AUTOMATED ENFORCEMENT AND TRAFFIC SAFETY

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ABSTRACT

Traffic safety poses a persistent challenge for society and public policy. Conventional law enforcement by human police is often cost-ineffective due to information asymmetry and negative externalities of unsafe driving behaviors. Automated enforcement, in the form of traffic cameras on the road, has gained prominence in recent decades, yet its effectiveness and underlying mechanisms remain debated. This study examines the impact of traffic cameras on road safety using longitudinal data from a metropolitan city in China. We distinguish between *advanced* cameras, which use machine learning to detect various traffic violations and constantly record video, and *conventional* cameras, which rely on triggered image capture for a limited number of violations. Using an event study design with staggered camera installations at road intersections, we observe a significant and sustained reduction in accidents near advanced cameras, compared to locations with no cameras or only conventional cameras. Further analysis identifies three key mechanisms driving the effects of advanced cameras: (i) *automated detection effect*—superior technical capabilities to automate violation detection; (ii) *real-time recording effect*— continuous monitoring and recording capability to augment accident cause identification; and (iii) *driver learning effect*—technology-enabled deterrence to increase driver awareness of these cameras and encourage behavioral adjustments to mitigate accident risks. This study contributes to information systems, transportation economics, and criminology, offering policy insights into the effective design and deployment of automated enforcement to improve traffic safety.

Keywords: automated enforcement, traffic safety, deterrence, event study

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1. Introduction

According to a recent *Global Status Report on Road Safety* by the World Health Organization (2023), 1.19 million people died in road crashes worldwide in 2021. Strikingly, road traffic injury is the leading cause of death for children and young people aged 5-29 years. The global macroeconomic cost of road traffic injuries is estimated at U.S. $1.8 trillion, or roughly 10-12% of the global gross domestic product (GDP). This issue also intensifies regional inequality, as 92% of the traffic fatalities occur in middle- and low-income countries and the risk of death is 3 times higher in low-income countries than in high-income ones. Enhancing traffic safety has, therefore, been considered a significant endeavor for policymakers, especially in developing countries.

Since the 1950s, various traffic safety measures have been introduced, including engineering innovations (e.g., airbags), product design regulations (e.g., child restraint laws), and behavioral mandates (e.g., speed limits). However, their effectiveness remains debated (Burris et al. 2013). For example, Pelzman (1975) proposed the "risk compensation hypothesis," suggesting that safety measures (e.g., seatbelts) might inadvertently lead drivers to drive more carelessly, as the measures make them feel safer. This increases the likelihood of crashes and transfers risks to unprotected individuals such as pedestrians. Enforcing traffic safety regulations is also challenging. The most common approach, the presence of human police, is often costly and ineffective. Limited officer coverage leads drivers to perceive low odds of being caught, encouraging riskier driving. Moreover, gathering clear evidence and determining accident causes is difficult when accidents occur, further incentivizing unsafe driving. As a result, conventional law enforcement is often cost-ineffective due to information asymmetry and negative externalities (Edlin and Karaca-Mandic 2006).

In recent decades, automated enforcement, such as speed checkers and red-light cameras, has been deployed on roads. Automated enforcement, increasingly driven by machine learning algorithms, differs from conventional methods in several key ways. First, traffic cameras detect violations automatically and operate 24/7. Second, unlike police officers, whose availability and deployment change constantly, traffic cameras are fixed and always active, making unsafe driving costly. Lastly, traffic cameras continuously gather evidence during accidents, reducing uncertainty in cause and liability identification. Therefore, the advantages of automated enforcement—monitoring road traffic, detecting violations, and recording evidence—address information asymmetry and negative externalities, improving traffic safety more effectively than conventional law enforcement.

Nevertheless, prior research has shown mixed results on the effectiveness of traffic cameras in improving road safety (see a brief review in Table A-1 in Appendix A). Most studies indicate *positive* effects. Blais and Carnis (2015) found that the automated speed enforcement program (ASEP) in France was associated with a decrease of 19.7% in road crashes. Llau et al. (2015) reported that in a U.S. county, sites with red light cameras experienced a decrease in all types of injury crashes. Wang et al. (2020) found that traffic cameras were associated with a decrease in regional crash risk. In contrast, several studies documented *negative* or *adverse* effects. Lee et al. (2015) found that red light cameras increase fatal crashes by 2% and injury crashes by 53% in a South Korean city, attributing this increase to higher average speeds on arterial roads. Likewise, Claros et al. (2017) observed that rear-end crashes increased by 16.5% after the installation of red-light cameras. Furthermore, several recent studies presented *null* or mixed effects. For example, De Pauw et al. (2014) found no statistical evidence of changes in injury crashes after the installation of fixed-speed cameras, although there was a significant decrease in deaths and serious injuries. Gallagher and Fisher (2020) found no evidence that red light cameras in Houston, Texas, reduced the total number of accidents or injuries, though they did change the composition of accidents.

Given the mixed findings in the literature, uncertainty remains regarding the effectiveness of traffic cameras in enhancing road safety. A careful review of these studies reveals several gaps: *First*, most studies in transportation and safety literature mainly focused on the presence of traffic cameras, without unpacking the nuanced interplays among technical capabilities of automated enforcement, drivers' risk-taking behaviors, and traffic safety outcomes. This presents an opportune direction for information systems (IS) scholars to theorize the role of technologies, particularly machine learning applications, in traffic safety. *Second*, most studies either used city-level aggregate accident data or selected a limited number of road intersections to estimate the effect of camera installation. *Third*, many studies focused solely on cameras that detect only one type of violation (e.g., running a red light), rather than those capable of simultaneously detecting various types of violations. *Lastly*, existing research primarily examined conventional cameras triggered by separate sensors (e.g., speeding radar) to capture violation images, with limited attention given to a new generation of automated enforcement that leverages the recent development in machine learning algorithms.

Our work is hence well positioned to tackle the scholarly and policy challenges, including (i) the ever-increasing concerns about traffic safety, (ii) the touted promises of the traffic enforcement cameras juxtaposed with mixed assessment outcomes, (iii) the lack of granular data for deeper insights, and (iv) limited understanding of nuanced mechanisms in prior research. As IS scholars, we recognize the imminent importance of assessing the roles of automated enforcement enabled by machine learning and pattern recognition algorithms with a solid theoretical understanding and more rigorous empirical analyses. Thus, we ask the following research questions: (i) *What is the impact of traffic enforcement cameras on road safety?* (ii) *To what extent can their deployment reduce human and economic costs of traffic accidents?* (iii) *How can we explain their potential effects?*

To answer these questions, we study dynamic changes in traffic accidents at road intersections in a metropolitan city in China, comparing locations with and without traffic cameras. We focus on two types of cameras: *advanced* cameras, which detect various traffic violations via constant video capture and real-time pattern recognition enabled by embedded machine learning algorithms, and *conventional* ones, which detect a limited number of violations via electromagnetic devices that trigger temporary image capture. We consolidate a panel dataset of traffic camera installations and local police reports of road accidents in the vicinity of comparable road intersections of this city in the mid-2010s.

Econometrically, we first employ the event study method to exploit the staggered installation of cameras across road intersections over time. We identify a statistically significant and persistent decrease in total accidents by an average of 8.3% near the road intersections installed with advanced cameras, compared to the locations without cameras or with only conventional cameras. The estimates remain consistent across a battery of robustness tests, such as leveraging different sets of covariates, changing the sampling strategies for the control intersections, and conducting a falsification test with randomly assigned pseudo treatments. Second, we use newly developed event study estimates in the econometrics literature (e.g., de Chaisemartin and D'Haultfœuille 2020, Borusyak et al. 2021, Sun and Abraham 2021) to relax the assumption of homogeneous treatment effects across space and time. The consistent results from these analyses lend credence to the downward trends in accidents at the intersections with advanced camera installations.

What explains this baseline effect? We theorize the role of automated enforcement, drawing on the deterrence literature that originated from Becker (1968) on crime and punishment, which highlighted how monitoring resources and publishment severity deter violations. Unlike prior studies that focused on publishment severity (e.g., Hansen 2015, Goncalves and Mello 2017), our work emphasizes (i) monitoring resources, (ii) automated enforcement, including its technical features and presence, and (iii) aggregate-level deterrence and traffic safety outcomes. Specifically, we argue that the technical features of advanced cameras (*automated violation detection* and *real-time recording*) substantially improve traffic enforcement capabilities in violation identification and detection, establishing a technology-enabled deterrence. This, in turn, leads to *drivers' learning* of the presence and functions of the traffic enforcement cameras, ultimately influencing their driving behaviors in a way to avoid violations and mitigate accident risks.

To empirically test the technical capabilities and driver learning, we categorize accidents according to the cameras' functions (i.e., either proactively or passively capturing violations; see §5). Our analyses yield statistically significant evidence not only supporting the proposed mechanisms but also explaining the differing effects of the two types of cameras. Compared to conventional cameras, advanced cameras (i) significantly reduce both the variety and incidence of accidents due to ML-enabled *automated detection*, evident in the extensive margin (i.e., reduction in more types of accidents; see Figure 3) and the intensive margin (i.e., greater reduction within the same accident types; see Figure 4);[1] (ii) have a unique impact on accidents by *real-time video recording*, helping

[1] The *extensive margin* captures the breadth of the impact, referring to the reduction in the number of different types of accidents (e.g., rear-end collisions, running a red light, etc.), while the *intensive margin* measures the depth of the impact, referring to the extent of reduction within the same type of accidents (e.g., a 30% reduction in rear-end collisions). These metrics together comprehensively capture how advanced cameras outperform conventional cameras in improving traffic safety.

identify accident causes (Figure 5); and (iii) create a *driver learning* effect, making drivers more aware of the cameras' presence and functions and extending deterrence to areas even without these cameras (Figure 6). These findings highlight the superior technological and psychological deterrence of advanced cameras, explaining the significant reduction in total accidents nearby.

Additional findings further support these mechanisms and rule out alternative explanations: *First,* the effect of automated enforcement is more pronounced for *whom* and *where* risky driving is more likely to occur, further corroborating the technology-enabled deterrence. *Second,* the effect of automated enforcement does persist over time but does not transfer to locations without cameras, demonstrating the absence of a displacement effect and further mitigating information asymmetry concerns over deterrence in non-camera areas. *Third,* accident risks are not transferred to other road users (e.g., pedestrians) after camera installations, failing to support the risk compensation hypothesis (Peltzman 1975) and mitigating potential negative externalities beyond motor-and-motor collisions.

This work makes notable contributions to the IS literature and related disciplines. First, our investigation of AI-enabled solutions for traffic safety and their mechanisms enriches the scholarship on the societal impact of IT, particularly within the emerging IS literature on IT in transportation (see a brief review in Table A-2 in Appendix A). Specifically, (i) the IS literature has rarely addressed the critical topic of traffic safety, with exceptions such as Greenwood and Wattal (2020) on alcohol-related vehicle fatalities. Our study expands this area by exploring the role of automated law enforcement on various accident outcomes and leveraging IS domain knowledge to unpack human-technology interactions driving these effects. (ii) While prior studies have predominantly focused on ride-hailing platforms and their consequences (e.g., Barbar and Burtch 2020, Liu et al. 2021, Rhee et al. 2023), our work shifts attention to automated enforcement, specifically advanced cameras as an AI application in the public domain. (iii) Most IS studies on transportation emphasized the *unintended* consequences of digital platforms on traffic demands, with limited focus on IT-enabled interventions aimed at traffic management. Notable exceptions include Cheng et al. (2020) on federally-supported intelligent transportation systems and Zhang et al. (2020) on GPS-related driver learning. Addressing this gap, our study explores the *intended* impact of automated enforcement on traffic safety, focusing on its nuanced technical functions and behavioral implications. This focus is essential, as technology-driven transportation solutions often produce mixed or unintended effects (Table A-1, Appendix A). By employing fine-grained data and rigorous methods, we analyze whether traffic enforcement cameras deliver their safety promises and how their effect arises via technical capabilities and behavioral deterrence. In doing so, this work responds to recent calls for IS research on smart mobility interventions (Ketter et al. 2023) by advancing the understanding of IT/AI-enabled solutions for safer and more sustainable transportation systems.

Second, our findings align with and contribute to the economics of traffic safety (e.g., Hansen 1997, Makowsky and Stratmann 2009). This literature has examined various traffic safety interventions that either decrease personal and social costs during an accident (e.g., seat belts, airbags) or increase the cost of unsafe driving (e.g., speeding tickets) before an accident (Edlin and Karca-Mandic 2006). Nevertheless, the literature has shown mixed evidence for the efficacy of these interventions due to concerns such as risk compensation and negative externalities. Without rigorous analyses, one might assume that traffic cameras share similar concerns with conventional safety interventions and may not necessarily reduce accident risks. To address this, we theorize the roles of automated enforcement and offer credible evidence that the installation of traffic cameras does not shift risks from reckless or careless drivers to other road users (e.g., pedestrians), thereby mitigating the concerns of risk compensation and negative externalities. This is because the functions and presence of such technology help reduce information asymmetry in monitoring and enforcement, preventing risk-taking behaviors and their associated accidents.

Third, this work extends criminology literature (Becker 1968, Chalfin and McCrary 2017), which has primarily focused on police deployment and its deterrent effect (Welsh and Farrington 2009, Priks 2015). Human police deployment is costly and temporal and may not systematically reduce crimes due to spatial displacement (to areas with police absence) and temporal displacement (to a later time when police presence diminishes). Our findings highlight key differences between human police and traffic enforcement cameras—such as real-time constant monitoring, permanent deployment, and fewer cognitive errors and biases, demonstrating the comparative advantages of automated enforcement, such as cost reduction and enhanced monitoring and enforcement capabilities, in improving traffic safety. Additionally, this study emphasizes that the deterrence of automated traffic law enforcement arises from its technical capabilities in automated detection and real-time recording, an underexplored mechanism in criminology literature.

Finally, our findings provide important policy insights. Given that ensuring traffic safety is one of the primary responsibilities of governments (Hansen 1997, World Health Organization 2023), we aim to influence transportation policy and its enforcement by deepening the understanding of automated enforcement on the road. This is largely due to the economic significance and societal benefits of deploying traffic enforcement cameras. Notably, our conservative estimates indicate that, on average, the studied city could have reduced 1,190 accidents (including 379 casualty cases), saved 496 people involved in fatal and injury cases, and saved ¥6,298,780 property loss from vehicular damage per year *had* the city installed advanced cameras in all of its signal-controlled intersections.

The remainder of the paper is organized as follows: Section 2 provides background on automated enforcement, the empirical context, data, and descriptive statistics. Section 3 outlines the empirical strategy, main results, robustness checks, and economic significance. Section 4 explores mechanisms and presents empirical tests. Section 5 examines heterogeneous effects, and Section 6 discusses implications and concludes.

2. Background, Data, and Descriptive Analysis

2.1. Research Background

Automated enforcement, in the form of traffic cameras such as speed checkers and red-light cameras, has seen widespread adoption across various countries, known as automated enforcement in the United States (U.S.), electronic police in China, and traffic enforcement cameras in the United Kingdom and several other European nations. This technology executes automated traffic law enforcement by detecting violations and collecting evidence. Utilizing state-of-the-art ML algorithms, some traffic cameras can recognize license plate numbers and characters within 0.7 milliseconds after detecting a speeding vehicle. The predictive accuracy of such algorithms often exceeds 97% (Tang et al. 2022). In regions such as China, Europe, and the U.S., ML techniques have reached a high level of maturity, particularly in identifying common violations such as running red lights or speeding. This could even result in automatic penalty issuance via text messages, with offenders retaining the right to contest violations and access evidence.

While automated enforcement has been implemented to address traffic violations and their ramifications, evidence of its effectiveness in reducing traffic accidents has been mixed (See Table A-1 in Appendix A for a brief review). Furthermore, the underlying mechanisms—how automated enforcement, through its functions and present, affect drivers' behaviors and subsequent accident risk—remain inadequately explained in the literature. To comprehensively investigate this increasingly prevalent monitoring technology in the public domain, our study conducts rigorous empirical identification and mechanism tests.

2.2. Empirical Context

Our study is conducted in a metropolitan city in Southern China with a population of approximately 13.3 million as of 2024. Over the past decade, this city has experienced two major waves of traffic camera deployment. In the initial wave of 2010-2016, the city installed conventional cameras capable of capturing violation images and transmitting data to a central database. The ongoing second wave, commencing in 2014 and continuing to the present, involves the deployment of advanced cameras equipped with ML-enabled computer vision algorithms for real-time pattern recognition, video analytics, and automatic traffic violation detection.

Our investigation focuses on the period from 2014 to 2016, when both conventional and advanced cameras were concurrently deployed throughout the city. We analyze two types of cameras: *conventional* traffic cameras that only detect limited violations based on temporary image capture and *advanced* cameras that employ constant video capture and pattern recognition to identify a broader range of violations. See more details below and in Table B-3 and Figure B-5 in Appendix B. Notably, during this period, the replacement of conventional cameras with advanced ones in the same locations was rare due to the former's durability (lasting at least 5-10 years) and the impracticality of dismantling them.

Two notable differences exist between conventional and advanced cameras: (i) the range of violations to detect and (ii) the detection methods. First, conventional cameras only detect *running red lights* or *retrograde* (moving backward), whereas advanced ones detect as many as thirty traffic violations, such as *speeding*, *failure to follow traffic signs/signals*, and *driving in the wrong lane.* Second, conventional cameras detect and capture violations only when triggered. Specifically, an electromagnetic device (a physical sensor) equipped below the ground (often below the crossroad) detects moving, or reversed-moving, objects when a red light is on and triggers conventional cameras nearby to capture the scene when a vehicle runs the red light. These cameras often take several images—capturing both the red light and the moving vehicle with a clear license plate—to document the violation. In contrast, advanced cameras constantly detect violations because the detection is based on real-time video capture and analytics. As the advanced camera is constantly in operation, most violations nearby are captured in real-time video streams. Therefore, all advanced cameras are much more capable than any conventional ones of detecting more violations.

Despite these differences, conventional and advanced cameras share similar appearances, with advanced cameras typically accompanied by lighting devices. Moreover, violations captured by both are automatically written into a backend database, automatically generating text messages to notify offenders of the breach and associated fines. Hereafter, throughout this study, we interchangeably refer to advanced and conventional cameras as "new" and "old," respectively.

To better understand local traffic safety measures, we conducted field interviews with senior officials from the traffic surveillance unit, the accident unit, and the IT unit of the city police department. These interviews provided valuable insights, revealing that police officer deployment—including staffing and patrol schedules—was independent of traffic camera installations during the sample period (2014-2016). This separation existed because distinct units were responsible for different aspects of enforcement deployment, with minimal coordination between the two units. According to the interviewees, coordination "*only exists when the traffic surveillance unit detects a large accident and calls for dispatching more police officers to the accident site.*" Such coordination is, hence, unlikely to affect police officer deployment *prior to* the accidents or the schedule of camera installations. Additionally, during our sample period, the local police department lacked the capability to utilize data analytics to analyze accident locations and times for planning camera placements.[2]

[2] Instead, the camera installation at a location was often planned long in advance (even years before the installation) and determined mainly by two criteria: (a) a road network density and (b) a prior camera installation status. Regarding (a), camera installations were prioritized in the road- or population-dense areas to achieve relatively full coverage of traffic surveillance in the city's core districts. Regarding (b), while it is common to have multiple traffic cameras in the same area, cameras (either conventional or advanced) were more likely to be installed at the road intersections without cameras installed before. In our analysis, we account for the first criterion by using the road-intersection time-varying covariates and time-invariant fixed effects, and to test and account for the second criterion, we use the number of previously installed cameras nearby (0-300 meters near a focal intersection) as a time-varying covariate.

