Evaluating the Impact of Technology-Based Law Enforcement on Traffic Accidents and Injuries: Evidence from Taipei City

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Abstract

This paper investigates the impact of technology-based law enforcement on traffic accidents and injuries, using data from Taipei City between 2022 and 2023. Specifically, it examines the effects of automated enforcement devices on the frequency of traffic accidents and the incidence of injuries. Employing a Difference-in-Differences (DiD) approach, we analyze accident rates before and after the activation of enforcement devices, controlling for factors such as vehicle density and weather conditions. The results suggest that the activation of these devices is associated with reductions in both traffic accidents and injuries, though these effects are not statistically significant at conventional levels. The reductions are localized primarily within 10 to 15 meters of the devices. Despite the lack of statistical significance, the findings provide valuable insights into the potential of technology-based law enforcement to improve urban traffic safety and inform future policy decisions on the broader implementation of such devices.

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1 Introduction

Traffic accidents, particularly those resulting in injuries or fatalities, continue to pose significant risks to public safety and well-being. In Taiwan, from January to September 2024, over 290,000 accidents occurred, leading to more than 2,000 deaths and 380,000 injuries[1]. In response, the government has increasingly turned to technology-based law enforcement systems aimed at deterring traffic violations, reducing accidents, and enhancing road safety. As smart city initiatives gain traction, these enforcement technologies have become integral to urban traffic management. However, a critical question remains: Do these technological interventions effectively reduce traffic accidents, and if so, how significant is their impact?

The research question addressed in this study is: *Does technology-based law enforcement effectively reduce the number of traffic accidents?* Specifically, we investigate the effect of automated enforcement devices on both the frequency of traffic accidents and the incidence of traffic injuries. Our primary hypothesis is that the activation of these devices leads to a reduction in traffic accidents, while a secondary hypothesis suggests that such technology also reduces the number of injuries resulting from these accidents.

To address this question, we employ a Difference-in-Differences (DiD) approach to analyze traffic accident and injury data from Taipei City between 2022 and 2023. This study effectively utilizes the rollout of automated enforcement devices as a natural experiment, allowing for a clear comparison of accident rates before and after their activation at specific locations. Our model robustly controls for variables such as vehicle density and weather, effectively isolating the impact of these enforcement devices.

The results show that while the activation of enforcement devices is associated with reductions in both traffic accidents and injuries, these effects do not reach statistical significance at conventional levels. The reductions appear to be localized, primarily within 10 to 15 meters of the devices. Although the effects are not statistically significant, the

[1] Source: Road Safety Mobilization, https://roadsafety.tw/AccLocCbi

findings provide important insights into the potential of technology-based law enforcement in improving urban traffic management.

The paper is organized as follows: Section 2 outlines the data and sample, and Section 3 details the empirical methodology used in the analysis. Section 4.1 and 4.2 present graphical evidence and main results, followed by robustness checks in Section 4.3. Finally, Section 5 discusses the findings and suggestions for future research.

2 Data and Sample

2.1 Data

This study utilizes datasets sourced from *data.taipei* to conduct the empirical analysis. Specifically, we utilize three datasets: (1) Traffic Accident Data [2], which provides panel data for the years 2022 and 2023; (2) Traffic Accident Detail Data [3], which offers more granular accident information; and (3) Equipment Data [4], a cross-sectional dataset detailing law enforcement equipment, including the locations and activation times of enforcement devices. The Traffic Accident Data and Detail Data contain comprehensive records of accidents, while the Equipment Data focuses on the enforcement devices. We merge these datasets by calculating the distance between accident locations and enforcement devices, categorizing observations by time periods to enable trend analysis and assessments of equipment distribution. Additionally, we incorporate variables such as weather conditions and vehicle registration statistics to enrich the analysis.

One notable limitation of these data is the absence of detailed device-level information. For example, weather data are aggregated at the city level, which may reduce the accuracy of localized weather impact analysis.

