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Abstract: The Data Driven Approaches to Crime and Traffic Safety approach identifies opportunities where a single enforcement deployment can achieve multiple objectives: reduce collision and crime rates. Previous research focused on modeling both events separately despite evidence suggesting a high correlation. Additionally, there is a limited understanding of the impact of Mobile Automated Enforcement (MAE) on crime or the impact of changing a deployment strategy on collision and crime dates. For this reason, this study categorized MAE deployment into three different clusters. A random-parameter multivariate Tobit model was developed under the Bayesian framework to understand the impact of changing the deployment on collision and crime rates in a neighborhood. Firstly, the results of the analysis quantified the high correlation between collision and crime rates (0.86) which suggest that locations with high collision rates also coincide with locations with high crime rates. The results also demonstrated the safety effectiveness (i.e., reduced crime and collision rates) increased for the clusters that are associated with an increased enforcement duration at a neighborhood level. Understanding how changing the deployment strategy at a macro-level affects collision and crime rates provides enforcement agencies with the opportunity to maximize the efficiency of their existing resources.

Keywords: Mobile Automated Enforcement; traffic safety; Tobit model; random parameter; multivariate; collision rates; crime rates; photo radar

1. Introduction

Enforcement agencies are pressured to create programs to increase safety by reducing rates of collisions and crime but they are typically asked to complete these goals using limited and strict resources and budgets. Early research has shown that the highest rate of traffic citations per officer experienced the lowest rates of crime as well as a reduced frequency and severity in traffic crashes [1]. The underlying premise is that the presence of more traffic officers provided more opportunities for them to identify high-risk drivers as well as discourage the presence of criminals in both targeted and surrounding areas. This phenomenon led to the creation of a new data-driven approach that integrates location-based traffic collision and crime data to optimize their deployment strategy and resources. This new approach is referred to as the Data Driven Approaches to Crime and Traffic Safety (DDACTS).

Any successful DDACTS program has three distinct elements: (1) targeting locations, (2) perceived correlation between collisions and crime, and (3) creating a visualization or a map. The first element includes a shift in the premise of where enforcement occurs. Instead of focusing enforcement efforts by targeting high-risk individuals, the DDACTS focuses on high risk locations. This shift addresses any concerns that exist as a result of preconceived notions regarding how enforcement is conducted and rather emphasizes that the approach is scientific and based on informative analytics [2].



Citation: Ibrahim, S.; Sayed, T. Using Bayesian Tobit Models to Understand the Impact of Mobile Automated Enforcement on Collision and Crime Rates. *Sustainability* **2021**, *13*, 6422. https://doi.org/10.3390/su13116422

Academic Editor: Marco Guerrieri

Received: 4 May 2021 Accepted: 24 May 2021 Published: 5 June 2021

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). The second element recognizes that locations with a high frequency of crashes also overlapped visually with locations with a high frequency of crime. Michalowski [3] explained this relationship by suggesting that the premise for this is the aggressive and violent tendencies of people that manifests itself in all aspects of their life. This relationship is intuitive and logical despite that it has only been quantified recently in the literature [4,5].

The final element focuses on creating tools to help enforcement agencies visualize this overlap between collisions and crime to analytically identify the high crash locations and hotspots. These tools vary in complexity, ranging from a display of collision and crime counts on a map to more statistically advanced techniques which involve accounting for spatial autocorrelation. Together, these three elements form the framework for enforcement agencies so they could incorporate the DDACTS model in the deployment of their policing resources [6].

Evaluations of the DDACTS programs found significant reductions in events, collisions, and crime [7]. However, there were limitations related to the data, methodology, and statistical rigor that were applied [8]. The first limitation was related to the level of aggregation; most of the analysis was conducted at a national or city-level. This type of aggregation ignores trends in collisions and traffic volumes as well as any other confounding variables that could impact the results. This means that a more appropriate unit of analysis is required to better inform a strong deployment strategy. The second limitation is the type of analysis that was conducted. Most of the research utilized simple before/after evaluation which suffers from site-selection bias and the regression-to-the-mean effect [9,10]. A more statistically rigorous methodology can address these limitations and can accurately quantify the effectiveness of the DDACTS programs.

