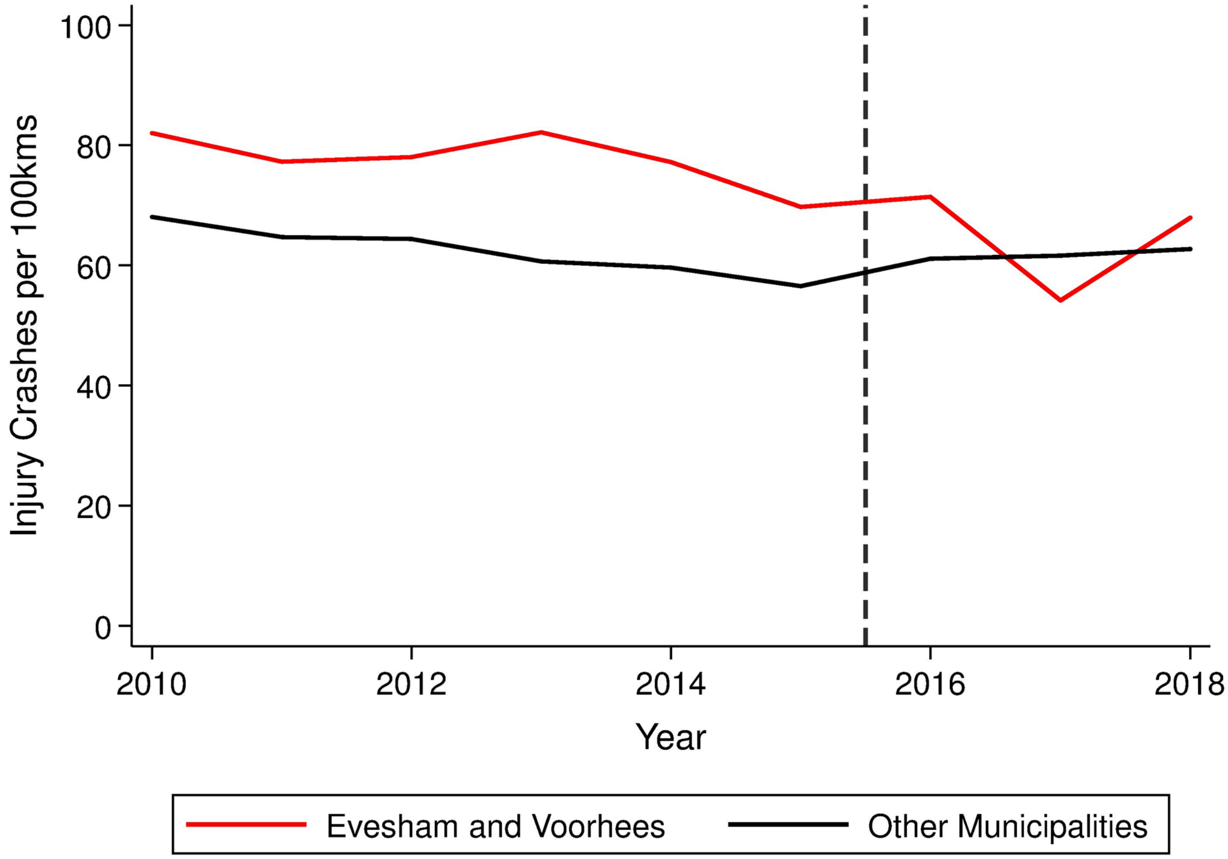

Figure 2.
Trends per year for mean injury crashes per 100 kilometer (km) for Evesham and Voorhees (cases) and other municipalities (controls), 2010–2018.