2.3. Data

Our analyses rely primarily on three data sources. The first data source is local police reports of road accidents, with accident information and characteristics. The second provides the time and location in which each traffic enforcement camera was installed. The third consists of characteristics related to each road intersection.

Accident Data. We obtain a proprietary dataset of road accidents from the police department. The dataset records detailed information on all reported traffic accidents (237,255) in 2014-2016. It includes the specific time and location of each accident, the number of injuries and deaths involved, the accident causes (e.g., associated traffic violations), and driver characteristics, such as age, gender, and years of driving experience, among others. For the main analyses, we restrict our sample to accidents close to road intersections within a radius of 0-100 meters. This is because (i) these accident locations were more accurately recorded, and (ii) the accidents near the road intersections were more likely influenced by traffic cameras (the majority of which are located at the intersections). Accidents far away (e.g., 100-300 meters) from cameras are beyond the effective monitoring range; thus, their changes may not be attributed to the direct treatment effect of automated enforcement. However, these distant accidents allow us to measure the spatial displacement effect, which we will discuss below in §4.3. The restriction to accidents in the 0-100m radius results in a sample of 51,364 accidents, and 43.3% of them are involved with casualties (deaths and/or injuries).

The accident data has several key features. First, all accidents were documented by traffic police after they occurred. Second, 99.4% of these accidents resulted from specific traffic violations. Third, the dataset does not include violations that did not lead to accidents, though some may have been captured by traffic cameras. This is because the accident data comes from police reports, not camera recordings that capture violations. For more details, see Figures B-1, B-2, and Table B-1 in Appendix B and descriptive statistics in Table C-1 in Appendix C.

Traffic Camera Installation Data. We manually collect the information on all traffic cameras installed until September 2021 from the city website. The data includes the location and time of each installation, as well as the functions (i.e., traffic violations designed to detect) of each camera. Two aspects of camera installation data are worth noting: First, the data includes not only the installations during the sample period but also those between January 2017 and September 2021. In our main analyses, we use road intersections installed with cameras after 2016 as our control group because both control and treatment intersections "need" camera installations, thereby being relatively comparable to each other. This is akin to a "lookahead matching" approach (e.g., Bapna et al. 2018), which matches the treatment group at time t to a comparable control group in which units are eventually treated at $t + k$. Second, we exclude cameras installed at non-intersection locations (e.g., in the middle of a road segment) because, in such cases, the locations of camera installations and accidents nearby are less likely to be accurate. See the details of camera installation data in Figures B-3, B-4, B-5, and Table B-2 in Appendix B.

Road Intersection Data. We obtain road intersection-level features from Baidu Map API, a web mapping application in China. Its features include the average traffic congestion level (measured between 0 and 100), the road types (e.g., state, provincial, or urban roads that require different levels of engineering to accommodate varying speed limits and vehicles of different weights passing through the intersections), and the coordinates of educational institutions (including elementary and secondary schools), bus stops, train stations, subway stations (in operation or under construction), residential areas, commercial buildings, food shops (e.g., restaurants), tourist spots, parking spaces, and government agencies. We consider these facilities as they may affect both camera installations and accident propensities for a given location. We count the number of these facilities within a 0-500m radius to capture their effects (except for train stations and tourist spots, for which we use a 0-1000m radius to accommodate heavier traffic near them). See the detailed measurements of road intersection covariates in Table C-2 in Appendix C.

After mapping and compiling the above data (see more details in Appendix B), we obtain a balanced longitudinal panel dataset of 1,564 road intersections over 36 months. The total number of intersections in our sample was 2,522 before the "lookahead matching," and in a robustness check later, we use all intersections for analysis. The time unit of analysis is a month, rather than a week or a day, so that we can accommodate random errors of temporal distance between the actual camera installation date and the announcement date that we manually collect from the city website.[3]. Also, it would be a sparse dataset of accidents (many zeros) if aggregated to the week or day level, posing a statistical challenge. Hence, we use a month as a more accurate unit to not only measure the camera installation times more accurately but also accumulate a stable aggregation of accidents.

Our empirical context has a few advantageous properties in identifying the effects of camera installations. *First*, camera installations were rolled out with both geographical and temporal variations, offering us a quasi-experimental setup (Figures B-6 in Appendix B). *Second*, we are able to use location fixed-effects to tease out time-invariant confounding effects from, for example, road complexity, bus traffic, and other traffic safety measures. We also control for location-specific time-varying factors, such as the changes in nearby public and private facilities (See Table C-2 in Appendix C). *Third*, camera installations were not anticipated by drivers *ex ante*, reducing the endogeneity of the treatment. *Fourth*, we control for potential interferences among road intersections. Specifically, we account for the number of cameras installed at neighboring road intersections and segments (within 0-300 meters of a focal intersection). Additionally, standard errors are clustered at the block level to account for correlated unaccounted factors due to geographical connections. *Lastly,* the presence of cameras is made visible and noticeable to drivers (Figure B-7), as required by traffic safety laws in China. Also, all sampled cameras are located at road intersections so that drivers can

[3] Sometimes the announcement was one or two weeks late; but usually, it was issued on the same week of camera installation, according to our field interviews.

easily notice them when waiting for a green light. It is still possible that drivers passing through the green light at speed may not be aware of the cameras. Nevertheless, if we are able to identify any measurable effect of these cameras, it would serve as the lower bound of the true treatment effect, as the cameras would become more effective when they are more visible.

2.4. Descriptive Statistics

Using raw statistics, we conduct a non-parametric comparison of accidents near intersections treated and untreated (control) with installations during the sample period, as well as a comparison of accidents at the treated intersections before and after camera installations. The model-free comparisons yield several observations (see Table C-4 in Appendix C). First, before any camera installation, on average, the road intersections later treated with advanced cameras had experienced more accidents, whereas intersections later treated with conventional cameras had experienced fewer accidents than the control interventions. Second, at the treated intersections, on average, accidents decrease after advanced camera installation. Third, at treatment intersections, on average, accidents increase after conventional camera installation. These observations can hardly be causal evidence for the effects of camera installation, but they reveal at least two identification challenges: (i) the city might have selected locations to install advanced and conventional cameras for unobserved reasons, and (ii) time-varying confounders may explain the accident dynamics following their installations. We address these concerns through various empirical strategies detailed in §3 below.

3. Empirical Strategy and Results

3.1. Event Study Design

To obtain estimates that can be more credibly interpreted as causal, we leverage the staggered installation of traffic cameras across road intersections over time. The quasi-experimental variation allows us to estimate the effect of traffic cameras on road accidents using an event study design. This strategy *compares* accident trends at treated road intersections before and after the treatment (i.e., camera installation) *with* those at control intersections over the same timeframe.

The event study design offers several advantages over the conventional two-way fixed-effects difference-in-differences (TWFE-DiD) design. First, it captures the dynamic effects of traffic cameras, discerning whether effects are persistent or temporal and providing more transparent estimates than DiD. Second, it avoids issues like the assumption of constant treatment effect within treated units over time, which often arise in staggered DiD designs (Goodman-Bacon 2021). Third, it visualizes parallel pre-intervention trends in accidents, allowing us to intuitively assess if there are any selection biases over time. This, to a large extent, addresses challenges identified in the descriptive analysis (§2.4). We implement the event study using an OLS estimator below:

$$Accident_{it} = \sum_j \tau_j PreCamera_{it}(j) + \sum_k \omega_k PostCamera_{it}(k) + X'_{it}\gamma + u_i + v_t + \varepsilon_{it}, \quad \text{(Eq. 1)}$$

where $Accident_{it}$ is the log-transformed number of total accidents within the 0-100m range at road intersection *i* in month *t*. $PreCamera_{it}(j)$ and $PostCamera_{it}(k)$ denote pre-treatment placebos and post-treatment variables, respectively, that are equal to 1 if the temporal distance between month t and the month before (or after) the camera installation at intersection i is j (or k) months, respectively. We incorporate intersection-specific time-varying covariates (X_{it}), including the nearby public and private facilities, such as educational institutions, bus stops, train/subway stations, residential and commercial areas, parking spaces, and government agencies, as well as confounding changes in traffic safety regulations (e.g., a ban on riding electric bicycles in the studied city; see Panels (i) and (ii) in Table C-2 in Appendix C). In addition to time-varying covariates, we account for road intersection (u_i) and year-month fixed-effects (v_t). We cluster standard errors at the block level to account for both serial correlations within a block and potential spatially correlated factors among intersections clustered in the same block.[4] The vector ω_k represents the estimate of interests; a negative and statistically significant ω_k would indicate that a camera installation at the focal intersection reduces accidents nearby. Notably, the validity of event study estimates relies on the parallel trend assumption, where the intersections in the treatment and control groups do not differ in accident trends prior to a camera installation (i.e., the series of τ_j is statistically indifferent from zero).

We first use Eq. 1 to estimate the effect of *advanced* camera installations (relative to no installations) in a sample of road intersections that were installed with only *advanced* cameras and those without any camera installations during the sample period. We then replicate this estimate for the effect of *conventional* cameras (relative to no installations, advanced or conventional). Finally, we present both estimates (i.e., new vs. null, old vs. null) to compare the effect of advanced cameras with that of conventional ones on total accidents.

3.2. Main Results

The results from the event study are depicted in Figure 1 (also refer to Table D-1 in Appendix D for all tabulated point estimates and standard errors).

First, we find that the pre-trend estimates (τ_j) are not significantly different from zero (at the 95% confidence intervals), supporting the parallel trend assumption. Second, we observe a statistically significant and persistent decrease in total accidents after the installation of advanced cameras (in red in Figure 1). However, we do not find a significant decline in total accidents after the installation of conventional cameras (in blue). This insignificant effect may be attributed to the fact that conventional cameras detect much fewer types of traffic violations than advanced cameras and rely on temporal image captures rather than constant video recording. Additional evidence supports this notion: when we replace the total accidents with accidents caused by "running a red light" or "retrograde" as the dependent variable, we find that the decrease in such accidents is statistically significant with conventional cameras, as they are only designed to detect these two violations (See details below in Figure 4).

[4] A block is a broader geographical unit that consists of multiple intersections, and this city has 57 blocks.

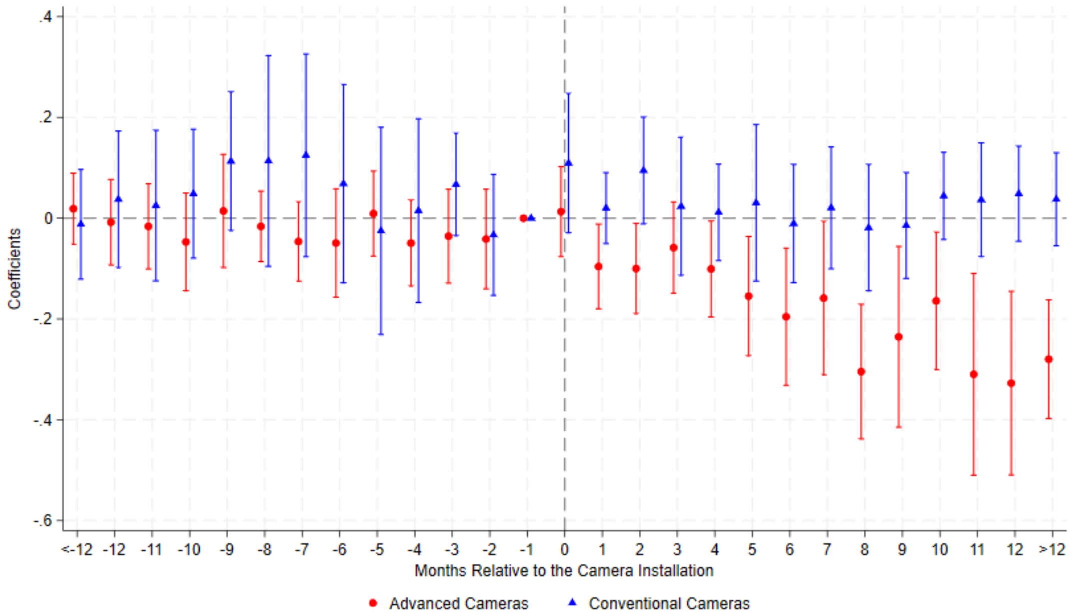


Figure 1. TWFE-OLS Estimates on the Dynamic Effects of Automated Enforcement

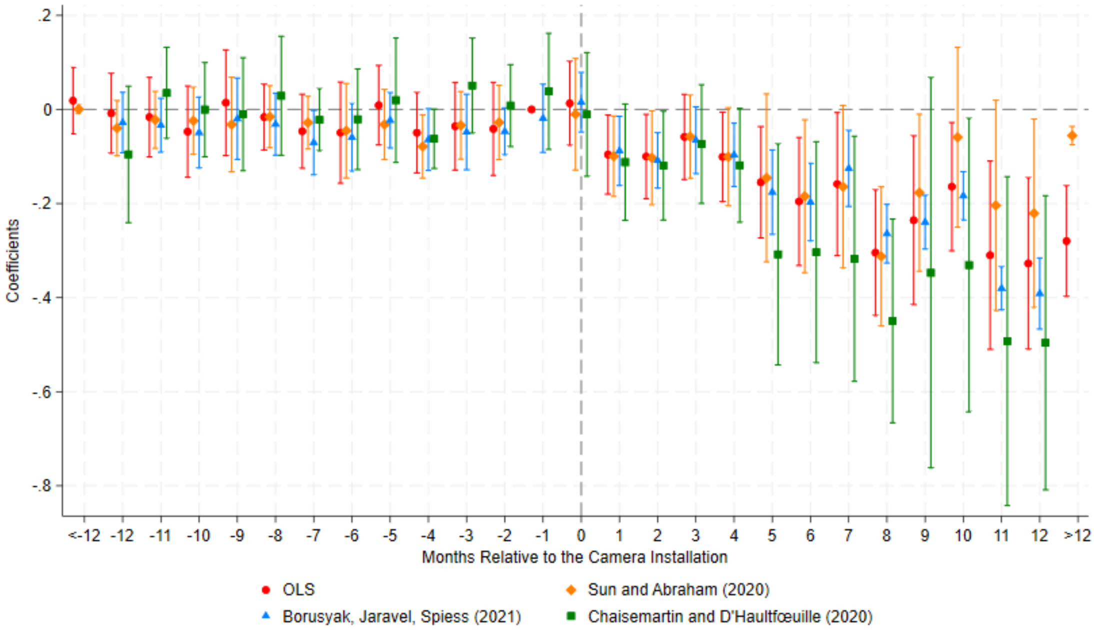
Notes: The red (blue) line depicts the accident trend near advanced (conventional) cameras, compared to that at intersections without cameras (horizontal line at zero). 95% confidence intervals of point estimates are shown.

3.3. Limitations of Baseline Estimates and Corresponding Remedies

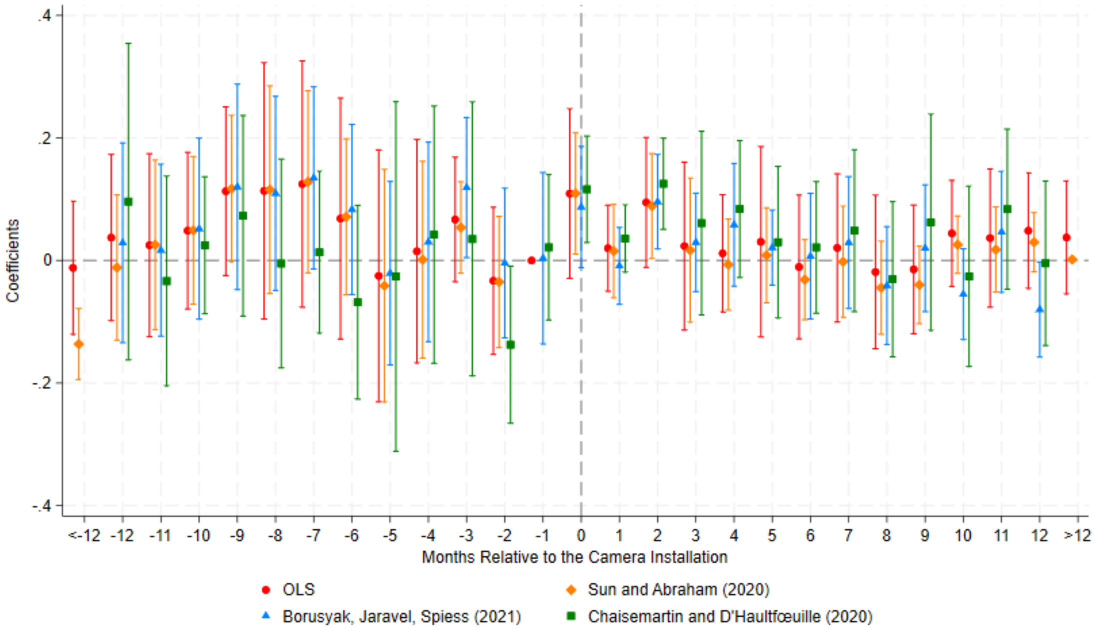
Although the TWFE specification similar to Eq. 1 has been widely adopted for staggered-adoption program evaluations, it has recently been demonstrated to deliver consistent estimates *only* under assumptions of homogeneous treatment effect (e.g., de Chaisemartin and D'Haultfœuille 2020, Borusyak et al. 2021, Callaway and Sant'Anna 2021, Goodman-Bacon 2021, Sun and Abraham 2021). An intuitive explanation is that the estimate from a TWFE model is a weighted average of all possible "2 (before and after) × 2 (treated and untreated units)" DiD comparisons. If the treatment effects are homogeneous across treated units and times, the TWFE estimator is consistent for the average treatment effect on the treated (ATT). Conversely, if the effects are heterogeneous across units and times, the TWFE estimator may not produce consistent ATT estimates.

To estimate the dynamic effects in a stagged-adoption design, we first follow Sun and Abraham's (2021) approach, which uses either the untreated cohorts or the last-treated cohorts as controls. Based on a regression-based method, their approach estimates the share of the cohorts as weights that are more interpretable than the weights underlying TWFE with staggered adoptions. We then resort to the imputation estimator proposed by Borusyak et al. (2021), which amounts to fitting a regression of the outcome on group and time fixed-effects in the sample of untreated observations and using that regression to predict the counterfactual outcome of treated observations. The estimated treatment effect of those observations is then merely obtained by subtracting their counterfactual from their actual outcome, making the estimator more efficient than that in Sun and Abraham (2021). We also use the estimators in de Chaisemartin and D'Haultfoeuille (2021) to incorporate time-varying covariates. This approach assumes that the trends are parallel once the linear effect of time-varying covariates is accounted for.