Another limitation of previous work was the focus on manned enforcement; none of the DDACTS programs highlighted or isolated the impact of mobile automated enforcement (MAE) specifically. Previous work has shown the impact that MAE has on improving safety by namely reducing collisions and criminal incidents [5], however, there is a need to further explore the impact of the deployment strategy itself on collisions and crime rates to optimize the use of the enforcement resources. For this reason, the objective of this paper is to determine the impact of MAE deployment strategy on both collision and crime rates by investigating the ratio of how often to visit a site per year and the length of time spent enforcing a site for each visit, at a neighborhood level.

2. Previous Work

2.1. Data Driven Approaches to Crime and Traffic Safety (DDACTS)

When researchers generated collision and crime hotspots, the results indicated that many locations exhibited a high frequency of both events. The result suggested that targeting those common hotspots could be an effective tool to focus the deployment of enforcement resources. The most common approach to generate the hotspot locations (i.e., locations that experience both a high frequency of crime and collisions) using DDACTs is the kernel density method. However, this approach is quite simplistic since it uses the observed frequency of criminal incidents and collisions [4]. Additionally, this approach cannot accurately identify a location as a hotspot since it does not account for regression-to-the-mean bias and other confounding factors [11]. Takyi et al. [4] proposed addressing these limitations by developing two sets of negative binomial models to separately predict collisions and crime. Based on these results, the authors identified collision and crime hotspots at a zonal level. These locations, referred to as the DDACTS locations, were then prioritized for enforcement activities to reduce collisions and crime, concurrently.

Past evaluations of the DDACTS programs have demonstrated that this program was effective at reducing collisions and criminal incidents [7]. In Baltimore, Maryland, a reduction of 16.6% was found in burglaries, 33.5% in robberies, and 40.9% reduction in vehicle thefts as a result of the enforcement agency's DDACTS deployment strategy. Similarly, LaFourche Parsh, Louisiana, reported a decrease in collisions (between 12.8% and 14.7%) as well as a decrease in crime (9.4%), at locations where the DDACTS approach

was applied [12]. St. Albans, Vermont, saw a reduction of 27–38% in crime and 19–25% in collisions [13]. Metropolitan Nashville, Tennessee, also reported success with the DDACTS program. They experienced their lowest crime rate in 1985 and the lowest fatality collisions in five years [14].

The results of the evaluations that have been completed demonstrate the effectiveness of the DDACTS approach. However, each jurisdiction followed a different enforcement strategy. The operational plans differed in the number of officers that were assigned to this program, as well as the duration of the enforcement period. Additionally, each police force had different enforcement methods which varied across agencies (e.g., the St Albans police force implemented a Neighborhood Watch program) and had different levels of public awareness and educational campaigns to increase the visibility of this program. Due to all these different elements, isolating the impact of one strategy and evaluating its effectiveness is quite challenging and has not been possible.

2.2. Automated Enforcement

Speed is at the core of traffic injuries and fatalities [15]. Speed and the impact it has on the severity of the outcome of a collision is well investigated and has been thoroughly documented in the literature [16]. The Nilsson Power model, a commonly used approach to predict the change in collisions resulting from a change in the speed of a vehicle, suggests that a 1 km/h increase in the average speed of a vehicle is associated with an increase of 4–5% increase in fatal collision occurrence [17]. To address this concern, enforcement agencies developed different enforcement approaches to manage and reduce speeds on the roads. These approaches vary from manned enforcement to automated enforcement to a combination of both. Manned enforcement involves a police officer who uses a speed measurement device to determine which vehicles are exceeding the speed limit. However, this approach is resource-intensive, costly, and could pose a significant risk to the officer (e.g., if enforcement is needed on high-speed roads) [18]. To address these challenges, MAE programs were devised to be used in combination with manned enforcement to create a complement of different enforcement tools.