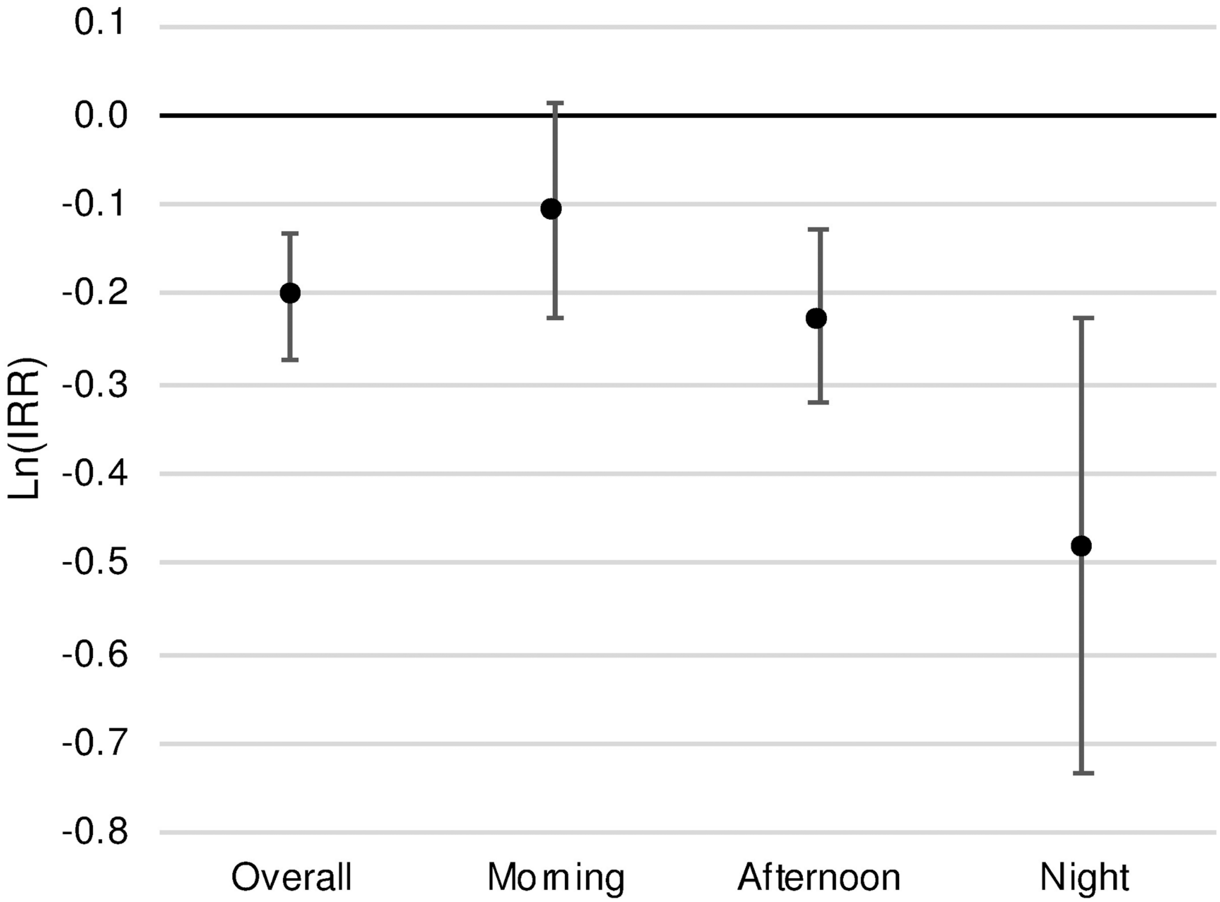

Figure 3.
Naturally logged incidence rate ratios for difference-in-difference terms for Bayesian conditional autoregressive Poisson models for counts of all injury crashes, morning crashes (5am-12:59pm), afternoon crashes (1pm-8:59pm), and night crashes (9pm-4:59am); Burlington and Camden Counties 2010–2018 (n = 693 municipality-years).

Table 1.

Injury crashes, rates per 100 roadway kilometres (km) and demographic characteristics; Burlington and Camden Counties 2010–2018 (n = 693 municipality-years).

	Treatment (n = 18) mean (SD)		Control (n = 675) mean (SD)		t-test
Injury crashes (count)					
All times	225.2	12.0	87.5	5.2	<0.001
Morning (5am-12:59pm)	19.8	2.1	11.5	0.7	0.069
Afternoon (1pm-8:59pm)	79.5	3.5	29.5	1.7	<0.001
Night (9pm-4:59am)	123.6	7.1	46.1	2.8	<0.001
Injury crashes (per 100km)					
All times	73.3	2.6	62.2	1.8	0.325
Morning (5am-12:59pm)	26.1	1.0	20.5	0.6	0.152
Afternoon (1pm-8:59pm)	40.8	1.6	33.3	1.0	0.232
Night (9pm-4:59am)	6.3	0.5	8.2	0.3	0.347
Demographic Characteristics					
Population	37372.4	1972.9	11818.2	574.9	<0.001
Age (median)	42.0	0.4	40.2	0.2	0.107
Male (%)	48.2	0.2	49.2	0.2	0.406
Vehicle commuters (%)	87.4	0.7	88.1	0.2	0.537
Median household income ($)	87056.4	1510.2	72589.6	795.7	0.003
Hispanic (%)	3.7	0.2	9.1	0.3	0.008
Non-Hispanic White (%)	75.7	2.1	70.7	0.8	0.317
No-Hispanic Black (%)	6.8	0.5	13.9	0.6	0.044
Asian (%)	11.5	1.4	3.4	0.1	<0.001
Concentrated Disadvantage	142.6	1.0	150.1	0.9	0.162