[2] Traffic Accident Data, https://data.taipei/dataset/detail?id=0554bac7-cbc2-4ef3-a55e-0aad3dd4ee1d

[3] Traffic Accident Detail Data, https:// data.taipei/ dataset/ detail? id=2f238b4f-1b27-4085-93e9-d684ef0e2735

[4] Equipment Data, https://td.police.gov.taipei/cp.aspx?n=6FEDE1F9DBFD656E

2.2 Sample

Our sample consists of traffic accident incidents that occurred within specific distances (e.g., 10 meters, 15 meters, and 30 meters) of traffic enforcement devices in Taipei City. The dataset spans the period from June 2022 to December 2023. We define the treatment group as incidents near enforcement devices activated on December 1, 2022, and the control group as incidents near devices activated after January 1, 2024. For each enforcement device, we calculate the monthly count of accidents occurring within the defined distances and classify them by accident type. Descriptive statistics are provided in Tables 1 for different distances. These statistics are reported separately for the treatment and control groups to highlight differences in traffic patterns around activated enforcement devices. Our final sample includes 19 months of data for 44 enforcement devices, with 20 devices in the treatment group and 24 devices in the control group.

3 Empirical Specifications

Our empirical strategy uses a Difference-in-Differences (DiD) approach to estimate the causal effect of technology-based law enforcement on traffic accidents. The regression equation is specified as follows:

$$Y_{it} = \alpha(D_i \times Post_t) + \boldsymbol{X}it\beta + \lambda_i + \gamma_t + \varepsilon it, \tag{1}$$

where Y_{it} represents the outcome variable (either the number of accidents $Accident_{it}$ or the number of injuries $Injury_{it}$ within 10 meters at location i in time period t. The dummy variable D_i indicates whether location i has implemented enforcement technology, while $Post_t$ equals 1 for post-intervention periods and 0 otherwise. The interaction term $D_i \times Post_t$ is the key variable of interest, with its coefficient α capturing the causal effect of the intervention.

To control for unobserved heterogeneity, λ_i denotes location-specific fixed effects, which account for time-invariant characteristics of each site, encompassing both district-level and site-level variations. Additionally, γ_t denotes time fixed effects, which capture month- and year-specific trends. The control variables X_{it} include factors such as the number of cars and motorcycles per thousand people, the number of rainy days per month, and the average monthly temperature. The error term ε_{it} captures unobserved factors that influence the number of traffic accidents.

This DiD approach relies on two critical assumptions: the parallel trends assumption and the exogeneity assumption. The parallel trends assumption ensures that, without the intervention, the treated and control groups would have experienced similar trends in traffic accidents. Figure 1 supports this assumption, showing comparable pre-treatment trends for both groups. The exogeneity assumption requires that the implementation of enforcement technology is not related to other unobserved factors influencing traffic accidents, ensuring that observed changes are solely due to the intervention.

4 Results

4.1 Graphical Evidence

Figure 1 displays the trends in average monthly injuries and accidents for the treatment and control groups within 10, 15, and 30 meters of enforcement devices. Among these, the trend for injuries is more distinct compared to accidents, and the patterns are more pronounced within 10 meters. Prior to the activation of enforcement devices, trends in injuries and accidents align closely between the treatment and control groups, supporting the parallel trends assumption of the Difference-in-Differences (DiD) framework. However, graphical evidence does not clearly demonstrate post-intervention effects. Therefore, we turn to the quantitative analysis in subsection 4.2 and Table 2 to further investigate the causal relationship.

4.2 The Effect of Enforcement Devices on Traffic Safety

Our analysis focuses on results within 10 meters of the enforcement devices, where the effects are most pronounced. Table 2 presents the estimated causal effects of enforcement device activation on monthly traffic injuries and accidents using the DiD model.

Panel A shows that enforcement device activation reduces monthly accidents by 0.089 (standard error: 0.11), while it indicates a reduction in monthly injuries by 0.2307 (standard error: 0.24). Among the fixed effects and control variables, the inclusion of car and motorcycle controls has the greatest influence on the estimates, whereas other controls have minimal impact. Overall, these reductions are not statistically significant at conventional levels. This suggests that the observed improvements in traffic safety cannot be definitively attributed to the policy intervention.