MAE programs have been shown to improve safety and previous research demonstrates their safety impacts. In Victoria, Australia, an evaluation of mobile speed cameras revealed a reduction of 20% in daytime injury and fatal crashes, and 27.9% in collision severity, statewide [19]. In British Columbia, Canada, an increase in the photo radar enforcement presence reduced daytime unsafe speed-related collisions, daytime injuries by 11%, daytime fatalities by 17%, and speed by 2.4 km/h [20]. In France, the use of photo radar led to a significant reduction in fatal and non-fatal injuries [21]. While these evaluations demonstrate the safety benefits associated with using MAE programs, aggregating the results at a state or a national level does not account to changes in collision trends, traffic volume, as well as other confounding factors that can negatively impact the quality of the statistical results [22,23].

To address this high level of aggregation, MAE programs were also evaluated at a road segment level. In South Wales, United Kingdom, an evaluation of the use of MAE estimated a reduction of 51% in injury collisions for road segments 500 m downstream and upstream of the location of the camera [24]. In Friesland, Netherlands, a similar evaluation showed a 21% reduction in injury collisions at locations where the cameras were located [25]. In Edmonton, Canada, an evaluation of the effectiveness of the MAE program showed collision reductions that ranged between 14% and 20% [18]. The results also indicated that a higher level of collision reduction was associated with sites with longer deployment hours. Further investigation of the impact of the enforcement indicators on the program's outcomes showed that as the number of speed related collisions decreased, the number of enforced sites and issued tickets increased [26]. Recent research also investigated the effectiveness of MAE on roads with different speed limits [27]. A meta-analysis was conducted to evaluate the effectiveness of MAE as well as point-to-point cameras and revealed that the use of MAE resulted in a 20% reduction in crashes [28]. While all of these

studies provide further evidence of the success of MAE programs, at such a micro-level, inference regarding an overall deployment strategy is challenging to make. For this reason, a more appropriate unit of analysis is needed.

Recent research identified that a more robust unit of analysis to address the concerns associated with high-level aggregation (i.e., at a national/city level) as well as the micro-level aggregation (i.e., intersection). Ibrahim and Sayed [5,29] investigated the impact of MAE on collisions at a Traffic Analysis Zone (TAZ) level. The authors found that collision reductions for each TAZ were associated with spending a longer time enforcing a site for each visit in a deployment. The authors also found that an increase in the number of tickets that were issued to drivers who exceeded the speed limit resulted in a decrease in all collision severities.

Most of the research on MAE programs has been focused on studying their impact on speed and collisions; one study did investigate their impact on crime [29]. In this study, the authors quantified the correlation between collisions and crime. The results of their analysis also revealed that an increased enforcement presence resulted in a reduction in collisions and crime. While these results are very promising, further investigation is needed to fully understand the impact of the deployment strategy not only on collisions but also on crime. Since MAE is part of a complement of enforcement strategies, understanding the impact that MAE has on crime would assist in the planning of their resources as it allows agencies with an opportunity to achieve multiple objectives from a single deployment.

3. Methodology

While more research has been focused on modeling collision frequencies, recent research has shown that Tobit regression models provide some advantages [30,31]. Instead of using collision counts, this technique considers collision rates which neutralizes the effect of the exposure variable and measures the risk of collision involvement [32–34] and was first applied by Anastasopoulos et al. [29] in the field of traffic safety. Since then, other studies applied the Tobit model to understanding the influencing factors of collision rates [33,35].