Figure 2 presents and compares the event study estimates generated by TWFE-OLS and the ones based on Sun and Abraham (2021), Borusyak et al. (2021), and de Chaisemartin and D'Haultfoeuille (2021). All estimates are consistent with our baseline TWFE-OLS results in Figure 1.



(i) Intersections w/ Advanced Cameras vs. w/o any Cameras



(ii) Intersections w/ Conventional Cameras vs. w/o any Cameras

Figure 2. Heterogeneity-Robust Event Study Estimators

Notes: These figures present and compare the event study estimates generated by TWFE-OLS (our baseline event study estimates) with those based on Sun and Abraham (2021), Borusyak et al. (2021), and de Chaisemartin and D'Haultfoeuille (2021). The point estimates and 95% confidence intervals are used here.

3.4. Robustness Checks

In what follows, we conduct a battery of tests to probe the robustness of our baseline event study estimates, with a summary in Table 1 and the results reported in Appendix E.

First, we examine if our estimates are sensitive to including different sets of covariates (e.g., traffic congestion levels, traffic cameras not located at the focal intersection but nearby within the 300-meter range). Results with different covariates indicate that the estimates are consistent (Figure E-1). Second, we test the sensitivity of our estimates to the sampling strategy. In the baseline analyses, we use a "lookahead matching" approach to construct the control group from intersections treated with cameras after the sample period. We consider two alternatives: (i) using all intersections without camera installation during the sample period as the control group and (ii) applying matching techniques, specifically coarsened exact matching (CEM) and only including observations (covariates-)matched to the treatment intersections as the control group (see Table E-1). Results remain consistent (Figure E-2).

Third, the baseline estimates might be biased when unaccounted time-varying confounders influence treated and untreated road intersections differently. To address this issue, we employ a generalized synthetic control (GSC) method (Xu 2017). The results in Figure E-3 corroborate the validity of the event study. Fourth, advanced cameras might be selected to be installed at intersections with higher accident risks. We test this possibility using a hazard logit model to predict the camera installation at the focal intersection using its past accident records. However, we find no statistically significant evidence for potential reverse causality (see Table E-2).

Fifth, the significant downward trend in accidents might be due to its spurious relations with camera installation or serial correlations of accidents within intersections. We conduct a falsification test by applying randomly assigned pseudo treatments to road intersections and months. Results do not indicate that autocorrelation exists or statistical effects are picked up at random (Figure E-4). Sixth, the distribution of accidents caters to a count data model, and as such, we apply a Poisson regression to the TWFE event study model. Results remain qualitatively consistent with the baseline estimates (Figure E-5).

Seventh, one would still be curious about the overall effect of camera installation, regardless of camera type. We test it and find that the downward trend in total accidents remains following any camera installation (Figure E-6). Finally, it is important to test the effect of camera installation directly on traffic violations. One limitation of our data is that it only records violations associated with accidents, potentially missing many non-accident violations. To study the changes in violations, we replace the accidents with punishment for violations as the dependent variable, measured by penalty points and fines aggregated at the intersection-month level. Our analysis reveals a significant drop in punishment near advanced cameras, indicating fewer violations, while conventional cameras show no significant effect (Figure E-7). Although our dataset does not capture all violations, the estimated decline provides a conservative lower bound for the impact of automated enforcement.

Table 1. Summary of Robustness Checks

Empirical Challenges	Empirical Tests	Results	Location
Are the estimates sensitive to including different sets of covariates?	(1) Drop all covariates and all fixed effects	Results remain consistent	Figure E-1
	(2) Only maintain intersection and year-month fixed effects and drop all intersection-specific time-varying covariates		
	(3) Maintain all covariates in the baseline model and add the interactions between all covariates and the year-month fixed-effects		
	(4) Additionally control for the traffic congestion level of each intersection by interacting it with year-month fixed-effects		
	(5) Additionally control for the total accident and casualty cases in the past three months		
	(6) Add the counts of old cameras, new cameras, or other types of cameras within the 300-meter range of the focal intersection		
Are the estimates sensitive to the sampling strategy?	(1) Use intersections without camera installation during the sample period as the control group	Results remain consistent	Figure E-2
	(2) Employ the coarsened exact matching (CEM) method		
Unaccounted time-varying confounders	Employ the generalized synthetic control (GSC) method	Results remain consistent	Figure E-3
Advanced cameras might be selected to be installed at intersections with higher accident risks.	Use a hazard logit model to predict the camera installation at the focal intersection using its past accident records	No statistically significant evidence for the potential selectivity issue.	Table E-1
Spurious correlation?	Conduct a falsification test by applying randomly assigned pseudo treatments to road intersections and months.	No evidence for autocorrelation or statistical effects being picked up at random	Figure E-4
The distribution of accidents caters to a count data model	Apply a Poisson regression	Results remain consistent	Figure E-5
The overall effect, regardless of camera type	Treat all camera installations the same and replicate the baseline analysis with this composite treatment measure	The downward trend in total accidents remains	Figure E-6
How about the direct effect of camera installation on traffic violations?	Replace accidents with punishment for violations as the dependent variable, measured by the penalty points and fines aggregated at the intersection-month level	Results remain consistent	Figure E-7
Is the TWFE model with a stagged-adoption design consistent?	Use the estimators proposed by Sun and Abraham (2021), Borusyak et al. (2021), and de Chaisemartin and D'Haultfoeuille (2021), respectively	Results remain consistent	Figure 2

3.5. Average Effects and Economic Significance

While the event study design demonstrates the dynamic effects of traffic cameras over time, it does not capture their overall effect during the sample period. To address this, we estimate the average treatment effect of traffic camera installation using a conventional TWFE-DiD approach, followed by a robustness check with Callaway and Sant'Anna's (2021) method, which mitigates bias in staggered DiD settings by accounting for treatment effect heterogeneity across installation cohorts (details in §3.3). These estimates allow for a welfare analysis to assess the economic significance of automated enforcement deployment. Specifically, we evaluate the average changes in accident counts, human costs (e.g., the number of deaths, serious, and minor injuries), and the monetary value of property loss involved in the accidents near the treated road intersections before and after camera installation.

Table 2 presents TWFE-DiD and Callaway and Sant'Anna's (2021) estimates for the effects of advanced cameras (versus no cameras) in Panel A and the effect of conventional cameras (versus no cameras) in Panel B. The TWFE-DiD estimates indicate that advanced traffic camera installations are statistically significantly associated with reductions in total accidents (–8.3%), casualty cases involving deaths and injuries (–6.3%), and non-casualty cases involving only vehicular damage (–3.2%). Examining the specific components of human and economic loss involved, we find that advanced traffic cameras reduce deaths (–0.5%), serious injuries (–0.1%), minor injuries (–6.8%), and property loss (–31.8%). In contrast, we do not find statistically significant evidence that conventional camera installations affect accident counts, human loss, or property damage. The estimates using Callaway and Sant'Anna's (2021) method are largely consistent with the baseline results, though they exhibit larger effect magnitudes and inevitably inflated standard errors. Consequently, the TWFE-DiD estimates can be considered a credible and conservative lower bound for the effects of interest.

Table 2. Estimated Average Effects of Camera Installations on Road Accidents and Associated Human and Economic Costs

DV: log(Y+1)	# Accident Case (1)	# Casualty Case (2)	# Non-Casualty Case (3)	# Deaths (4)	# Serious Injuries (5)	# Minor Injuries (6)	¥ Property Loss (7)
Panel A:							
TWFE-DiD							
Advanced cameras	-0.083***	-0.063***	-0.032**	-0.005**	-0.0012*	-0.068***	-0.318**
	(0.016)	(0.016)	(0.013)	(0.002)	(0.0007)	(0.018)	(0.138)
Callaway and Sant'Anna (2021)							
Advanced cameras	-0.149***	-0.096**	-0.062*	-0.012	-0.002*	-0.104**	-0.439
	(0.044)	(0.042)	(0.037)	(0.009)	(0.001)	(0.050)	(0.293)
Mean of Y w/o cameras	0.474	0.199	0.276	0.005	0.001	0.241	654.490
Panel B:							
TWFE-DiD							
Conventional cameras	0.009	-0.005	0.010	0.002	-0.000	-0.006	-0.119
	(0.029)	(0.017)	(0.020)	(0.003)	(0.001)	(0.021)	(0.223)
Callaway and Sant'Anna (2021)							
Conventional cameras	0.050	-0.004	0.048	0.002	0.001	0.001	0.422
	(0.041)	(0.026)	(0.035)	(0.003)	(0.002)	(0.027)	(0.282)
Mean of Y w/o cameras	0.455	0.188	0.267	0.004	0.001	0.228	654.669

Notes: In all specifications, we control for intersection fixed effects, year-month fixed effects, and location-specific time-varying control variables. Panel A shows the estimated effects of advanced camera installations (relative to no installations) in a sample of road intersections that were installed with only advanced cameras and those without any camera installations during the sample period. Panel B shows the estimates for the effect of conventional cameras (relative to no installations) in a sample of intersections that were installed with only conventional cameras and those without any camera installations. In each panel, we first implement a TWFE-DiD estimation, followed by a robustness check using Callaway and Sant'Anna (2021), with both approaches yielding consistent results. Robust standard errors (clustered at the block level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A back-of-the-envelope calculation using TWFE-DiD estimates suggests that *if the city had installed* advanced cameras at all signal-controlled intersections, it could have potentially prevented 1,190 accidents (including 379 casualty cases) annually,[5] saving 496 lives involved in fatal and injury-related incidents, and reducing property loss from vehicular damage by ¥6,298,780 (≈ US $969,043). Beyond this counterfactual estimation, we also estimate the incremental economic and human cost savings associated with the *actual* installation of advanced cameras during our sample period. Economic savings are again measured by reductions in property loss from vehicular damage, while human cost savings are now calculated based on decreased expenses related to bodily injuries and lost lifetime income due to the installation of advanced cameras. As a result, the total societal benefits from the actual deployment of advanced cameras amount to ¥426,003 (≈ $65,538) before 2017, ¥1,438,508 (≈ $221,308) before 2018, and ¥2,727,687 (≈ $419,644) before 2019 (See detailed calculations in Appendix G). A note of caution is warranted when interpreting or extrapolating these estimates. While our analysis focuses on the traffic safety benefits of automated enforcement, potential costs—such as the negative aspects of increased surveillance—should not be overlooked, even though they fall outside the scope of this research.

4. Underlying Mechanisms

4.1. Key Explanations

How to explain the overall decline in accidents after the installation of advanced cameras, relative to conventional ones? We draw upon deterrence literature to discuss the underlying mechanisms.

Traffic cameras, as automated law enforcement tools, naturally connect this study to criminology and economics literature on monitoring. Becker (1968) argued that crime levels are determined by individuals' rational evaluation of costs and benefits, where the expected cost of crime is shaped by monitoring resources (which increase the probability of apprehension) and punishment severity (which raises the potential penalty). He further suggested that this framework could be extended to encompass various types of violations, including traffic offenses (p. 170). This has inspired research on traffic safety as a matter of law enforcement. For instance, Hansen (2015) found harsher punishments reduce driving-under-influence offenses, and Goncalves and Mello (2017) studied the impact of speeding penalties on the future driving behavior of cited drivers. Our work differs by focusing on (i) monitoring resources rather than punishment severity, (ii) automated enforcement (including its functions and presence) rather than human police presence, and (iii) aggregate-level deterrence and traffic safety outcomes rather than individual behaviors.

Drawing on deterrence literature (Chalfin and McCrary 2017), we argue that (i) traffic cameras' technical capabilities increase the likelihood of identifying and apprehending traffic

[5] The reduction of 1,190 total accidents is computed as 0.474 (mean of total accidents at baseline intersections without any cameras) × 0.083 (the estimated average effects of advanced cameras) × 12 (months) × 2,522 (the number of all signal-controlled intersections). 0.474 and 0.083 are from Column 1 in Panel A of Table 2.

violators, and (ii) drivers' awareness of these cameras influences their driving behaviors, with both mechanisms collectively reducing accident risks. Notably, the first mechanism (i) represents the technological source of deterrence, while the second (ii) is the psychological manifestation of deterrence. These mechanisms are interdependent, and both are essential to materialize the overall deterrent effect. To illustrate, if traffic cameras lack sufficient technical capacities (e.g., limited detection functions in conventional cameras) or are not functioning, drivers may adapt to their limitations, resulting in weak deterrence. Similarly, if drivers are unaware of the cameras' presence or functionality, psychological deterrence is undermined, and violations and accidents are unlikely to decrease. Recognizing this, we explore the nature of these two factors in our empirical context.

The primary technical capability of traffic cameras lies in their built-in functions with ML to constantly and automatically detect violations (*automated detection effect*). Compared to human police, automated law enforcement increases monitoring visibility and the range of violations to detect. Traffic cameras not only mimic the presence of human police but also operate more durably and ubiquitously, providing 24/7 violation detection. Before camera deployment, traffic law enforcement efficacy was relatively low and could only be improved by allocating more police officers and checkpoints, a costly endeavor. Even so, some violations, such as non-seatbelt use, are difficult for officers to detect, especially in heavy traffic or high-speed scenarios. In contrast, advanced cameras, equipped with ML algorithms, can recognize and detect many more violations simultaneously in real-time, making them more effective than conventional cameras and police patrols in deterring violators and preventing accidents.

The other technical capability of traffic cameras is their ability to monitor and record, providing unambiguous evidence to assist law enforcement in identifying accident causes and liability (*real-time recording effect*). This function is more effective in advanced cameras. Conventional cameras only operate when triggered by separate sensors to detect specific violations (e.g., radar to detect speeding) and only take a few pictures. In contrast, advanced cameras constantly monitor traffic and record video. This video may happen to record some violations during an accident as evidence for the identification of accident cause and liability. Without traffic cameras, evidence for violations or accidents would often be incomplete. While professional investigators can inspect accident scenes, they are prone to inaccuracy and subjectivity, relying on post-crash human judgment. Advanced cameras offer instantaneous, objective facts through images or video footage for accident scenes. Individuals involved in accidents can request this evidence for an accurate account of the causes of the accidents. In our sample, some accidents lack the accurate on-site information needed to specify their causes. Installing advanced traffic cameras can reduce such unclear reports by recording evidence during accidents.

Finally, due to their *automated detection* and *real-time recording* capabilities, traffic cameras can effectively deter risky driving and traffic violations, thereby reducing road accidents. This deterrent effect arises from human-technology interactions; drivers become more cautious and prioritize safety when they feel deterred by such cameras. Technology-enabled deterrence materializes when drivers consciously or unconsciously *associate* the *presence* of cameras *with* their powerful *functions* of automated enforcement and punishment, rather than their mere presence. Notably, even if the cameras are not de facto operating or not within their deterrence coverage, drivers can still be psychologically deterred, as they understand the cameras' technical capabilities, regardless of whether they are aware of their functionality. This psychological deterrence leads drivers to learn where and when cameras are installed and adjust their risk-taking behaviors while driving. In essence, *driver learning* channels the deterrent effects from their technical origins to driving behavior changes, ultimately reducing accident risks.

In summary, the theoretical underpinnings laid out above aim to understand the deterrent effect of automated enforcement and its technological sources. Drawing on deterrence literature, the *automated detection* and *real-time recording* features of cameras improve the effectiveness of monitoring and increase the likelihood of violation apprehension, and such technical capabilities lead to drivers' learning about the cameras' presence and functions, which ultimately explains the overall decline in accidents near the cameras.

4.2. Mechanism Analyses

While the above explanations for the roles of automated enforcement are theoretically elucidated, empirically demonstrating these mechanisms—(i) technical capabilities (including automated detection and real-time recording) and (ii) driver learning—is challenging because these individual mechanisms are intertwined and collectively explain the overall changes in accidents. Next, we explore these mechanisms empirically using different types of road accidents detailed below.

Table 3. Different Types of Accidents Recorded in the Police Reports

Accident Type	Function	Description	Types of cameras	Examples
A1	Proactive	Accidents for which associated violations are detectable by cameras given their design	Advanced	"driving in the wrong lane," or "causing traffic congestion"
A2			Conventional	only "running a red light" and "retrograde"
B	Passive	Accidents for which associated violations cameras are not designed to detect but can capture evidence for accident cause identification through video recording	Advanced	"not wearing a seatbelt," "texting while driving," or "other distracted driving"
C	Neither proactive nor passive	Accidents are due to violations that cameras are not designed to detect and cannot capture evidence to identify accident cause even with recording	Neither conventional nor advanced	"drunk driving," "driving without a license"

Notes: Type A2 accidents are a subset of type A accidents and refer to accidents for which the associated violations could be detected by conventional cameras. On a separate note, we conducted a falsification test to assess the effects of advanced and conventional cameras on type C accidents. The results in Figure F-1 in Appendix F are statistically insignificant, indicating that cameras without the necessary technical capabilities cannot reduce the corresponding accidents.

We classify road accidents into three classes based on whether they are associated with violations that cameras can or cannot capture (Table 3): (A) accidents for which associated violations could have been captured by the proactive (i.e., primarily designed) functions of the cameras (e.g., "running a red light"), (B) accidents for which associated violations could have been captured by the passive and complementary (mainly real-time recording) functions of the cameras (e.g., "improper motor operation" such as texting while driving, captured by constant video but not designed to detect), and (C) accidents neither proactively nor passively captured by the cameras (e.g., "drunk driving" that only other means, such as a breath alcohol test, can help detect and identify the causes). Taken in sum, Type A accidents can be captured by either advanced or conventional cameras or both, Type B accidents can only be captured by advanced cameras (due to their constant video recording), and Type C accidents cannot be captured by either type of camera.

Automated Detection Effect. We explore the effect of the cameras' automated detection capability by focusing on accidents linked to violations captured by the cameras' proactive functions (i.e., Type A accidents). We separate the analyses for advanced and conventional cameras, as their proactive functions exhibit different coverage of violations; advanced cameras can detect over 30 types of violations, while conventional cameras detect only 2 ("running a red light" and "retrograde"). Figure 3 presents the baseline estimates using the number of accidents for which associated violations could have been captured by *advanced* cameras' proactive functions as the dependent variable. The post-treatment estimates indicate a statistically significant downward trend (in red), empirically supporting the automated detection effect. Figure 4 presents the estimates using accidents linked to accidents captured by *conventional* cameras' proactive functions. The post-treatment estimates indicate a similar downward trend after the installation of both conventional cameras (in blue) and advanced ones (in red), corroborating the automated detection effect.