4.3 Robustness Checks

To assess the robustness of our findings, we conducted additional analyses using alternative DiD model specifications and varying sample definitions, as presented in Table 2. In Panels B (15m), C (30m), and D (50m), the coefficients for $D_i \times Post_t$ consistently remain negative, suggesting a reduction in both injuries and accidents following the activation of enforcement devices. However, none of these estimates achieve statistical significance.

Interestingly, the effects are strongest within 15 meters and gradually diminish at 30 and 50 meters, occasionally surpassing the observed effects within 10 meters. This pattern highlights that the impact of enforcement devices is highly localized, with the most substantial effects occurring in close proximity to the devices and diminishing with increased distance.

5 Discussion and Conclusion

Our results suggest that the activation of enforcement devices is associated with reductions in both monthly traffic accidents and injuries, particularly within 10 to 15 meters of the devices. Although these reductions appear economically meaningful, they are not statistically significant at conventional levels, which limits our ability to conclusively attribute these improvements to the policy intervention. Furthermore, robustness checks reveal that the effects diminish as the distance from the devices increases, further supporting the localized nature of the impact.

Several limitations of this study should be considered. First, the lack of statistically significant results may be attributed to the relatively short post-implementation observation period. A longer study period might reveal more definitive trends and effects. Second, potential confounding factors, such as changes in driver behavior or the introduction of other concurrent safety measures, could not be fully accounted for in the analysis. Additionally, the study relies on fixed geographic boundaries, which may not precisely capture the true exposure radius of the enforcement devices.

Future research could address these limitations in several ways. Extending the study period to capture longer-term effects of enforcement devices would provide a more comprehensive understanding of their impact. Incorporating additional variables, such as detailed traffic flow patterns, driver demographics, and real-time enforcement data, could improve the precision of the estimates. Furthermore, using advanced geospatial analysis techniques to refine the definition of treatment and control areas may enhance the accuracy of the results.

In conclusion, while our findings suggest a potential benefit of enforcement devices in improving traffic safety, further research is necessary to confirm their effectiveness and explore the broader implications for urban traffic management policies.

6 Code availability

The code is on GitHub: https://github.com/HsuShengHui/AppliedEconometrics.git.

Tables

Table 1: Descriptive Statistics for Accident and Injury Counts at Different Distance Thresholds

	Distance Threshold = 10m		Distance Threshold = 15m		Distance Threshold = 30m	
	Treatment Group (n=20)	Control Group (n=24)	Treatment Group (n=20)	Control Group (n=24)	Treatment Group (n=20)	Control Group (n=24)
Accident Count	0.49	0.22	0.77	0.35	1.68	0.91
	(0.93)	(0.53)	(1.22)	(0.66)	(1.72)	(1.23)
Injury Count	0.81	0.32	1.19	0.5	2.49	1.22
	(1.85)	(0.85)	(2.27)	(1.02)	(3.00)	(1.74)
Cars per thousand people	466.84	469.69	466.84	469.69	466.84	469.69
	(239.77)	(206.08)	(239.77)	(206.08)	(239.77)	(206.08)
Motorcycles per thousand people	480.97	420.20	480.97	420.20	480.97	420.20
	(156.51)	(195.31)	(156.51)	(195.31)	(156.51)	(195.31)
Temperature Average	24.66	24.66	24.66	24.66	24.66	24.66
	(4.76)	(4.76)	(4.76)	(4.76)	(4.76)	(4.76)
Rainy Days	11.53	11.53	11.53	11.53	11.53	11.53
	(3.90)	(3.90)	(3.90)	(3.90)	(3.90)	(3.90)
Number of observations			836			

Notes: The data used in this study include traffic accident records and law enforcement equipment information from June 2022 to December 2023. We focus on accidents that occurred within specific distances (10 meters, 15 meters, and 30 meters) of enforcement devices in Taipei City. This table shows the means and standard deviations of the outcome variable and relevant characteristics, categorized by treatment (devices activated on December 1, 2022) and control groups (devices activated after January 1, 2024). The accident count is categorized by type and proximity to the enforcement devices. Additionally, variables such as weather conditions, vehicle registration statistics, and the presence of enforcement technology are included. Standard deviations are reported in parentheses.