However, traditional Tobit models ignore the unobserved heterogeneity that is present across observations in the data. Ignoring this inherent variability could lead to incorrect inferences and may lead to a bias in parameter estimates. To address this, researchers have proposed developing random parameter Tobit models to analyze collision rates and to overcome this limitation [30,35–41]. More recent studies have also attempted to account for the correlation between collision severities by developing multivariate Tobit models. Anastasopoulos [42] developed a random parameter multivariate Tobit model to account for the unobserved heterogeneity of collision injury rates by severity. Other research also developed a random parameter multivariate Tobit model to analyze the crash rate by injury severity and found significant heterogeneous effects of estimates which varied across observations [43,44]. Guo et al. [45] modeled the correlation and heterogeneity in crash rates by different collision types by developing a random parameters multivariate Tobit model.

Unlike analysis of collision frequencies, there were no studies conducted to analyze the impact of automated enforcement on collision and crime rates. For this reason, a random parameter multivariate Tobit model will be developed in this paper. The correlation between collision rates and crime rates can be confirmed using this model and the impact of changing the deployment parameter (e.g., increased time spent enforcing a site) can be understood.

The random parameter multivariate Tobit model for fitting collision and crime rates is given as:

$$Y_i^{k*} = \beta_{i0}^k + \beta_{i1}^k X_{i1}^k + \beta_{i2}^k X_{i2}^k + \dots + \beta_{ij}^k X_{ij}^k + \epsilon_i^k$$
(1)

where Y_i^k is the dependent variable for the *k*th event (k = 2, 1 for collision rate, and 2 for crime rate), X_i^k is the explanatory variable for observation *i*, and β_i^k is the coefficient

corresponding to the kth event. The random parameters $(\beta_{i1}^k, \beta_{i2}^k, \dots, \beta_{ij}^k)$ are assumed to be multinormally distributed as $\beta^{ij} \sim N_k(B_j, \phi_j)$, where,

$$\beta^{ij} = \begin{pmatrix} \beta_{ij}^1 \\ \beta_{ij}^2 \\ \cdots \\ \beta_{ij}^K \\ \beta_{ij}^K \end{pmatrix}, \beta^j = \begin{pmatrix} \beta_j^1 \\ \beta_j^2 \\ \cdots \\ \beta_j^K \\ \beta_j^K \end{pmatrix}, \emptyset_j = \begin{pmatrix} \varphi_{11}^{j2} & \varphi_{12}^{j2} & \cdots & \varphi_{1K}^{j2} \\ \varphi_{21}^{j2} & \varphi_{22}^{j2} & \cdots & \varphi_{2K}^{j2} \\ \cdots & \cdots & \cdots & \cdots \\ \varphi_{K1}^{j2} & \varphi_{K2}^{j2} & \cdots & \varphi_{KK}^{j2} \end{pmatrix}$$
(2)

4. Data Description

In this paper, the macro-level models were created based on 206 neighborhoods in the city of Edmonton (COE). Each explanatory variable was aggregated based on the neighborhood geographical boundaries that were provided by the COE.

4.1. Crime and Collision Data

The crime data were extracted from the COE Open Data Catalogue. As part of the crime assessment conducted by Edmonton's police force, seven indicators of crime are captured and monitored by the neighborhood. Those include: the number of assaults, number of break and enters, number of robberies, number of sexual assaults, number of reported incidences of thefts from vehicle, number of reported incidents of vehicle thefts, and number of homicides. These criminal indicators were grouped into two categories: personal and property crimes. A personal crime is defined as a criminal incident that is committed against an individual; conversely, a property crime is defined as an incident that is related to a property. This study focused on personal crime. Since the exact location of these criminal incidents was not provided due to privacy concerns, the aggregate number was used for each neighborhood.

Collision data were extracted for each of the 206 neighborhoods based on the COE database. A collision is defined by an event that involved at least one motor vehicle which resulted in at least CAD 2000 worth of damage and which occurred on public road right of way within the COE boundaries.

All data points were extracted for both collisions and crime for the same three-year period: 2013 to 2015 inclusive. Table 1 summarizes the collision and crime data that were used in this study.

Variable	Symbol	MIN	MEAN	MAX	STDEV
# Criminal Incidences (3 yrs)	crime	8	305	1371	177
Total # Collisions (3 yrs)	collisions	17	314	1629	220

Table 1. Summary of crime and collision data.