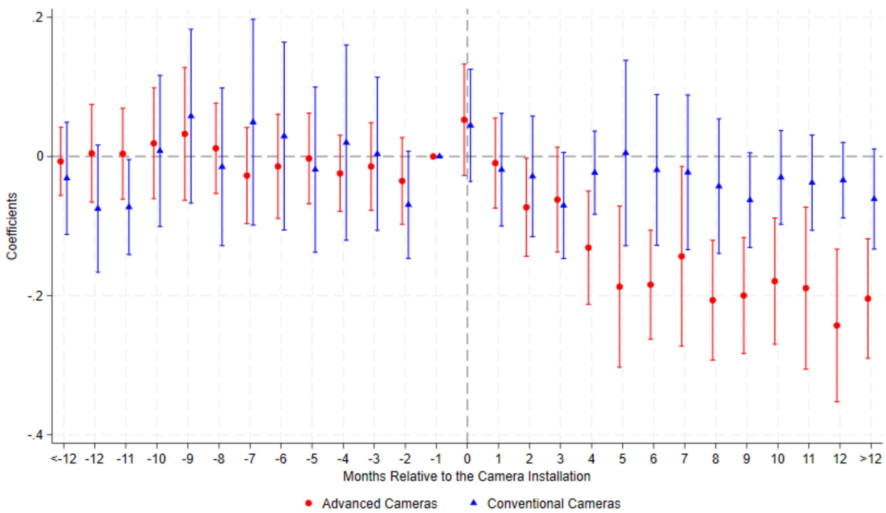


Figure 3. Effect of Camera Installation on Traffic Accidents Linked to Violations Captured by *Advanced* Cameras' <u>Proactive</u> Functions

Notes: Examples of accidents nearby for which associated violations captured by the advanced cameras' proactive functions are "running a red light," "driving in the wrong lane," or "causing traffic congestion."

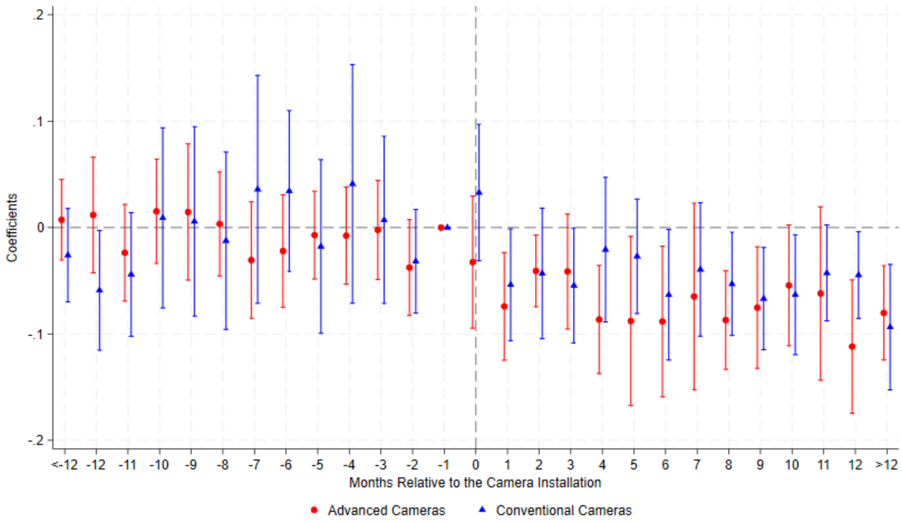


Figure 4. Effect of Camera Installation on Traffic Accidents Linked to Violations Captured by *Conventional* Cameras' Proactive Functions

Notes: Accidents nearby for which associated violations could have been captured by the conventional cameras' proactive functions are only "running a red light" and "retrograde."

Additionally, advanced cameras outperform conventional ones in reducing two types of accidents linked to violations both cameras can detect (post-estimates in red vs. those in blue in Figure 4). Notably, despite their ability to detect more violations and prevent a broader range of accidents, advanced cameras are also cheaper and easier to install. Unlike conventional cameras, which require an electromagnetic device embedded beneath the intersection, advanced cameras operate without this additional infrastructure, reducing costs and streamlining deployment.

Real-time Recording Effect. We explore the effect of the cameras' real-time recording capabilities by focusing on accidents for which associated violations could have been captured by *advanced* cameras' passive functions (Type B accidents). We only focus on advanced cameras here, because conventional cameras barely record accident cause evidence beyond the two violations they are designed to detect. Figure 5 presents the baseline estimates using the number of accidents for which associated violations could have been captured by advanced cameras' passive functions as the dependent variable. The post-treatment estimates indicate a statistically significant downward trend (in red), empirically supporting the real-time recording effect. However, we find such accidents remain statistically unchanged following the conventional camera installation, which serves as falsification evidence that the real-time recording effect does not arise if a camera is not technically capable of capturing video evidence to assist with accident cause identification.

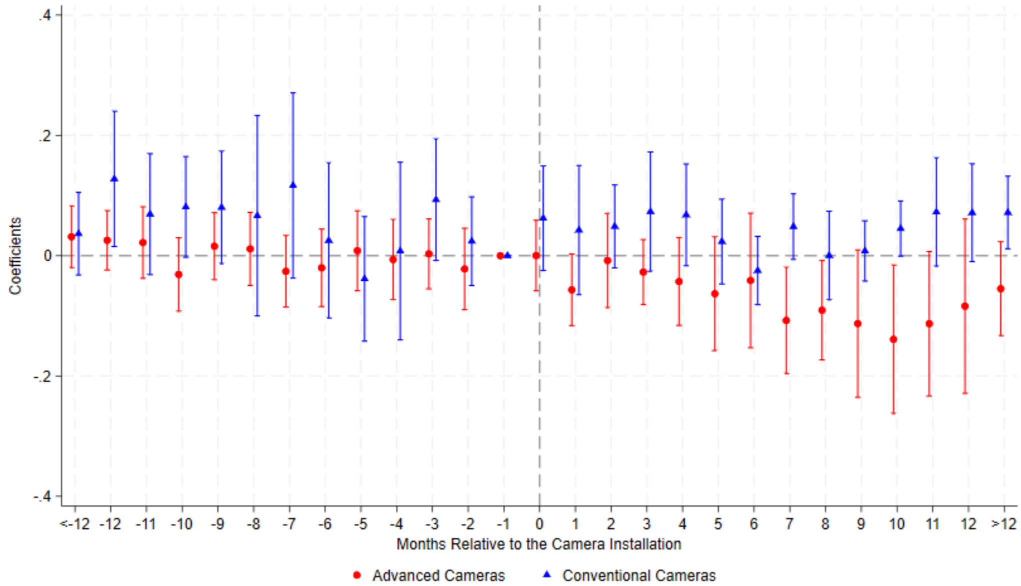


Figure 5. Effect of Camera Installation on Traffic Accidents Linked to Violations Captured by *Advanced* Cameras' <u>Passive</u> Functions

Note: Examples of accidents for which associated violations could have been captured by advanced cameras' passive functions are "improper motor operation" or "not wearing a seat belt." Although the post-treatment estimates (red line) are not all statistically significant, raising concerns about whether the real-time recording effect is overstated, we find a negative and statistically significant average effect on accidents (-0.046 using TWFE-DiD estimates and -0.059 using Callaway and Santa'Anna (2021), $p < 0.05$) (see Table 4).

Driver Learning Effect. Drivers may change their behavior through learning from technologies (e.g., Zhang et al. 2020). In our context, we investigate whether driver learning arises from deterrence under ML-enabled automated enforcement. Specifically, we analyze changes in accidents linked to violations that advanced cameras' proactive functions could have captured. This analysis focuses on focal intersections equipped with conventional cameras and examines the impact of advanced cameras newly installed at neighboring intersections 100–300 meters away (see Figure F-2 in Appendix F).

For this analysis, we use a subset of the full sample comprising intersections with conventional cameras installed prior to the installation of advanced cameras in nearby areas. This setting allows us to observe the behaviors of drivers who are exposed to both limited deterrence from conventional cameras—capable of detecting only two types of violations—and the broader deterrence of advanced cameras nearby. The similar appearance of advanced and conventional cameras may lead drivers to mistakenly *attribute* past punishments for violations (the experience they learned) *to* a conventional camera at a focal intersection, believing it to be an advanced camera with proactive detection capabilities, even though the actual advanced camera is located nearby in the broader area.

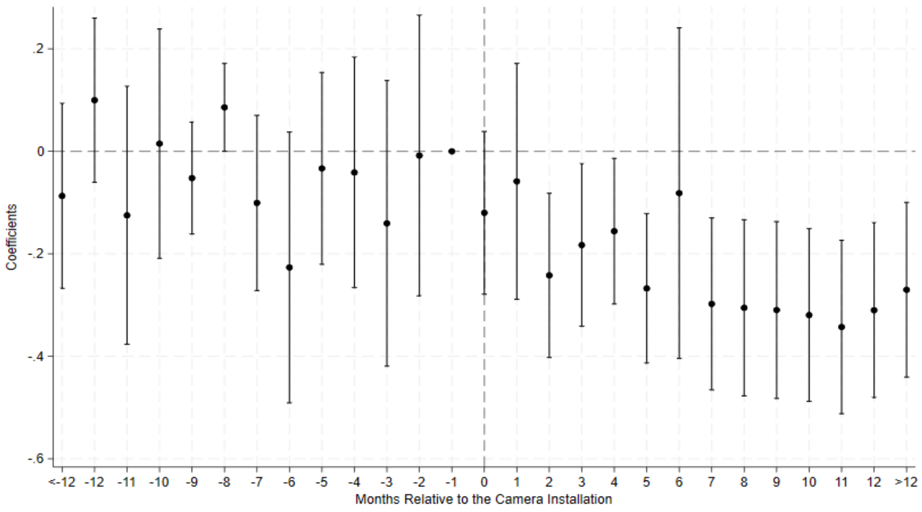


Figure 6. Spillover Effect of Advanced Cameras at Nearby Intersections on Accidents (Linked to Violations Captured by Their Proactive Functions) at the Focal Intersection

Notes: It is important to highlight that both neighboring and focal intersections were installed with conventional cameras to ensure drivers' awareness of their presence. The analysis here aims to understand whether the addition of an advanced camera to the neighboring intersection prompts driver learning and extends deterrence from the neighboring intersections (100-300m away from the focal one) to the focal intersection beyond the detection coverage of neighboring cameras. We also examine driver learning by estimating the changes in accidents for which associated violations could have been captured by advanced cameras' passive functions and not captured by any functions, with results in Figure F-3 and Figure F-4 do not yield any significant patterns (see details in Appendix F).

This deterrence spillover effect arises solely from driver learning for the following reasons. (i) Advanced cameras at neighboring intersections cannot capture violations occurring 100-300 meters away. (ii) Conventional cameras at the focal intersections cannot detect certain violations (e.g., speeding) that are detectable only through advanced cameras' proactive functions. (iii) The reduction in accidents can only be attributed to drivers learning about the presence and function of advanced cameras nearby, based on past experiences, extending this deterrence to the conventional camera they encounter at focal intersections.[6] Figure 6 shows a significant downward trend in accidents at focal intersections following the installation of advanced cameras nearby, providing notable evidence for the driver learning effects.

Taken together, advanced cameras more effectively reduce accidents than conventional cameras through three mechanisms. First, the *automated detection effect* improves violation identification, leading to fewer accidents. Advanced cameras not only reduce overall accident occurrence by detecting a wider range of violations (extensive margin, Figure 3) but also further

[6] One alternative explanation for this spillover effect is GPS alerts notifying drivers of nearby advanced cameras, even when they are not directly passing them. While standard GPS alerts typically do not cover cameras beyond 100 meters on urban roads, if they do, such alerts would reinforce rather than contradict the driver learning effect. In this case, they could further enhance driver awareness, implying that our estimate—though statistically significant—may represent a conservative lower bound of the driving learning effect. We appreciate an anonymous reviewer for suggesting this alternative explanation.

decrease accidents where associated violations could have been proactively captured by conventional cameras (intensive margin, Figure 4). Second, the *real-time recording effect* enables passive monitoring through continuously capturing video, aiding in accident cause identification and improving post-accident analysis (Figure 5). Finally, the *driver learning effect* increases driver awareness over time. Drivers adjust their behavior in response to the presence and functions of advanced cameras and even extend this awareness to locations without effective deterrence (Figure 6).

Beyond the event study estimates on these mechanisms, we also report the average effects using both TWFE-DiD and Callaway and Santa'Anna (2021) estimates in Table 4. The results indicate substantial effect magnitudes and statistical significance, aligning with the mechanisms discussed above.[7] These findings suggest that advanced cameras provide greater technological and psychological deterrence than conventional ones, further corroborating the baseline result of a significant reduction in accidents observed near advanced cameras.

Table 4. Estimated Average Effects of the Mechanisms

Mechanisms	Camera Type	Accident Type	Corresponding Event Study Estimates	TWFE-DiD	Callaway and Sant'Anna (2021)
Automated Detection Effects	Advanced Cameras	A1	Figure 3	-0.055*** (0.014)	-0.096*** (0.028)
	Advanced Cameras	A2	Figure 4	-0.057*** (0.013)	-0.050** (0.019)
	Conventional Cameras	A2	Figure 4	-0.050*** (0.018)	-0.064** (0.025)
Real-time Recording Effect	Advanced Cameras	B	Figure 5	-0.046** (0.018)	-0.059** (0.026)
Driver Learning Effect	Neighboring Advanced Cameras	A1	Figure 6	-0.085* (0.044)	-0.161** (0.069)

Notes: This table presents the results of the mechanism analysis based on the estimated average effects of advanced (or conventional) cameras, complementing the event study estimates in Figures 3-6, which may not fully capture the magnitude and statistical significance of the overall effects. In all specifications, we control for intersection fixed effects, year-month fixed effects, and location-specific time-varying control variables. Each analysis begins with a TWFE-DiD estimation, followed by a robustness check using Callaway and Santa'Anna (2021), with both approaches yielding consistent results. Robust standard errors (clustered at the block level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[7] The estimates for driver learning effects (-0.085 for TWFE-DiD estimation and -0.161 for Callaway and Santa'Anna (2021) method) seemed larger than the main effects of advanced cameras on A1 type accidents (-0.055 for TWFE-DiD estimation and -0.096 for Callaway and Sant' Anna's method). This is because the subsample we used for driver learning effect analysis differs from the ones used for other tests. When using the same subsample, the main effect of advanced cameras is larger than the estimated driver learning effect. To further supplement the analysis of accident types (characterized as A, B, and C in Table 3), we also analyze specific accidents (top 5 in our accident data) and the impact of cameras. The results shown in Table F-2 in Appendix F are consistent with those from the main mechanism analyses in §4.2.

4.3. Confounding Explanations

There could be other confounding mechanisms that may obscure the interpretation of the observed effects. We first discuss one such mechanism—*displacement*—that would support the deterrent effects but does not improve the overall traffic safety of the studied city. Then, we explore two other explanations—*distraction* and *risk compensation*—that may increase accident propensities and potentially offset the deterrent effects.

Temporal and Spatial Displacement. In line with the scholarly debate in criminology on whether deterrence primarily displaces, rather than reduces, crimes (e.g., Banerjee et al. 2019), we empirically test the accident displacement effect in our setting. We find no evidence of *temporal displacement*, as the effects of cameras are sustained once they are permanently installed (Figures 1 and 2). *Spatial displacement* is possible if drivers become more strategic in risky driving, especially when they are not in camera detection range. Yet, we find that it is unlikely either, as there are no significant changes in accidents within a 100-300m radius of a focal intersection after camera installation (Figure G-1 in Appendix G).

Distraction. Newly installed cameras may distract drivers when they pass the intersections where cameras are installed. If a driver suddenly notices the cameras nearby and slams on the break, the vehicles behind would have to follow suit. If the latter cannot respond as promptly as possible, rear-end collisions occur. These cases could increase the number of accidents immediately after the camera installation. To empirically test this possibility, we replicate the baseline estimation but only focus on rear-end collisions and do not find evidence of such a distraction effect (Figure G-2).

Risk Compensation. Despite the existence of deterrence, there are still cases where a decline in accidents is not seen, as predicted by the risk compensation effect (Peltzman 1975). Because only drivers, but not pedestrians or cyclists, are deterred by traffic cameras, the drivers may become more careful than others on the road. If this is the case, the main effect would be explained only by a decline in motor-and-motor accidents, but not pedestrian-and-motor accidents or single motor accidents (non-motor accidents thereafter). It is possible that accident risk is *transferred* from those who are under the deterrence (drivers) *to*—or *compensated by*—those who are not (pedestrians or cyclists), thereby increasing the accidents of the latter. If so, such a risk compensation effect would offset the deterrent effects. To check this possibility, we replicate the analyses but only focus on the changes in non-motor accidents. We do not find any statistically significant evidence that supports the risk compensation explanation (Figure G-3).

5. Effect Heterogeneity

We further examine the varying effects of contextual factors to understand *for whom* and *when* advanced cameras improve traffic safety. The results are in Table I-1 in Appendix I.

First, traffic cameras can deter risky driving behaviors more effectively among those who take more risks. Consistent with traffic safety literature (e.g., Makowsky and Stratmann 2009), our data shows that male drivers are more accident-prone than female drivers. Additionally, experienced drivers have higher accident rates than novice drivers (e.g., 0-3 years post-licensing). These facts in our context might be due to (i) the higher proportion of male and experienced drivers and/or (ii) these drivers generally driving more, being over-confident, and less cautious. Consequently, male and experienced drivers' behaviors should be more impacted by traffic cameras. Our findings support this, showing a significant reduction in accidents involving these driver groups post-camera installation.

Second, since accidents are less likely to occur at lower speeds (Peltzman 1975), cameras should be more effective where traffic speed is higher. Urban traffic speeds are influenced by the severity of congestion. The speeds are lower during peak hours (7:00-9:00 am and 5:30-7:30 pm in our setting) but higher during off-peak hours. We classify the accident times into peak and off-peak hours and find that advanced cameras reduce accidents in off-peak hours, but not in peak hours, reinforcing their role in deterring risky driving.

Finally, the advantage of automated enforcement over police officers lies in its constant presence and extensive coverage. Police deployment on the road is often disproportionate across time in a day – for example, more in the daytime and less at night. In addition, the ability of officers to detect traffic violations is weaker at night than in the daytime. In contrast, traffic cameras can operate effectively 24/7 under various light conditions. We analyze the effect of advanced cameras during daytime (6 am to 6 pm) and nighttime (6 pm to 6 am) separately. Results show that advanced camera installations lead to a statistically significant reduction in accidents in both periods, with a notably larger effect at night. These findings further support the benefits of automated enforcement's constant and pervasive operations in preventing traffic accidents.

6. Discussion and Conclusion

6.1. Summary of Findings

In this paper, we examine the role of automated enforcement in traffic safety. Using a unique longitudinal dataset on road accidents and traffic camera installations in a metropolitan city in China in the mid-2010s, our event study estimates consistently demonstrate a statistically significant and persistent downward trend in total accidents near advanced cameras. The installation of conventional cameras does not have a material effect on the total accidents, but it leads to a decrease in a limited type of accidents because such cameras are designed to detect limited violations.

More importantly, we further theorize the sources of the effect: the *technical capability* and *driver learning* associated with the cameras. Our findings show that the unique technical capabilities – *automated detection* enabled by ML techniques and *real-time recording* – differentiate the trends in accidents near advanced cameras from those near conventional cameras or no cameras. Compared to conventional cameras, advanced cameras exhibit larger effects on accidents due to their proactive functions (i.e., enhanced violation detection). This relative effect is evident in both the extensive margin (a decrease in more types of accidents) and the intensive margin (a greater reduction in the same accident types). Furthermore, advanced cameras exhibit a unique effect on reducing more types of accidents for which associated violations could have been captured by their passive functions (i.e., real-time video recording), an effect not observed for conventional cameras. These capabilities of advanced cameras help establish a *technology-enabled deterrence*, wherein drivers are aware of and learn the presence and functions of advanced cameras. This awareness and learning carry over to other locations, even where effective deterrence does not exist, by affecting drivers' behaviors in a way to avoid violations and reduce their accident risks.