Table 2: Impact of Policy on Number of Accidents and Injuries

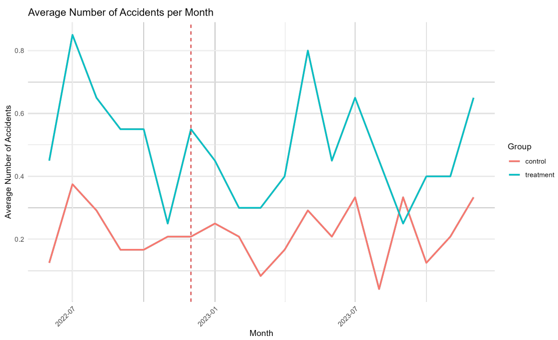
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of Accidents (10m)						
$D_i \times Post_t$	-0.0867 (0.11)	-0.0867 (0.12)	-0.0867 (0.13)	-0.0867 (0.12)	-0.0867 (0.12)	-0.089 (0.11)
Panel B: Number of Accidents (15m)						
$D_i \times Post_t$	-0.1843 (0.14)	-0.1843 (0.15)	-0.1843 (0.15)	-0.1843 (0.13)	-0.1843 (0.13)	-0.1865 (0.13)
Panel C: Number of Accidents (30m)						
$D_i \times Post_t$	-0.0845 (0.21)	-0.0845 (0.20)	-0.0845 (0.21)	-0.0845 (0.20)	-0.0845 (0.21)	-0.0933 (0.21)
Panel D: Number of Accidents (50m)						
$D_i \times Post_t$	-0.0070 (0.28)	-0.0070 (0.25)	-0.0070 (0.26)	-0.0070 (0.26)	-0.0070 (0.26)	0.0031 (0.27)
Panel A: Number of Injuries (10m)						
$D_i \times Post_t$	-0.2334 (0.20)	-0.2334 (0.26)	-0.2334 (0.27)	-0.2334 (0.26)	-0.2334 (0.26)	-0.2307 (0.24)
Panel B: Number of Injuries (15m)						
$D_i \times Post_t$	-0.3463 (0.24)	-0.3463 (0.32)	-0.3463 (0.33)	-0.3463 (0.29)	-0.3463 (0.29)	-0.3488 (0.28)
Panel C: Number of Injuries (30m)						
$D_i \times Post_t$	-0.2761 (0.34)	-0.2761 (0.40)	-0.2761 (0.41)	-0.2761 (0.39)	-0.2761 (0.39)	-0.2825 (0.39)
Panel D: Number of Injuries (50m)						
$D_i \times Post_t$	-0.2216 (0.44)	-0.2216 (0.44)	-0.2216 (0.46)	-0.2216 (0.44)	-0.2216 (0.44)	-0.2128 (0.44)
Observations			836			
Basic DID	✓	✓	✓	✓	✓	✓
District FE		✓	✓	✓	✓	✓
Location FE			✓	✓	✓	✓
Year and Month FE				✓	✓	✓
Weather Controls					✓	✓
Car/Motorcycle Controls						✓

Notes: This table reports the estimated coefficients from regressions examining the impact of enforcement device activation on the number of traffic accidents and injuries. The outcome variables are either the number of accidents ($Accident_{it}$) or the number of injuries ($Injury_{it}$) within specific meters of the enforcement device at location i in time period t. The regression model includes the following control variables: weather controls (such as the number of rainy days per month and average monthly temperature), and vehicle-related controls (including the number of cars and motorcycles per thousand people). The model also accounts for unobserved heterogeneity with location-specific fixed effects (λ_i) and time fixed effects (γ_t) to capture district-level, site-level, and month- and year-specific trends. Standard errors are in parentheses. Columns add progressively more controls and fixed effects. *** significant at the 0.1 percent level, ** significant at the 1 percent level, and * significant at the 5 percent level.