4.2. Exposure Data

In order to account for traffic volumes and to calculate the collision rate, Vehicle-KM-Traveled (VKT) data were needed. These data were obtained from the COE's Emme/2 model output files. The EMME/2 is a travel forecasting and transportation planning model which includes four different stages: trip generation, trip distribution, trip mode, and finally, trip assignment [46]. The model outputs include a variety of different transportation planning indicators including the VKT data which can be aggregated by zone or neighborhood. This VKT variable was used to model traffic exposure for the collision data.

Alternatively, the traffic volume cannot be used as an exposure variable for crime due to the lack of relationship between increased traffic volume in a neighborhood and the rate of criminal incidents. Previous research on the topic of development models to predict different crime indicators used the population data as a means of exposure. Therefore, for this paper, the results of the 2014 Municipal Census in the City of Edmonton were used to calculate the crime rate. Since the population data were already aggregated by neighborhood, no further analysis was needed. Table 2 summarizes the exposure variables for both collisions and crime.

Table 2. Summary of volume and population data.

Variable	Symbol	MIN	MEAN	MAX	STDEV
Vehicle KM Traveled	VKT	1152	6296	26,998	4196
Population	рор	345	3263	15,038	1950

4.3. MAE Data

The final dataset that was used for this analysis was the MAE data shown in Table 3. The COE uses photo radar devices that are installed in marked and unmarked vehicles to conduct speed enforcement. A trained peace officer is in the vehicle at all times to observe and make a note of violating vehicles. The officers use the devices to monitor and record any violations by vehicles that exceed the speed limit of the road. The data used in this paper are related to the COE's deployment strategy and include two indicators: *hpersite*, the number of hours spend enforcing a site for each visit, and *vpersite*, the number of times a site was visited. These indicators characterize the enforcement strategy and were aggregated by neighborhood to match the other datasets that were generated in this analysis. The time period for the extracted data was taken from 2013–2015 inclusive. The assignment of the enforcement data followed the same process as the collision data.

Table 3. Summary of MAE data.

Variable	Symbol	MIN	MEAN	MAX	STDEV
Average # hours spent enforcing a site	hpersite	13	44	495	71
Average # of visits for each enforcement site	Vpersite	5	30	174	25
The ratio of hours of enforcement per site to the frequency of visits per site	ratio	1	2.3	3.2	0.5

Since the two variables *hpersite* and *vpersite* are clearly highly correlated, they were not used directly in the model. Instead, a new indicator was the calculated *ratio* which was ratio of the hours of enforcement per site to the frequency of visits per site. In order to account for the heterogeneity, the deployment parameter *ratio* was divided into three different clusters. These clusters were generated using the FASTCLUS Procedure in SAS. This approach performs a disjoint cluster analysis based on the distance that is computed from one or more quantitative variable [47]. As a result, the data were separated into the three different clusters, the first cluster is *ratio* between 1 and 1.9 h of enforcement per visit per site, and the third and final cluster is *ratio* between 2.7 and 3.2 h of enforcement per visit per site.

5. Results and Discussion

To understand how varying the MAE deployment strategy impacts collision and crime rates, a random parameters multivariate Tobit model was developed. Table 4 summarizes the parameter estimates. The posterior summaries were computed using WinBUGS with two chains with 100,000 iterations with a burn-in sample of 10,000. The results of the BGR statistics and the ratios of the Monte Carlo errors compared to the standard deviation of the estimates and the model parameter trace plots indicated convergence. As shown in the table, the parameter estimates were all statistically significant at the 95% credible interval. The coefficient of the *ratio* indicator is positive for cluster 1 and negative for clusters 2 and 3; this suggests that longer enforcement duration per visit was associated with lower collision rates. This indicates to agencies that the highest safety benefits can be yielded from a single deployment when enforcement is conducted for a longer time period per shift per visit.