Additional findings from tests of confounding explanations, heterogeneous effects, and welfare analyses further substantiate the impact of automated enforcement. *First,* the overall reduction in accidents persists over time and does not shift to locations further away from cameras, assuaging concerns about temporal or spatial displacement that is common with human police deployment. *Second,* we find no evidence of accident risks transferring to other road users (e.g., pedestrians, cyclists) after camera installations, addressing concerns about risk compensation and negative externalities to motor and pedestrian collisions. *Third,* the effects of advanced cameras are stronger for male and experienced drivers, as well as during non-peak hours and nighttime, when risky driving is more likely, corroborating the deterrence mechanism. *Finally,* the estimated total societal benefit associated with the advanced cameras is economically significant, with the potential decrease of 1,190 accidents, 496 people involved in fatal and injury cases, and ¥6,298,780 (≈ US $969,043) in property loss annually, *had* they been installed at all signal-controlled intersections in the studied city.

6.2. Contributions to Research and Policymaking

This study makes significant contributions to research and practice. First, it advances research on traffic safety by distinguishing the capabilities of advanced, AI-driven systems from conventional interventions. Prior studies have largely focused on conventional cameras, often overlooking their technical features, and reported mixed or limited effects (De Pauw et al. 2014, Gallagher and Fisher 2020). In contrast, we examine how technical features—such as ML-enabled multi-violation detection and real-time recordings—reshape road safety. Our findings suggest that advanced cameras address key limitations of conventional enforcement, including information asymmetry and negative externalities (Edlin and Karaca-Mandic 2006), while enhancing deterrence and encouraging drivers to internalize and comply with traffic regulations. By analyzing the interplays between technical capabilities and behavioral deterrence, we show how advanced cameras reduce accidents and foster sustained behavioral changes, even beyond monitored areas, bridging critical gaps in the literature on traffic management and road safety.

Moreover, this study advances criminology and law enforcement scholarship (Becker 1968, Nagin 2013, Chalfin and McCrary 2017) by exploring the role of *automated*, AI-enabled enforcement. Although research has linked public surveillance cameras to crime deterrence (e.g., Priks 2015), the socio-technical aspects of automated enforcement remain under-theorized. We provide theoretical insights into how traffic cameras' automated detection and real-time recording capabilities can evolve into effective technology-enabled deterrence. Further, our findings advance the debate on deterrence efficacy in traffic safety (e.g., Banerjee et al. 2019), demonstrating that technology-enabled deterrence mitigates concerns over risk displacement or compensation (Pelzman 1975) and highlighting comparative advantages of automated over conventional law enforcement in improving road safety.

Further, this research enriches the broader discourse on the societal impact of IT (e.g., Chan and Ghose 2014, Chan et al. 2016, Cheng et al. 2020, 2022, Liu and Bharadwaj 2020, Park et al. 2021). By examining a machine learning application in the public domain, we extend the scope of IS literature on IT and transportation, offering new insights into the role of emerging technologies in addressing enduring challenges in road safety and public health.

Finally, the findings of this work hold significant implications for policymakers. To enhance traffic law enforcement, policymakers and transportation planners should prioritize *technology-augmented* policy interventions. More importantly, they must develop a deeper understanding of *how*, *why*, and *when* automated enforcement is most effective. The significant and persistent reduction in road accidents following the installation of advanced cameras, compared to conventional ones, delivers a key policy insight; for *technology-enabled deterrence* to be materially effective, it is essential to evaluate the technical capabilities, drivers' behavioral changes, and overall effectiveness of such systems, rather than narrowly focusing on whether to deploy them or how many to install. Key questions to consider include: *What types of violations can these cameras detect? How effectively do they apprehend traffic violators? Can they provide constant traffic monitoring and collect evidence to determine accident causes and liabilities? How do they influence drivers' learning and behavioral adjustment toward safe driving?* Insights from this study offer a foundation for policymakers to navigate the complexities of procuring and deploying automated enforcement systems and to cautiously and dynamically assess their impact on traffic safety.

6.3. Limitations and Future Work

To understand the extent to which our findings on automated enforcement and its effects can inform real-world considerations and applications, we highlight several important limitations. One key limitation lies in our focus on traffic safety, measured by changes in road accidents. While this approach provides valuable insights, a more detailed analysis of traffic violations following camera deployment could shed light on the underlying deterrence mechanisms. Since our analysis is based on police accident reports, it does not account for violations that do not result in accidents. A more comprehensive dataset, including all recorded violations, could reveal a broader deterrent effect, but such data were not available for this study.

Another constraint is the inability to conduct a complete cost-benefit analysis due to limited data on camera installation costs. Expenses for camera purchase, installation, and maintenance vary significantly depending on the contracts between the city government and private vendors. Moreover, procurement details for traffic cameras in our context were not publicly disclosed. Despite this limitation, our welfare estimates indicate that the impact of automated enforcement on traffic safety is both statistically and economically significant.

A further consideration is the ongoing ethical and societal debate surrounding surveillance technologies (e.g., Acemoglu 2021, Crawford 2021, Zuboff 2019). We emphasize that the primary aim of this study is to provide rigorous scientific evidence on the impact of automated enforcement on traffic safety, rather than addressing broader societal concerns, such as potential privacy violations associated with surveillance. To achieve this aim, we independently collected and consolidated data on camera installations and accidents, and we described and analyzed the dataset with due caution. To gain deeper insights into the context where automated enforcement operates, we also conducted field interviews with local police officers, drivers, and camera suppliers.

Building on these insights, we propose several directions for future research and practice. First and foremost, foundational research on deterrence mechanisms and behavioral insights is needed to better understand the implications of automated enforcement. Future studies can analyze traffic violations, including those not resulting in accidents, to better assess the effectiveness of AI-based deterrence. Driver-level analyses with individual-level data could offer more nuanced insights into behavioral adjustments under deterrence. Longitudinal research can track driver learning over time using telematics or digital driving records. These insights can inform the development of driver education programs that complement enforcement technologies.

In addition, actionable frameworks for optimizing automated enforcement deployment are needed. Comprehensive cost-benefit analyses—accounting for installation, maintenance, and operational expenses alongside accident reduction benefits—would aid in evaluating economic feasibility. Additionally, examining the varying impacts of advanced cameras across urban, suburban, and rural settings, as well as roads with different speed limits, can guide data-driven strategies for optimal camera placement, maximizing safety benefits and economic efficiency.

Furthermore, exploring synergies between automated enforcement, smart mobility technologies, and existing infrastructure is crucial. Research on integrated systems—combining automated enforcement with technological advancements (e.g., cameras to detect violations by non-motorized vehicles), real-time traffic management, and safety policies—could help urban planners align enforcement technologies with broader smart city initiatives.

Last but not least, addressing societal implications and fostering public acceptance of automated enforcement is vital. Future research can investigate public perceptions—including concerns about surveillance, privacy, and trust in institutions—and compare enforcement effectiveness across diverse policy environments and cultural contexts. Such studies could inform transparent communication strategies to build greater public trust and acceptance and provide comparative insights for global adoption and standardization of automated enforcement. Addressing these directions allows future research and practice to expand upon our study, advancing traffic safety, economic efficiency, and societal integration of automated enforcement.

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AUTOMATED ENFORCEMENT AND TRAFFIC SAFETY

Online Supplementary Appendices

Appendix A: Literature Reviews

Table A-1. A Brief Review of Studies on Traffic Enforcement Cameras and Road Accidents (2014-2024)

Authors (Year)	**Cameras for multiple violations?**	**Technology behind?**	**Accident measurements**	**Geo-Units**	**Traffic safety effect**
Blais and Carnis (2015)	No (speed cameras)	Unspecified	Fatal and injury crashes	1 country (France)	Positive
Claros et al. (2017)	No (red light cameras)	Unspecified	Rear-end, angle crashes	59 intersections	Mixed
De Pauw et al. (2014)	Yes, but limited (speed & red light)	Unspecified	Injury, rear-end, side crashes	253 intersections	Mixed
Gallagher and Fisher (2020)	No (red light cameras)	Unspecified	Total accidents and injuries	66 intersections	Null
Graham et al. (2019)	No (speed cameras)	Unspecified	Personal injury collisions	771 camera sites	Positive
Hu and Cicchino (2017)	No (red light cameras)	Unspecified	Fatal crashes	33 U.S. Cities	Positive
Hu and McCartt (2016)	No (speed cameras)	Unspecified	Speed, crashes involved an incapacitating or fatal injury	117 U.S. cities	Positive
Langland-Orban et al. (2014)	No (red light cameras)	Unspecified	Fatal crashes	62 U.S. Cities	Null
Lee et al. (2015)	No (red light cameras)	Unspecified	Fatal and injury crashes	200 intersections	Negative
Llau et al. (2015)	No (red light cameras)	Unspecified	injuries	20 intersections	Positive
Martínez-Ruí et al. (2019)	Yes, but limited (e.g., speeding, red light running, blocking crosswalks)	Unspecified	All crashes, injury and fatal crashes	88 intervention areas in a city	Positive
Quistberg et al. (2019)	No (speed cameras)	Unspecified	Motorist speeds and speed violation rates	4 school areas in a city	Positive
Tilahun et al. (2022)	No (speed cameras)	Unspecified	Injury and fatal crashes	101 camera locations in a city	Positive
Wang et al. (2020)	Yes, but limited (e.g., speeding, red-light running, illegal lane changing)	Unspecified	Injury and non-injury crashes	49 traffic analysis zones in a city	Positive
Wong (2014)	No (red light cameras)	Unspecified	Red light crashes, injury crashes, all crashes	32 treated intersections	Mixed
This paper	Yes	Specified	Total and various accidents	2,522 intersections	Positive

Table A-2. A Brief Review of IS Literature on IT in Transportation

Authors (Year)	Technology	Topic in Transportation	Intended effect?	Key Findings
Agarwal et al. (2023)	Ride-hailing platform (Uber)	Traffic congestion	No	Uber exit led to a decrease in travel time.
Barbar and Burtch (2020)	Ride-hailing platform (Uber)	Public transit utilization	No	Uber entry led to a decrease in bus services but an increase in commuter rail services.
Cheng et al. (2020)	Federally-supported intelligent transportation systems (ITS)	Traffic congestion	Yes	Government ITS adoption facilitates urban mobility and traffic management
Greenwood and Wattal (2017)	Ride-hailing platform (Uber)	Traffic safety	No	Uber entry reduces alcohol-related motor vehicle fatalities
Li et al. (2022)	Ride-sharing platform (Uber)	Traffic congestion	No	Uber entry increases traffic congestion in compact areas but decreases it in sprawling urban areas.
Liu et al. (2021)	Ride-hailing platform (Uber)	Taxi and ridesharing service quality	Yes	Platform design increases service efficiency and reduces moral hazard
Rhee et al. (2023)	Information sharing via ride-hailing platform	Taxi and other public transit utilization	No	Information sharing via ride-hailing apps effectively allocates traffic demand across transportation means.
Zhang et al. (2020)	Global Positioning Systems (GPS)	Drivers' demand learning and driving decisions	Yes	Information provided by GPS helps drivers to learn the distribution of demand and make more efficient driving decisions.
Zhang et al. (2023)	Ridesharing platforms (Uber)	Taxi and ridesharing utilization	No	The ridesharing platform outperforms (and is more resilient than) taxis under urban anomalies (e.g., terrorist attacks).
This paper	Automated enforcement (in the form of traffic cameras)	Traffic safety	Yes	Automated enforcement, depending on its technical capabilities, can establish deterrence to influence driver behaviors, reducing traffic violations and accident risks.

Appendix B: Data, Sample Construction, and Contextual Properties

B.1. Accident Data

We obtained a proprietary dataset of road accidents from the local police department. The dataset records detailed information on all reported traffic accidents (237,255) in this city between 2014 and 2016 (accident data before 2014 and after 2017 were not made available to us for security control reasons). It includes the specific *time and location of each accident*, *the number of injuries* and *deaths* involved, *the cause of each accident*, as well as drivers' characteristics, such as *age*, *gender*, and *years of driving experience*, among others. Figure B-1 illustrates part of the information collected from a traffic accident report in our context.

道路交通一般事故基本信息采集表（示例 1）

Accident ID 事故编号	440307120180000274	公里（路口/路段）Kilometres (near intersection or section)	1001	米数 Metres	10		
Cross section position 横断面位置	■1 机动车道 □2 非机动车道 □3 机非混合道 □4 人行道 □5 人行横道 □6 紧急停车带 □9 其他 □10 公交停靠泊位 □11 小汽车停车泊位						
# deaths ★死亡人数	2	★受伤人数 # injured	2	抢救无效死亡 # failed rescue and died	2	★下落不明 # whereabout unknown	0
# total persons involved ☆事故涉及人员总数	5	☆行人数量 # pedestrians	4	☆机动车数量 # motor vehicles	1	☆非机动车数量 # non-motor vehicles	0
Accident forms ☆事故形态	□1 碰撞运动车辆 □2 碰撞静止车辆 □3 其他车辆间事故 □4 刮撞行人 □5 碾压行人 □6 碰撞后碾压行人 □7 其他车辆与行人事故 ■8 侧翻 □9 滚翻 □10 坠车 □11 失火 □12 撞固定物 □13 撞非固定物 □14 自身摺叠 □15 乘员跌落或抛出 □16 其他单车事故						
Inter-vehicle accident forms ☆车辆间事故碰撞形态（选填）□填 ■不填	□1 追尾碰撞 □2 正面碰撞 □3 侧面碰撞（同向）□4 侧面碰撞（对向）□5 侧面碰撞（直角）□6 侧面碰撞（角度不确定） □7 同向刮擦 □8 对向刮擦 □9 其他角度碰撞 Angles and ways that vehicles collide with each other.						
Single-vehicle accident forms ☆单车事故(碰撞对象)（选填）□填 ■不填	□1 中央隔离设施 □2 同向护栏 □3 对向护栏 □4 交通标识支撑物 □5 缓冲物 □6 树木 □7 直立的杆或路灯杆 □8 桥墩 □9 隧道 □10 挡墙 □11 建筑物 □12 山体 □13 动物 □14 作业/维修设备 □15 其他 Objects that the single vehicle crashed into						
★现场形态 Status of the accident scene	■1 原始 □2 变动 □3 驾车逃逸 □4 弃车逃逸 □5 无现场 □6 二次现场 □7 伪造现场						
是否运载危险品 Dangerous goods carried [Y/N]	□1 是 ■2 否						
☆危险品事故后果 Accident outcomes duet to dangerous goods carried	□1 爆炸 □2 气体泄漏 □3 液体泄漏 □4 辐射泄漏 □5 燃烧 □6 翻倾 ■7 无后果						
事故类型 Accident types	■1 死亡事故 □2 伤人事故 □3 财产损失事故 1. accidents with deaths, 2. accident with injuries, 3. accident with property loss						
事故初查原因 Accident causes	驾驶有安全隐患的机动车 Driving a motor vehicle with safety hazard						
直接财产损失 Direct property loss	20000						
★能见度 Visibility	□1：50 米以下 □2：50-100 米 □3：100-200 米 ■4：200 米以上 50 metres and below visible, 50-100m visible, 100-200 visible, 200m and above visible						
逃逸是否侦破 Escape detected [Y/N]	□1 是 □2 否	逃逸侦破时间	Escape detection time				
☆路表情况 Road surface condition	■1 干燥 □2 潮湿 □3 积水 □4 漫水 □5 冰雪 □6 泥泞 □7 油污 □8 其他						
☆照明条件 Lighting conditions	■1 白天 □2 夜间有路灯照明 □3 夜间无路灯照明 □4 黎明 □5 黄昏 □6 白天隧道有照明 □7 白天隧道无照明						
☆交通控制方式 Traffic control model	□1 无控制 □2 民警指挥 □3 信号灯 ■4 标志 ■5 标线 □6 其他安全措施 1. no control, 2. police command, 3. signal light, 4. signs, 5. lines, 6. other safety measures						

Location: motor lane, non-motor lane, mixed lane, sidewalk, crosswalk, emergency parking belt, other area, buss parking area, car parking area

Accident form: crashed into moving vehicle(s), stationery vehicle(s), scratch pedestrian(s), run over pedestrian(s), collision and then run over pedestrian(s), rollover, fire, hit fixed object(s), fit non-fixed object(s), self-folding, passenger(s) falling or throwing, other vehicular accidents

Accident scene: original, changed, escape by driving, abandon car and escape, no scene, 2nd scene, fake scene

Accident outcomes: explosion, gas leak, liquid leak, radiation leak, combustion, rollover, no consequences

Road surface condition: dry, wet, stagnant water, flooding, ice and snow, muddy, greasy, others

Lighting conditions: daytime, street lights at night, no street lights at night, dawn, dusk, daylight tunnel, daylight tunnel no lights

Figure B-1. An Example of a Traffic Accident Report

Our sample is restricted to accidents that are geographically close to the road intersections within a radius of 0-100 meters (See Table B-1). This is because (i) these accident locations were more accurately recorded, and (ii) the accident incidences were more likely influenced by traffic cameras (the majority of which are located at the road intersections). Accidents far away (e.g., 100-300 meters) from the cameras (thus beyond the effective monitoring coverage) do not contribute to the direct treatment effect of automated enforcement, but they allow us to measure the spatial displacement effect discussed in the main text. The restriction to accidents in the 0-100m radius of a road intersection results in a sample of 51,364 accidents, 43.3% of which were involved with casualties (deaths and/or injuries). The casualty rate does not differ much across samples, including accidents with different distances (e.g., 50 meters, 100 meters, 200 meters, or 300 meters) to the nearest intersections, which indicates the representativeness of our sample for analysis.

Table B-1. Accident Data by Distance from the Sampled Road Intersections

		Accidents	Casualty Cases	Rate
Data		237,255	78,466	0.331
	300m	106,371	47,249	0.444
	200m	81,382	36,204	0.445
Sample Data	100m	51,364	22,241	0.433
	50m	38,011	16,395	0.431

Notably, the monthly accidents in the studied city increased steadily over the sampled period from January 2014 to December 2016 (Figure B-2). Interestingly, this overall upward trend in accidents happened in the same timeframe during which the number of traffic camera installations increased. However, this positively covarying relationship cannot be interpreted as causal, as other confounding changes co-exist in this period but are not being accounted for. Hence, in the paper (§3), we use econometrics for formal causal identification.