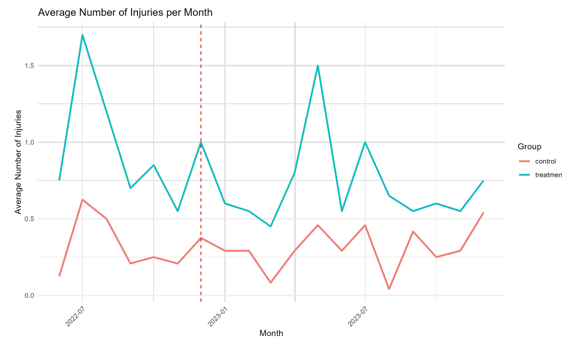
Figures

Figure 1: Trends in Traffic Accidents and Injuries at Different Distances

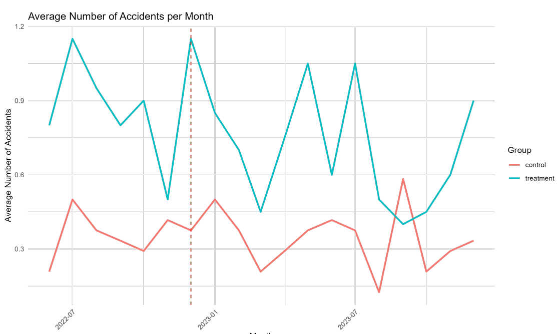
(a) Number of Accidents within 10 Meters



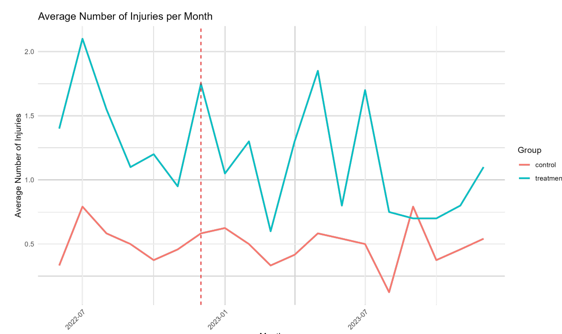
(b) Number of Injuries within 10 Meters



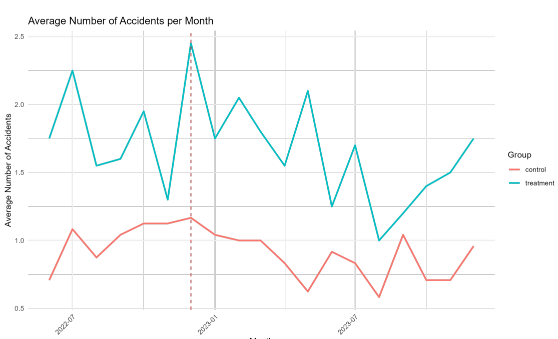
(c) Number of Accidents within 15 Meters



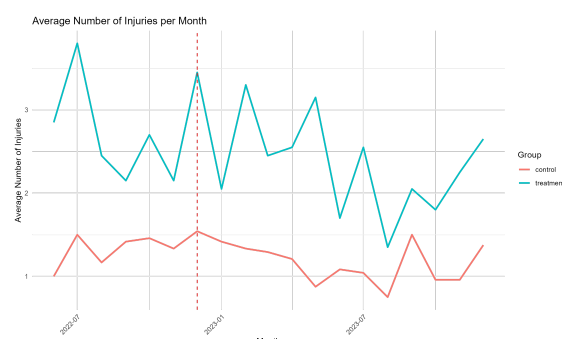
(d) Number of Injuries within 15 Meters



(e) Number of Accidents within 30 Meters



(f) Number of Injuries within 30 Meters



Notes: These figures illustrate the average trends in the number of traffic accidents and the number of injuries at distances of 10, 15, and 30 meters from the treatment and control locations. The treatment group includes locations where devices were activated on December 1, 2022, while the control group includes locations where devices were activated after January 1, 2024. The vertical axis represents the outcome measures at event time t, while the horizontal axis indicates the event time t. Each plot distinguishes between the pre-treatment and post-treatment periods, reflecting the impact of the intervention.