Variable		Estimate	STDEV	95% Confidence Interval				
Collisions								
Intercept	b ₀ [Cluster 1]	29.3	6.5	23.0	45.3			
	b ₀ [Cluster 2]	135.4	15.9	117.0	170.1			
	b ₀ [Cluster 3]	36.3	4.5	32.1	50.1			
	b ₁ [Cluster 1]	18.4	3.2	14.2	26.2			
Ratio	b ₁ [Cluster 2]	-43.5	4.8	-38.2	-54.1			
	b ₁ [Cluster 3]	-26.2	2.6	-33.8	-23.5			
	Crime							
	b ₀ [Cluster 1]	15.8	4.0	6.6	20.5			
Intercept	b ₀ [Cluster 2]	85.0	18.7	40.9	102.7			
_	b ₀ [Cluster 3]	20.5	6.6	7.1	28.8			
	b ₁ [Cluster 1]	11.8	2.0	7.2	14.1			
Ratio	b ₁ [Cluster 2]	-28.1	5.7	-14.8	-33.6			
	b ₁ [Cluster 3]	-17.0	4.0	-22.2	-8.9			
Correlation								
0.86								
	DIC							

Table 4. Parameter estimates and 95% confidence intervals.

The results are also similar for crime rates; where the coefficient of *ratio* is also negative for clusters 2 and 3. This indicates that an increased presence of enforcement activity is associated with a reduction in the crime rate. This also confirms the results of previous research that MAE is also successful in reducing incidences of crime, specifically, at locations where enforcement is conducted for longer durations. This reinforces the need to include MAE as a part of the DDACTS approach and to expand the scope of the program to not only focus on manned enforcement.

The random parameter multivariate Tobit model also quantified the correlation between collision and crime rates and is estimated at 0.86, which is a highly significant result. This means that locations that are identified as high crash hotspots were also very likely to be high crime hotspots. This confirms the premise of the DDACTS approach and provides further evidence that modeling these two events independently, as they have historically been in past research, results in imprecise road safety analysis and evaluation.

6. Conclusions

The DDACTS approach has been shown to improve crime and collisions across jurisdictions due to the highly correlated nature of both events. However, jurisdictions have applied the DDACTS approach very differently (e.g., number of officers designated to a deployment, hours of enforcement during each time period, the type of enforcement being conducted). This makes it very challenging to attribute the reductions in collisions or crime to one specific tool in their deployment strategy. Additionally, it makes it difficult for road safety agencies to understand the impact of a specific change in their enforcement strategy on collisions and crime. For this reason, this paper aimed to understand the impact of MAE on collision and crime rates and to better understand how different deployment parameters affect both events. The results confirmed the premise of the DDACTS approach since both collision and crime rates were highly correlated. The correlation of 0.86 indicates that locations with a high frequency of collision rates were also very likely to have high crime rates which suggests that continuing to model both events independently is inaccurate. Additionally, the results showed that increasing MAE was associated with reduced collision and crime rates, confirmed by results of clusters 2 and 3. The analysis demonstrates the impact of the deployment strategy, specifically that spending a longer time enforcing a site is needed to see benefits in both collision and crime rates. Since the findings of this

study are limited to the City of Edmonton, future work would build upon the work in this paper to develop models to understand the impact of MAE on collision and crime in other jurisdictions. Additional related work could develop more models that investigate different variables that could impact both collisions and crime rates. Future research could also include understanding the diminishing impact of higher values of *ratio* on neighborhoods to better optimize the use of enforcement resources.

Author Contributions: Conceptualization, S.I. and T.S.; methodology, S.I. and T.S.; software, S.I.; validation, S.I.; formal analysis, S.I.; investigation, S.I. and T.S.; data aggregation, S.I.; writing—original draft preparation, S.I.; writing—review and editing, S.I., and T.S.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: This research was made possible through the support from the Safe Mobility Section.

Conflicts of Interest: The authors declare no conflict of interest.

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