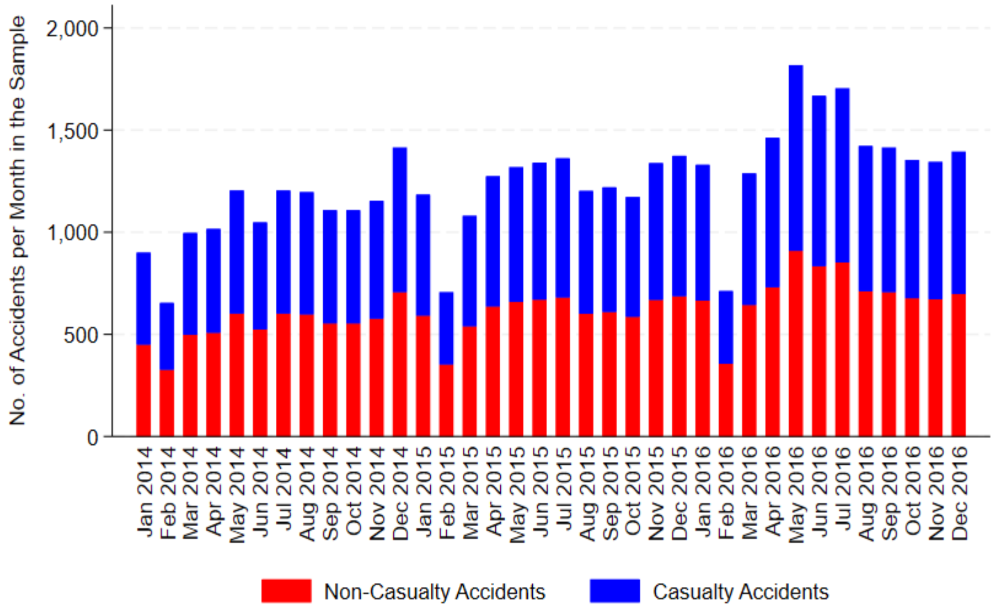


Figure B-2. Number of Accidents per Month, Over Time

B.2. Traffic Camera Installation Data

We manually collected information on all traffic cameras installed in this city from the local government website until September 2021. Such information is required by law to be made available to the public. The camera data we compiled include the *location* and *time of each camera installation*, as well as the *functions* (i.e., what types of traffic violations the camera detects) *of each camera installed*. Figure B-3 is an exemplary webpage of the local government site from which we collected the camera installation data.


无障碍浏览 进入关怀版

网上交警
市公安局交通警察局
Online Traffic Police
Traffic Police Station of City S
Public Security Bureau

请输入关键字 站内搜索

首 页 政务公开 政务服务 公众参与 宣传教育

当前位置：首页 > 政务信息公开 > 通知公告 > 监控设备
Current Location: Home Page > Government Information Disclosure > Notice and Announcement > Monitoring Devices

市公安局交通警察局关于130套交通技术监控设备启用的公告
Announcement on the use of 130 sets of traffic monitoring equipment

信息来源：公安局交通警察局 发布日期：2015-02-07 [内容纠错]
Source: Traffic Police Station of City S Public Security Bureau Date: Feb 27, 2015

为确保交通执法工作的公开公正、体现人性化管理，根据《道路交通安全违法行为处理程序规定》（公安部令105号）第十六条规定，现将我市近期启用的130套固定式交通技术监控设备，按行政区域、设备类型及设置地点进行公布：

"In order to ensure the open, fair, and humanized management of traffic law enforcement work, in accordance with the provisions of Article 17 of Regulations on Handling Illegal Behaviors of Road Traffic Safety (Order No. 105 of the Ministry of Public Security), 130 sets of fixed traffic monitoring equipment recently put into use in our city are now announced by administrative region, equipment type, and location."

序号 ID	区域 District	类型 Traffic Camera Type	设置地点 Location
1		冲红灯、逆行（标清） Running Red Lights, Retrograde (Standard Definition)	路口东方向
2		冲红灯、逆行（标清）	路口西方向
3		冲红灯、逆行（标清）	路口北方向
4		冲红灯、逆行（标清）	路口东方向
5		冲红灯、逆行（标清）	口西方向
6		冲红灯、逆行（标清）	路口东方向
7		冲红灯、逆行（标清）	路口西方向
8		冲红灯、逆行（标清）	路口南方向
9		冲红灯、逆行（标清）	路口东方向

Figure B-3. An Example of Local Government Webpage that Regularly Announced Camera Installations, the Camera Types, and Their Times and Locations

Two aspects of camera installation data are worth noting: *First,* the installation data we collected not only covers the sample period (5,969 installations between 2014-2016), but also includes camera installation information before January 2014 (3,405) and between January 2017 and September 2021 (7,977) (Table B-2). In the analysis, we use the road intersections that were later installed with cameras after 2017 as our *control group*, because both control and treatment intersections "need" camera installations, thereby relatively comparable. *Second,* we exclude cameras installed at non-intersection locations, such as those in the middle of a road segment, because, in such cases, locations of both camera installations and accidents nearby were less accurately recorded in the original dataset.

Table B-2. Accident Data by Distance from the Sampled Road Intersections

	before 2017	after 2017
Total Number of Cameras	9,374	7,977
Number of Cameras in the Sample (Installed at the Road Intersections)	5,969	

Figure B-4 summarizes the installations of traffic cameras per month over the extended period until September 2021. It reflects the staggered installation of traffic cameras, creating a quasi-experimental setting that allows for the use of an event study to examine changes in accidents resulting from the camera installations (§3.1).

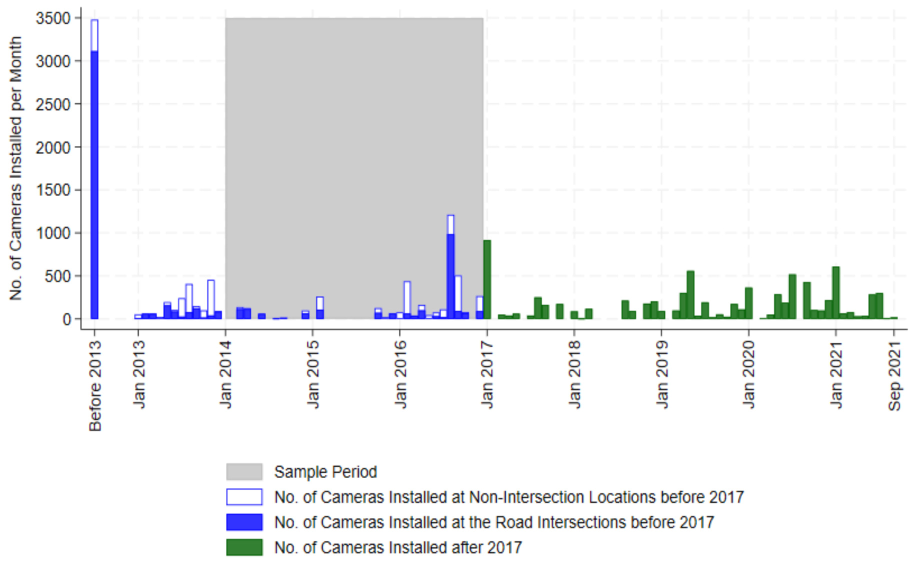


Figure B-4. Temporal Distribution of Road Intersections that were Installed with Traffic Cameras per Month

Notably, we study two types of cameras: *conventional* traffic cameras (which only detect limited violations based on temporary image capture) and *advanced* ones (which detect a greater variety of violations via constant video capturing and real-time pattern recognition). See the illustrations in Table B-3 and Figure B-5 for their differences and similarities.

There are two notable differences between these two types of cameras: the *coverage* and *method* of violation detection. *First*, conventional cameras only detect *running red lights* or *retrograde*, whereas advanced ones detect as many as thirty traffic violations, including some common ones such as *speeding, not following traffic signs/signals,* and *driving in the wrong lane. Second*, conventional cameras detect and capture violations *passively*. For example, when a vehicle runs a red light, the electromagnetic device laid below the ground (often below the crossroad) can detect the moving (or reversed-moving) objects when the red light is on, and the device triggers the cameras nearby to capture the violation scene. These conventional cameras often take two to three images—capturing both the red light and the moving vehicle with a clear license plate—to testify to the violation. In contrast, advanced cameras detect violations *proactively* because the detection is based on real-time video capture and analytics. As the advanced camera is constantly in operation, all violations nearby are captured in this real-time video stream. In practice, whether a type of violation is detected and recorded depends on whether the ML algorithms embedded in the camera have learned such a violation before and been programmed to detect it. In the studied context, advanced cameras vary in their functions (i.e., number of detectable violations), depending on the camera suppliers. Cameras of different installation cohorts may come from different suppliers. Nevertheless, in all cases, advanced cameras are much more capable than conventional ones of detecting violations.

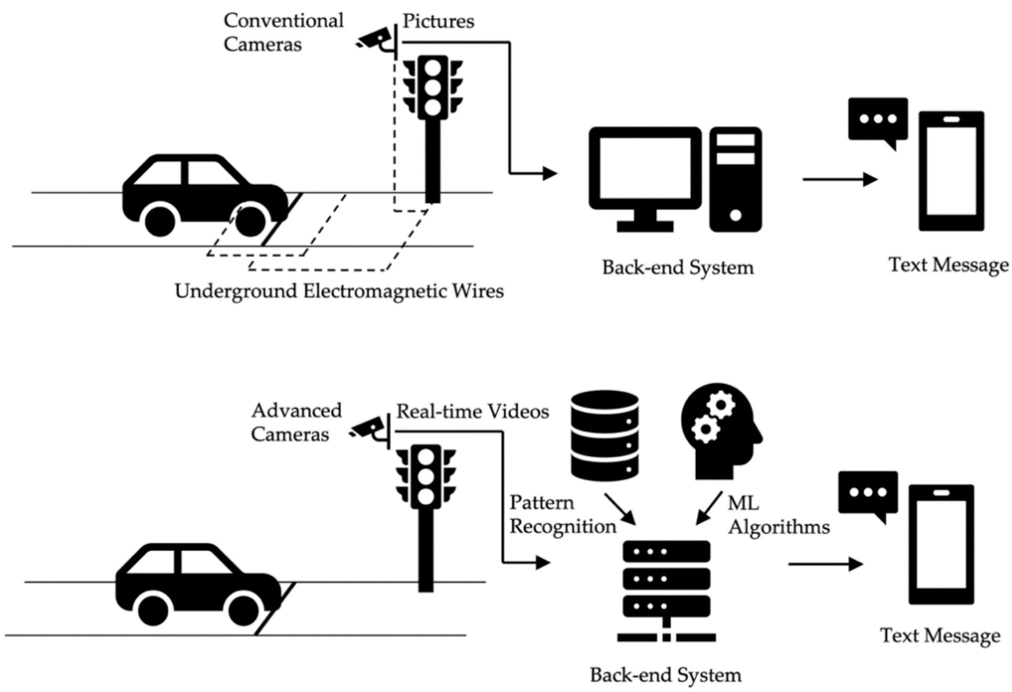


Figure B-5. Graphical Illustration of Conventional and Advanced Camera Enforcement

Table B-3. Differences between Conventional and Advanced Traffic Cameras

	Conventional Cameras	**Advanced Cameras**
Violations Detected (Fewer vs. More)	*Running red lights* and *retrograde*	Over 30 common traffic violations. Besides *running red lights* and *retrograde*, the violations detected mainly include *speeding*, *illegally overtaking other vehicles*, *U-turns in dangerous areas*, *not following traffic signs/signals*, and *driving in the wrong lane.*
Detection Methods (Passive vs. Proactive)	The violation can be detected by an underground electromagnetic device that triggers the cameras nearby to capture images of the violated vehicle with the license plate number.	The violation and the violated vehicle can be captured in the real-time video stream and identified by the pattern recognition algorithms embedded in the camera.

Despite these differences, conventional and advanced cameras are very similar in appearance, though the advanced camera is always with a lighting device nearby. Another similarity is that on-site violations captured by both types of cameras are automatically written into the backend database, which allows the generation of text messages (as a notice of violation and fine) to offenders. The text message also informs the offenders of the type of traffic violation as well as when and where the violation happened.

Throughout this paper, we use "new" and "old" cameras interchangeably for advanced and conventional cameras, respectively.

B.3. Road Intersection Data

We obtained the road intersection-level features from Baidu Map API, a web mapping service application in China. The features include the average traffic congestion levels, road types (e.g., state, provincial, or urban roads with varying engineering requirements to accommodate speed limits and vehicles of different weights) passing through the intersection, and the coordinates of all educational institutes (elementary and secondary schools), bus stops, train stations, subway stations (either in operation or under construction), restaurants, tourist spots, and government agencies. We consider these facilities as they might affect both the cameras needed and the accidents near the focal intersection. To control their effects, we count the number of such facilities within the 0-500 meters radius, except for train stations and tourist spots, where we use a 1000m radius, given significantly much heavier traffic of commercial vehicles and pedestrians near them.

To construct a dataset at the intersection-month level, we restricted the sample of road intersections to signal-controlled ones. This is because (i) in urban areas (and also in our sample), the most likely location for a traffic accident is the road intersection, and most traffic cameras are installed at the intersections rather than at the road segments; (ii) per local traffic regulation, all intersection cameras should be installed at the signal-controlled intersections; and (iii) as different intersections may exhibit substantial heterogeneity, we restrict the sample in this way to construct a comparable treatment-control sample for analysis. This restriction results in 2,522 signal-controlled intersections.

We manually matched all the cameras in our dataset with these signal-controlled intersections. We find that among these intersections, 958 have never installed cameras by September 2021, when data collection needed. Recall that we use the intersections that installed cameras later (2017-2021) as a counterfactual for the treated intersections with cameras in the sample period (2014-2016). Thus, we dropped these 958 less comparable intersections, resulting in 1,564 sampled ones.

Accidents were then matched to the vicinity (0-100 meters) of these intersections. In doing so, we compiled a dataset of camera installations and accidents to the same referenced map of road intersections. Among these 1,564 intersections, 990 were treated with cameras (thus the treatment group), and 574 were not (thus the control group). Within the treatment group, 138 had only advanced cameras, 765 had only conventional cameras, and 87 had both. We conducted two event study estimations, comparing (i) new vs. no cameras and (ii) old vs. no cameras. As shown in Figure B-6, most conventional cameras were installed earlier than advanced cameras, which reflects the transition from the first wave to the second wave of traffic camera deployment in this city.

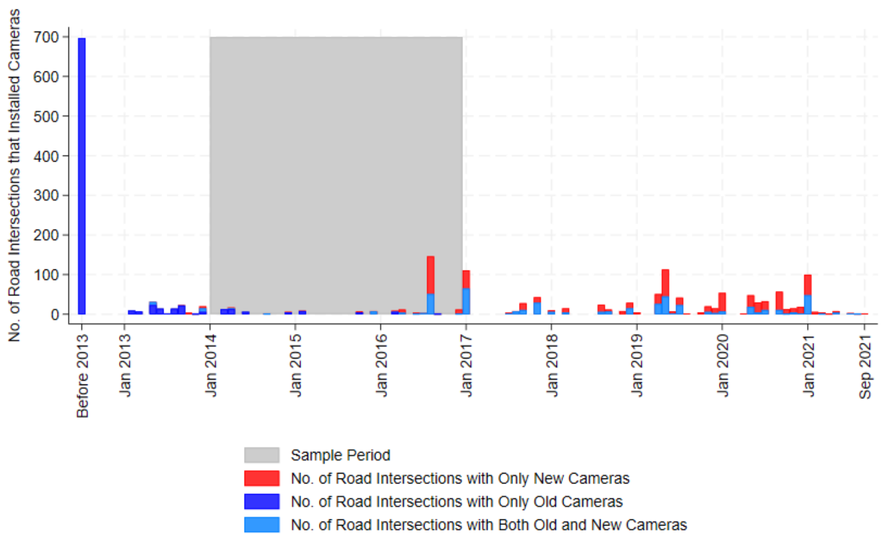


Figure B-6. Temporal Distribution of Road Intersections that Were Installed with Advanced and Conventional Traffic Cameras per Month

B.4. Contextual Properties

There are a few good properties in this context for identifying the effects of traffic camera installation: *First*, camera installations were rolled out with both geographical and temporal variations, which offers us a quasi-experimental setup. *Second*, we are able to use location fixed-effects to tease out time-invariant confounding effects from, for example, population density, road complexity, bus traffic, and past traffic measures. We also account for location-specific time-varying factors, such as traffic speed. *Third*, camera installations are not anticipated *ex ante* by drivers, which increases the confidence in the treatment exogeneity. *Fourth*, we control the potential interference among road intersections, i.e., the installation of cameras nearby imposes an effect on accidents at the focal intersection. Specifically, we control the number of cameras installed at neighboring road intersections and segments (within 0-300 meters of the focal intersection).

We note a valid concern about the non-compliance issue, i.e., whether the presence of cameras at the focal intersection is noticeable to drivers passing through; if not, this intersection is, *de facto*, not treated. Note that "non-compliance" here does not mean that drivers act against the traffic safety regulations; rather, it is a situation where cameras are too invisible to exert effect. In our setting, the non-compliance issue is not severe for several reasons.

(1) Traffic cameras in China are recognizable with clear signs next to them (Figure B-7), and *de jure*, all drivers have to be able to recognize such signs.
(2) The cameras in our sample were all installed at signal-controlled intersections, and vehicles have to stop and notice the presence of cameras when the red light switches on. Otherwise, they will almost be a 100% chance of getting caught, as all cameras can detect running red-light violations. If drivers get caught, they are essentially affected by the cameras, and then non-compliance is accounted for by the treatment effect.
(3) When the green light switches on and some drivers passing by at speed are not aware of the cameras, this is the situation that most likely reduces the effectiveness of the treatment. That said, if we identify any measurable effect, it will serve as the lower bound of the true effect, because cameras will surely exert a larger effect when they are more visible. This, however, does not weaken the informativeness of our estimates.

Figure B-7. Traffic Cameras with the Sign Next to Them

Appendix C: Descriptive Statistics, Covariates, and Camera Installation Prediction

Table C-1 summarizes the statistics of different accidents and associated consequences (e.g., death, injury, property loss, violation tickets) per intersection per month. Table C-2 presents the construction of intersection-level covariates that we use in the event study estimation. Table C-3 reports the exposure analysis where we use past accident levels (one month, two months, three months) and covariates to predict if a road intersection would be installed with either an advanced traffic camera or a conventional one. The results indicate that reverse causality might not be a concern, supporting the parallel trend assumption for the TWFE event study estimation. We also conduct a non-parametric comparison of accidents near intersections eventually treated (treatment group) and untreated (control group) with installations during the sample period, as well as a comparison of accidents at treatment intersections before and after camera installation, and the results are reported in Table C-4.

Table C-1. Summary Statistics of Accidents per Intersection per Month (N=56,304)

	Mean	S.D.	Min.	Max.
	(1)	(2)	(3)	(4)
Within the radius of 0-100 meters of the intersection				
# accident cases	0.649	1.153	0	23
# casualty cases	0.278	0.619	0	9
# non-casualty cases	0.371	0.845	0	18
# deaths	0.006	0.081	0	6
# injuries	0.338	0.841	0	49
¥ property loss	753.254	2,630.757	0	200,000
# accidents affected by new cameras' proactive function	0.272	0.692	0	14
# accidents affected by old cameras' proactive function	0.099	0.384	0	6
# accidents affected by new cameras' passive function	0.260	0.604	0	15
# accident not affected by any function	0.062	0.298	0	9
# female driver cases	0.233	0.639	0	17
# male driver cases	0.447	0.938	0	19
# novice driver cases	0.078	0.410	0	17
# experienced driver cases	0.634	1.141	0	23
# daytime cases	0.261	0.612	0	11
# night-time cases	0.387	0.805	0	15
# holiday cases	0.189	0.507	0	15
# workday cases	0.460	0.901	0	16
# peak hour cases	0.102	0.352	0	6
# off-peak hour cases	0.546	1.018	0	22
Within the range of 100-300 meters of the intersection				
# accident cases	0.630	1.165	0	22

Table C-2. Covariates and Definitions

Covariate	Definition
(i) Intersection-specific time-varying variables (yearly updated, lagged for one year)	
edu_500m_dum	=1 if at least one educational institution is located within the radius of 0-500m of the road intersection, =0 otherwise
car park_500m_dum	=1 if at least one car park is located within the radius of 0-500m of the road intersection, =0 otherwise
gov_500m_dum	=1 if at least one government office is located within the radius of 0-500m of the road intersection, =0 otherwise
resid_500m_dum	=1 if at least one residential district is located within the radius of 0-500m of the road intersection, =0 otherwise
comm_500m_dum	=1 if at least one commercial building is located within the radius of 0-500m of the road intersection, =0 otherwise
# catering_500m	number of food shops within a radius of 0-500m of the road intersection
# bus stop_500m	number of bus stops within a radius of 0-500m of the road intersection
(ii) Intersection-specific time-varying variables (monthly updated)	
train station_1000m_dum	=1 if at least one train station is located within the radius of 0-1000m of the road intersection, =0 otherwise
subway station_500m_dum	=1 if at least one subway station is located within the radius of 0-500m of the road intersection, =0 otherwise
subway station_uc_500m_dum	=1 if at least one subway station under construction is located within 0-500m of the road intersection, =0 otherwise
ban_post	=1 if there is a ban on riding the electric bicycle on the road, =0 otherwise
# old cameras_300m	number of neighboring conventional cameras within the radius of 0-300m of the road intersection
# new cameras_300m	number of neighboring advanced cameras within the radius of 0-300m of the road intersection
# accident cases in the past 3 months	total number of traffic accidents in the past three months
# casualty cases in the past 3 months	total number of casualty accidents in the past three months
(iii) Intersection-specific time-invariant variables	
traffic congestion level_200m	the traffic congestion level within 0-200m of the road intersection (a lower value represents severer congestion)
tourist_1000m_dum	=1 if at least one tourist spot is located within the radius of 0-1000m of the road intersection, =0 otherwise
road level2_dum	=1 if the maximum administrative level of road across the intersection is the 2nd level (county level), =0 otherwise
road level3_dum	=1 if the maximum administrative level of road across the intersection is the 3rd level (city level), =0 otherwise
distance to district gov	distance to the site of the district government
distance to city gov	distance to the site of the city government

Table C-3. Summary Statistics of Covariates Per Intersection and Per Month

	N	Mean	S.D.	Min.	Max.
Panel A: Intersection-specific time-varying variables (yearly updated, lagged for one year)					
edu_500m_dum	56,304	0.501	0.500	0	1
car park_500m_dum	56,304	0.680	0.466	0	1
gov_500m_dum	56,304	0.291	0.454	0	1
resid_500m_dum	56,304	0.357	0.479	0	1
comm_500m_dum	56,304	0.302	0.459	0	1
# catering_500m	56,304	25.310	56.311	0	501
# bus stop_500m	56,304	6.591	6.259	0	29
Panel B: Intersection-specific time-varying variables (monthly updated)					
train station_1000m_dum	56,304	0.034	0.181	0	1
subway station_500m_dum	56,304	0.190	0.393	0	1
subway station_uc_500m_dum	56,304	0.026	0.159	0	1
ban_post	56,304	0.696	0.460	0	1
# old cameras_300m	56,304	0.346	0.823	0	6
# new cameras_300m	56,304	0.017	0.236	0	6
# accident cases in the past 3 months	51,612	1.956	2.762	0	50
# casualty cases in the past 3 months	51,612	0.838	1.313	0	18
Panel C: Intersection-specific time-invariant variables					
traffic congestion level_200m	53,208	76.028	18.011	0	100
tourist_1000m_dum	56,304	0.016	0.125	0	1
road level2_dum	56,304	0.002	0.044	0	1
road level3_dum	56,304	0.004	0.062	0	1
distance to district gov	56,304	7.117	6.443	0.158	29.216
distance to city gov	56,304	18.771	10.348	0.201	49.446

Table C-4. Model-Free Comparisons

	Control	Treatment		
	Average	Average	Before	After
Panel A: Intersections w/ advanced cameras vs. Intersections w/o any cameras				
# accident cases	0.458	0.519	0.560	0.381
	(0.984)	(0.937)	(0.975)	(0.782)
log(# accident cases + 1)	0.256	0.292	0.314	0.220
	(0.437)	(0.457)	(0.468)	(0.408)
Panel B: Intersections w/ conventional cameras vs. intersections w/o any cameras				
# accident cases	0.458	0.779	0.325	0.788
	(0.984)	(1.260)	(0.688)	(1.270)
log(# accident cases +1)	0.256	0.414	0.196	0.419
	(0.437)	(0.525)	(0.373)	(0.527)

Notes: Standard deviation in parentheses.

Appendix D. Event Study Estimates

Table D-1 below presents the point estimates and standard errors for the baseline event study estimates in Figure 1.

Table D-1. TWFE-OLS Event Study Estimates for Figure 1

DV: log(# accident cases + 1)	New vs. Null (1)		Old vs. Null (2)	
Installed (-13 month)	0.019	(0.036)	-0.012	(0.056)
Installed (-12 month)	-0.008	(0.043)	0.037	(0.069)
Installed (-11 month)	-0.016	(0.043)	0.025	(0.076)
Installed (-10 month)	-0.047	(0.049)	0.049	(0.065)
Installed (-9 month)	0.014	(0.057)	0.113	(0.070)
Installed (-8 month)	-0.016	(0.036)	0.114	(0.107)
Installed (-7 month)	-0.046	(0.040)	0.125	(0.103)
Installed (-6 month)	-0.049	(0.055)	0.068	(0.100)
Installed (-5 month)	0.009	(0.043)	-0.025	(0.105)
Installed (-4 month)	-0.049	(0.044)	0.015	(0.093)
Installed (-3 month)	-0.036	(0.048)	0.067	(0.052)
Installed (-2 month)	-0.041	(0.050)	-0.033	(0.061)
Installed (-1 month)				
Installed (+0 month)	0.013	(0.046)	0.109	(0.071)
Installed (+1 month)	-0.096**	(0.043)	0.020	(0.036)
Installed (+2 month)	-0.100**	(0.046)	0.095*	(0.054)
Installed (+3 month)	-0.058	(0.046)	0.023	(0.070)
Installed (+4 month)	-0.101**	(0.049)	0.012	(0.049)
Installed (+5 month)	-0.155**	(0.060)	0.031	(0.079)
Installed (+6 month)	-0.196***	(0.069)	-0.011	(0.060)
Installed (+7 month)	-0.159**	(0.078)	0.021	(0.062)
Installed (+8 month)	-0.305***	(0.068)	-0.019	(0.064)
Installed (+9 month)	-0.235**	(0.092)	-0.015	(0.054)
Installed (+10 month)	-0.164**	(0.070)	0.044	(0.044)
Installed (+11 month)	-0.310***	(0.102)	0.037	(0.058)
Installed (+12 month)	-0.327***	(0.093)	0.049	(0.048)
Installed (+13 month)	-0.280***	(0.060)	0.038	(0.047)
# Treated Intersections	138		765	
# Untreated Intersections	574		574	
Road intersection FE	Yes		Yes	
Year-Month FE	Yes		Yes	
Time-Varying Control	Yes		Yes	
# Observations	25,632		48,204	
R-squared	0.340		0.376	

Note: Robust standard errors (clustered at the block level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix E: Robustness Checks for the Baseline Event Study Estimates

To the extent that this study would be advisory for traffic safety policymaking, it is essential that the empirical findings be reliable and robust. In what follows, we cross-validate the estimates from the event study method.

E.1. Altering Covariate Sets

We change the composition of the covariate set in various ways and examine if the based event study estimates (Eq. 1) are sensitive to such changes. Recall that the baseline TWFE-OLS event study specification includes intersection-specific time-varying covariates (i.e., number of train stations, subway stations in operation, subway stations under construction, bus stops, educational institutes (for elementary and secondary education), car parking spaces, restaurant and other catering facilities in the vicinity of the focal intersection per month), plus intersection and year-month fixed-effects.

(1) We drop all covariates and all fixed effects.

(2) We only maintain intersection and year-month fixed effects and drop all intersection-specific time-varying covariates.

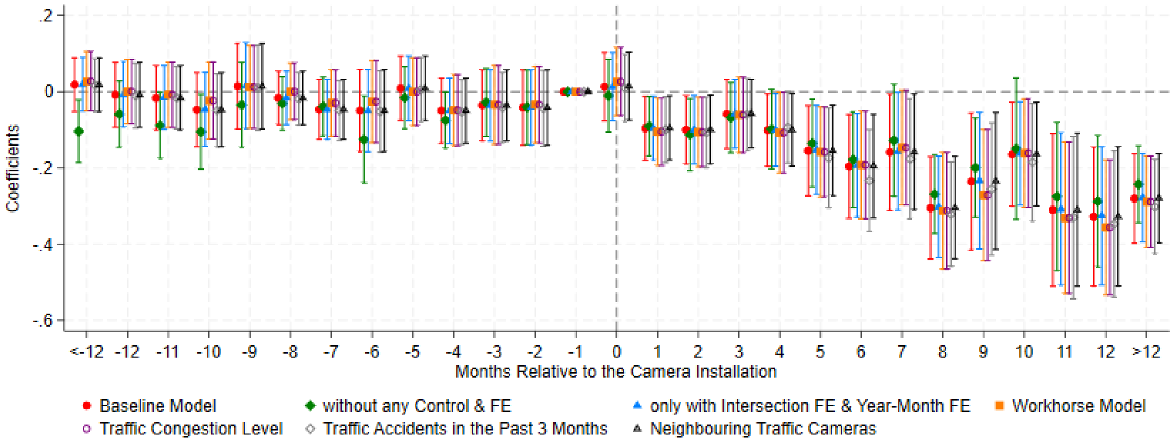
(3) We maintain all covariates in the baseline model and add the interactions between all covariates (except for time fixed-effects) and the year-month fixed-effects (dummies). This specification brings monthly variations of previously time-invariant variables such as road types and distance to district governments, expanding the control for time-varying factors.

(4) In addition to the baseline model, we control for the traffic congestion level (a static index of traffic density passing through the focal intersection, offered by Baidu API) of each intersection by interacting it with the year-month fixed-effects.

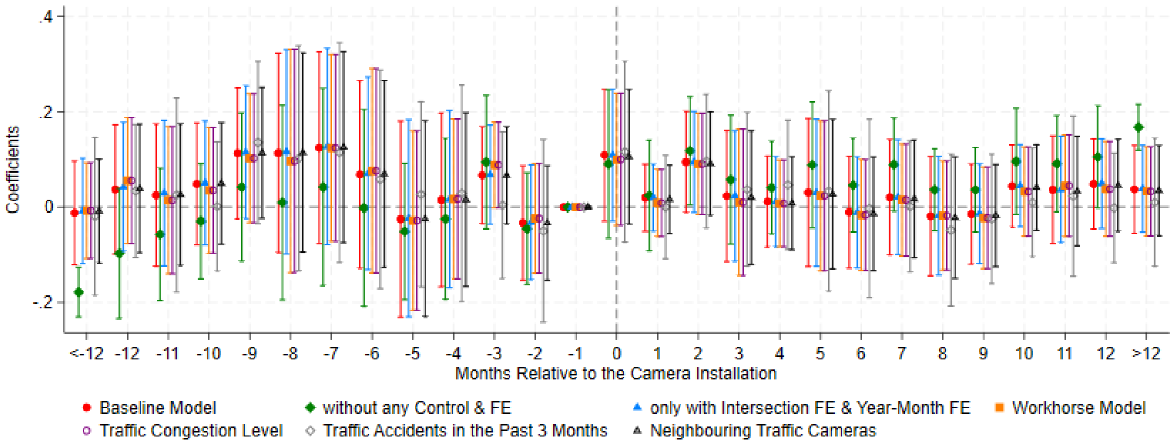
(5) We consider the influence of past accidents on the camera installation and accidents in the current month by additionally controlling for the total accident cases and casualty cases in the past three months (intersection-specific time-varying) to the baseline model

(6) We consider the spatial spillover effect of neighboring traffic cameras by adding (to the baseline model) the counts of old cameras, new cameras, or other types of cameras in the vicinity of the focal intersection within the 300-meter range. These cameras do not have to be installed in the road intersections but could also be on the road segments and anywhere else within the 300-meter range, meaning that we control effects from all cameras nearby (other than the focal one) on the accidents and camera installations in the focal intersection.

Figure E-1 presents all the estimates together for new vs. null and old vs. null, respectively: (0) baseline model, (1) without control & FE, (2) intersection-year FE, (3) workhorse model, (4) traffic congestion level, (5) traffic accidents in the past three months, and (6) neighboring traffic cameras. As seen, except for specification (2), all the other estimates (including point estimates and standard errors) are highly consistent across different specifications, corroborating our baseline TWFE-OLS event study estimates. The estimates of specification (2) indicate the potential bias caused by unobservable, without accounting for intersection and year-month fixed effects.



(1) New vs. Null



(2) Old vs. Null

Figure E-1. Event Study Estimates from Specifications with Different Covariates

E.2. Alternative Sampling Strategies

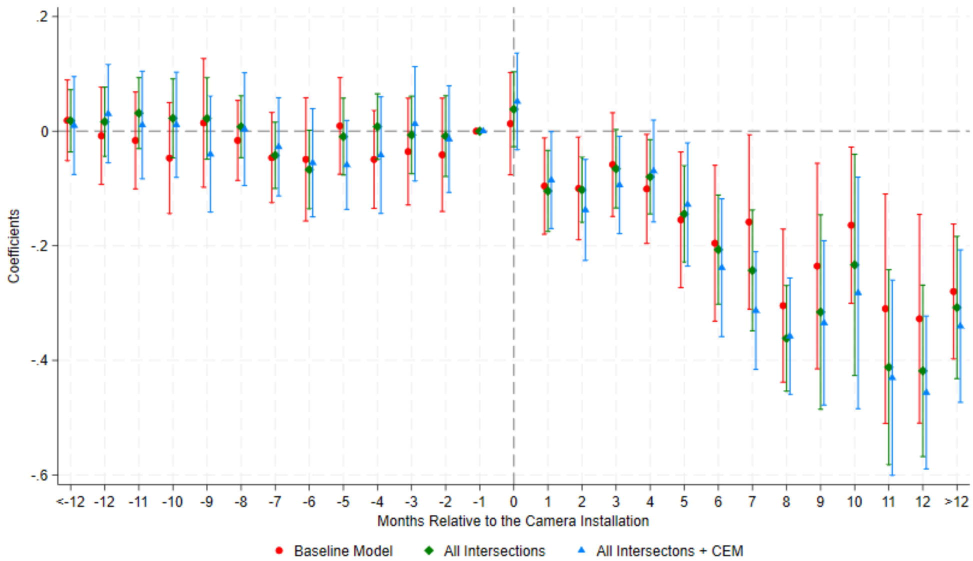
We change the sampling strategy to check the sensitivity of our based estimates of Eq. 1. We take two alternative strategies: (i) use all intersections without camera installation during the sample period as the control group, and (ii) apply the matching technique, specifically Coarsened Exact Matching (CEM) and only include observations (covariates-)matched to the treatment intersections as the control group. Table E-1 presents the covariates before and after applying CEM. The results (mean differences) demonstrate that CEM performed well in increasing the comparability between the treatment and control groups when using a sample of covariates-matched observations.

Table E-1. Balance Checks of Covariates Between Treatment (road intersections with advanced or conventional cameras) and Control Groups (intersections without cameras)

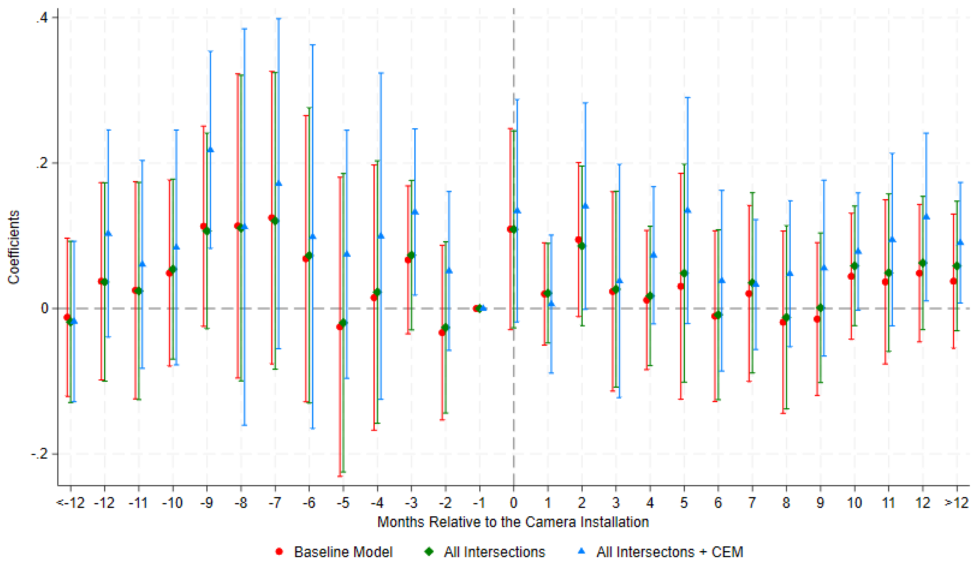
Covariates	Before CEM			After CEM		
Panel A: Advanced vs. No Camera	No Camera	Advanced Camera	Mean Diff	No Camera	Advanced Camera	Mean Diff
	(1)	(2)	(3)	(4)	(5)	(6)
train station_1000m_dum	0.025	0.014	0.011***	0.008	0.008	0
subway station_500m_dum	0.149	0.050	0.099***	0.027	0.027	0
subway station_uc_500m_dum	0.030	0.010	0.020***	0.003	0.003	0
ban_post	0.531	0.537	-0.006	0.525	0.525	0
log(#catering_500m + 1)	0.795	0.461	0.334***	0.206	0.208	-0.002
log(#bus stop_500m + 1)	1.184	0.849	0.336***	0.782	0.776	0.006
edu_500m_dum	0.422	0.372	0.050***	0.339	0.339	0
car park_500m_dum	0.584	0.495	0.089***	0.461	0.461	0
gov_500m_dum	0.209	0.133	0.076***	0.113	0.113	0
resid_500m_dum	0.221	0.138	0.084***	0.065	0.065	0
comm_500m_dum	0.184	0.07	0.114***	0.039	0.039	0
obs.	55152	4968		4276	4276	
Panel B: Conventional vs. No Camera	No Camera	Conventional Camera	Mean Diff	No Camera	Conventional Camera	Mean Diff
	(1)	(2)	(3)	(4)	(5)	(6)
train station_1000m_dum	0.025	0.048	-0.023***	0.016	0.016	0
subway station_500m_dum	0.149	0.251	-0.102***	0.169	0.169	0
subway station_uc_500m_dum	0.030	0.029	0.001	0.013	0.013	0
ban_post	0.531	0.816	-0.285***	0.772	0.772	0
log(#catering_500m + 1)	0.795	1.921	-1.126***	1.049	1.046	0.003
log(#bus stop_500m + 1)	1.184	1.869	-0.685***	1.591	1.592	-0.001
edu_500m_dum	0.422	0.582	-0.160***	0.546	0.546	0
car park_500m_dum	0.584	0.780	-0.195***	0.704	0.704	0
gov_500m_dum	0.209	0.390	-0.181***	0.313	0.313	0
resid_500m_dum	0.221	0.502	-0.281***	0.261	0.261	0
comm_500m_dum	0.184	0.434	-0.250***	0.234	0.234	0
obs.	55152	27540		14120	14120	

Notes: Panel A compares covariates for road intersections with advanced cameras and without any cameras, before and after applying CEM. As seen, the differences are wiped out after applying the matching technique. Panel B compares covariates for road intersections with conventional cameras and without any cameras, before and after CEM. The performance of matching in balancing the covariates is also notable. We do not compare covariates for road intersections with advanced cameras and conventional ones as we do not compare these intersections in our main analysis. The description of the covariates is in Table C-2, Appendix C.

Figure E-2 presents the two estimates together for new vs. null and old vs. null, respectively: (0) baseline model, (1) all intersections, and (2) all intersections + CEM. The estimates are consistent with our baseline event study results.



(1) New vs. Null



(2) Old vs. Null

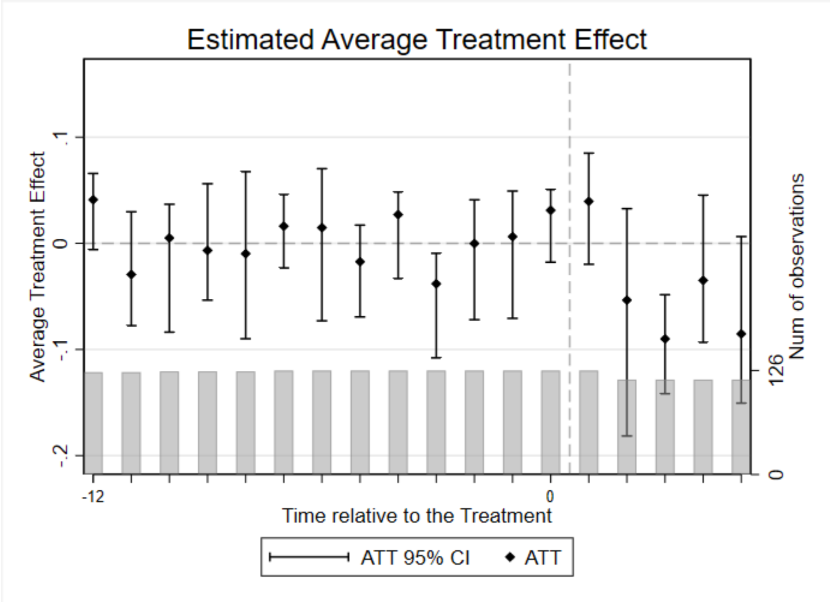
Figure E-2. Event Study Estimates from Alternative Sampling Strategies

E.3. Generalized Synthetic Control

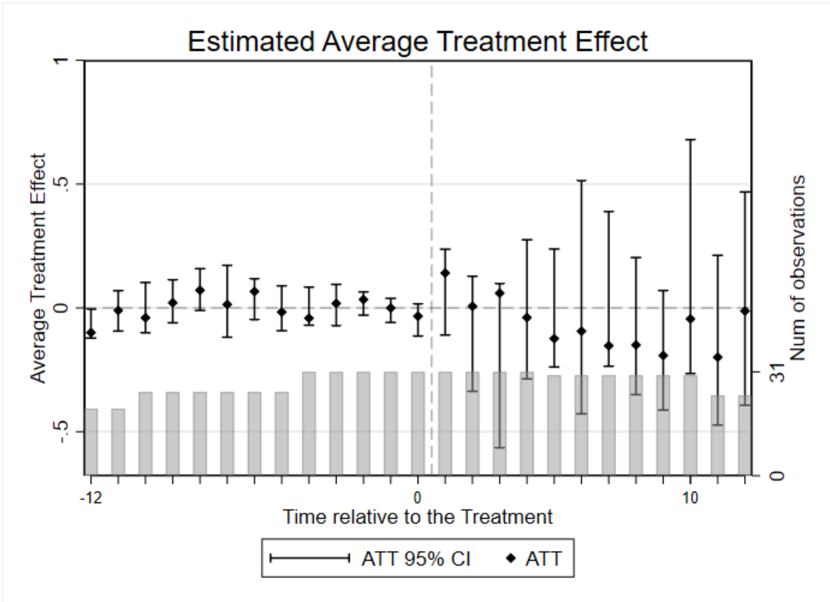
While the event study estimates have shown compelling evidence for the effects of traffic cameras on accidents at the installation intersection, it is possible that such estimates might be biased when unaccounted time-varying confounders influence treated and untreated road intersections differently. To address this issue, we employ the Synthetic Control (SC) method (Abadie et al. 2010). This method helps construct a weighted combination of untreated road intersections (i.e., synthetic controls) that closely resembles the covariates and past accident outcomes of the treatment intersections in the pre-installation periods, which offers a better counterfactual to satisfy the parallel trend assumption. In doing so, accident trends at both the treatment and control intersections should be very close (thus comparable) in the pre-treatment periods, and their differences in the post-treatment period should be solely driven by the treatment (i.e., camera installation).

In this study, we adopt a state-of-art variant of the SC method, Generalized Synthetic Control (GSC) (Xu 2017), which has gained popularity in the social science area for causal inference (Pattabhiramaiah et al. 2019, Guo et al. 2020); however, GSC and synthetic control methods are relatively new in the information systems research (with exceptions Krijestorac et al. 2020, Wang et al. 2021). We use the GSC method because it has two good properties that the traditional Synthetic Control method lacks: (i) incorporating a fixed-effect structure, and (ii) allowing multiple treated units and periods for the estimation. This is a good fit to our empirical context, i.e., multiple fixed-effects (for intersections and months) and the staggered installations of cameras at multiple road intersections at different times (instead of a one-time installation at one location).

Panel (1) and (2) of Figure E-3 below show the estimated dynamic effect of new cameras and old cameras, respectively, at installation intersections (relative to non-installation intersections). We find that the differences in trends of accidents are very similar to the main estimates from the event study: (i) accidents in the pre-installation periods are not statistically distinguishable between treatment and control intersections for both estimates, which supports the parallel trend assumption; and (ii) there is a significant and persistent downward trend in accidents followed by the advanced camera installation but no clear pattern followed by the conventional camera installation. Therefore, the GSC results further corroborate the validity of the event study estimates (Figure 1).



(1) New vs. Null



(2) Old vs. Null

Figure E-3. Generalized Synthetical Control with Stagged Camera Installation

E.4. Hazard Model to Check if Camera Installation is Predictable

It is possible that advanced cameras were selected to be installed at intersections with higher accident risks. We test this rationale using a hazard logit model to predict camera installation at the focal intersection using its past accident records. As shown in Table E-1, we do not find statistically significant evidence for reverse causality.

Table E-2. Predicting Advanced or Conventional Camera Installations Using Past Accidents and Intersection Level Covariates

	DV: advanced camera installed (=1 yes, otherwise 0)				DV: conventional camera installed (=1 yes, otherwise 0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(# accident cases+1)	0.516				0.853			
	(0.318)				(0.948)			
log(# casualty cases+1)	-0.241				-0.430			
	(0.430)				(1.167)			
L1. log(# accident cases+1)		0.335				-0.641		
		(0.325)				(0.858)		
L1. log(# casualty cases+1)		-0.088				1.042		
		(0.418)				(1.208)		
L2. log(# accident cases+1)			0.354				-0.284	
			(0.303)				(1.171)	
L2. log(# casualty cases+1)			-0.332				-1.943	
			(0.443)				(2.019)	
L3. log(# accident cases+1)				-0.130				1.154
				(0.350)				(1.518)
L3. log(# casualty cases+1)				0.204				-0.739
				(0.439)				(2.194)
Intersection-specific time-invariant variables								
tourist_1000m_dum	0.507	0.496	0.258	0.346	omitted	omitted	omitted	omitted
	(1.708)	(1.709)	(1.744)	(1.738)	(0)	(0)	(0)	(0)
road level2_dum	-1.517	-1.658	-1.660	-1.695	omitted	omitted	omitted	omitted
	(1.605)	(1.595)	(1.604)	(1.609)	(0)	(0)	(0)	(0)
road level3_dum	0.695	0.801	0.850	0.837	omitted	omitted	omitted	omitted
	(0.846)	(0.832)	(0.837)	(0.836)	(0)	(0)	(0)	(0)
log(distance to district gov)	0.268	0.286	0.228	0.221	3.601**	4.077**	5.134**	3.973
	(0.438)	(0.435)	(0.438)	(0.435)	(1.763)	(1.707)	(2.295)	(4.185)
log(distance to city gov)	4.637***	4.505***	4.794***	4.730***	-3.162	-2.697	-4.586	-0.193
	(1.345)	(1.337)	(1.354)	(1.353)	(5.057)	(4.996)	(5.822)	(8.526)
Intersection-specific time-varying variables								
edu_500m_dum	0.008	0.012	0.057	0.044	0.569	0.370	0.299	0.440
	(0.246)	(0.247)	(0.249)	(0.249)	(0.782)	(0.751)	(0.861)	(1.712)
car park_500m_dum	-0.112	-0.092	-0.099	-0.043	1.203	1.330	1.347	1.783
	(0.284)	(0.284)	(0.285)	(0.285)	(1.005)	(1.007)	(1.127)	(1.864)
gov_500m_dum	0.001	0.051	0.027	0.046	0.795	0.838	2.155	0.859
	(0.342)	(0.340)	(0.344)	(0.341)	(2.253)	(2.321)	(3.141)	(2.297)
resid_500m_dum	1.342**	1.379**	1.378**	1.385**	5.779***	6.290***	4.028	6.547
	(0.673)	(0.684)	(0.685)	(0.678)	(2.151)	(2.111)	(2.507)	(6.909)
comm_500m_dum	-0.692	-0.594	-0.564	-0.461	-1.977	-1.437	-2.132	-0.980
	(0.667)	(0.666)	(0.674)	(0.674)	(1.630)	(1.469)	(1.577)	(2.766)
log(# catering_500m+1)	-0.357*	-0.373*	-0.378*	-0.407*	-2.610***	-2.712***	-2.645***	-2.413
	(0.207)	(0.208)	(0.209)	(0.209)	(0.780)	(0.755)	(0.938)	(2.471)
log(# bus stop_500m+1)	-0.029	-0.041	-0.046	-0.062	-0.296	-0.548	-0.898	-2.870*
	(0.134)	(0.133)	(0.135)	(0.135)	(0.717)	(0.681)	(0.851)	(1.721)
train station_1000m_dum	1.524*	1.480*	1.600*	1.555*	0.481	0.809	0.569	0.966
	(0.866)	(0.858)	(0.859)	(0.852)	(1.246)	(1.146)	(1.407)	(1.939)

subway station_500m_dum	-0.665	-0.627	-0.648	-0.598	-0.444	-1.178	-5.124	-2.643
	(0.492)	(0.492)	(0.496)	(0.494)	(2.293)	(3.251)	(4.164)	(20.136)
subway station_uc_500m_dum	0.115	0.114	0.079	0.112	omitted	omitted	omitted	omitted
	(0.728)	(0.728)	(0.731)	(0.734)	(0)	(0)	(0)	(0)
ban_post	-0.062	-0.046	-0.078	-0.029	-1.225	-1.305	-1.739	0.330
	(0.249)	(0.248)	(0.250)	(0.248)	(1.012)	(1.030)	(1.234)	(2.102)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	24,606	22,512	20,418	18,325	604	520	436	360

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

E.5. Falsifying Spurious Effect or Autocorrelation

The observed significant downward trend of accidents might be possibly due to its spurious relations with camera installation or serial correlations of accidents within intersections. While we cluster standard errors at the intersection level, it is useful to implement a falsification test, as suggested by Bertrand et al. (2004). Following extant literature (e.g., Burtch et al. 2018), we execute a permutation test by randomly generating and assigning dichotomous pseudo (or placebo) treatment to the observations of intersection-month. For intersections that do not receive such a "treatment," they are the control group. For those that receive the "treatment" at a specific month, prior to that month will be the pre-treatment period ("treatment" = 0), and the months after that month (including itself) will be the post-treatment period ("treatment" =1). Replacing the actual installation status with the pseudo indicator, we rerun our baseline regression, stored the estimates, and replicated the procedure 500 times. This test allows us to identify more cleanly if the correlation within intersection-month is unaccounted for and to check if our estimates are driven by outliers.

Figure E-4 shows the accident trends at both "treatment" and control intersections for new vs. null and old vs. null. As it is clear, the point estimates vacillate intermittently above and below zero, with large standard errors. This suggests that accident trends do not vary across intersections at both pre-treatment and post-treatment periods. Contrast the estimates from this permutation test with the main estimates in Figure 1, it is unlikely that the observed downward accident trends are spurious or have severe autocorrelation issues.

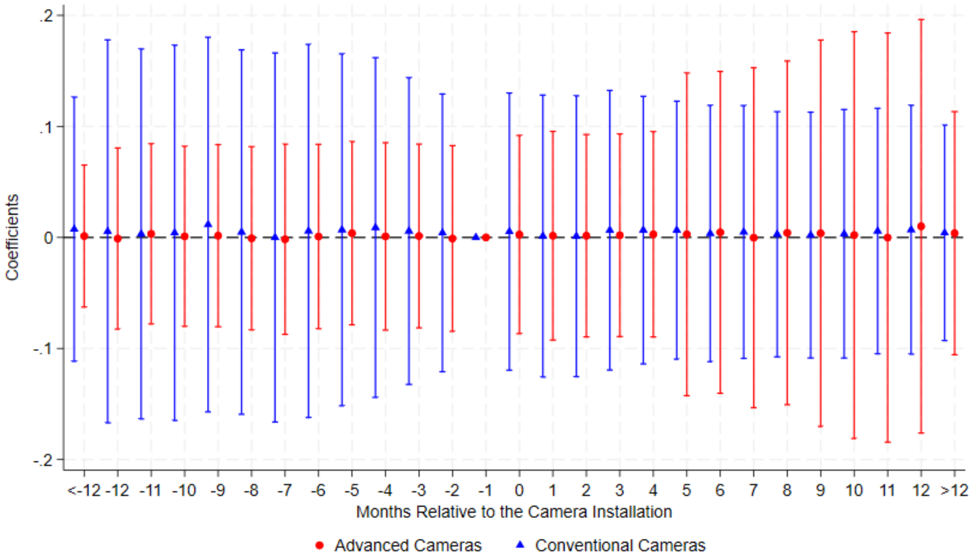


Figure E-4. Permutation Test for Falsification

E.6. Poisson Estimation

We consider the distribution of accidents and used the count data model for the event study estimation. As seen in Figure E-5, the Poisson estimates are qualitatively similar to the OLS ones, and the decline in accidents at intersections after the installation of advanced cameras remains significant.

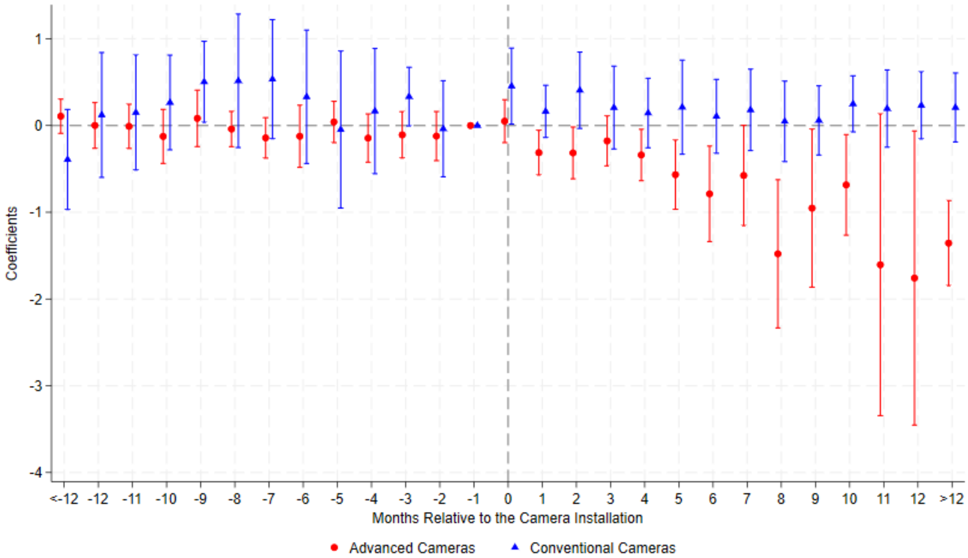


Figure E-5. TWFE-Poisson Estimates on the Dynamic Effects of Automated Enforcement

E.7. Overall Dynamic Effects of Traffic Camera Installation

While advanced and conventional cameras differ a lot in functions, one would still be curious about the overall effect of camera installation, regardless of whichever the camera type is. Then we treat all camera installations the same and replicate the analysis with this composite treatment measure. The estimates remain consistent, and the downward trend of accidents is mainly driven by the effect of advanced cameras (Figure E-6).

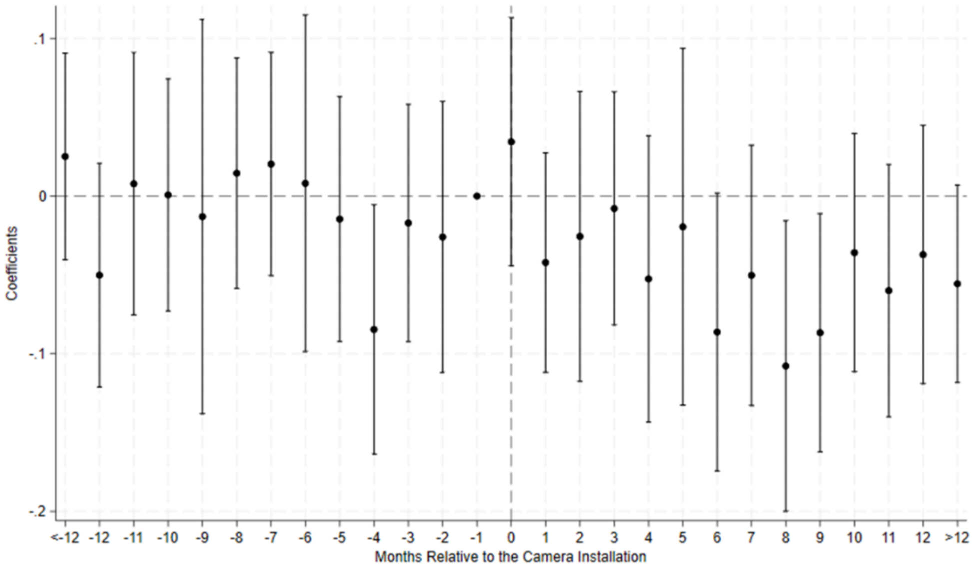
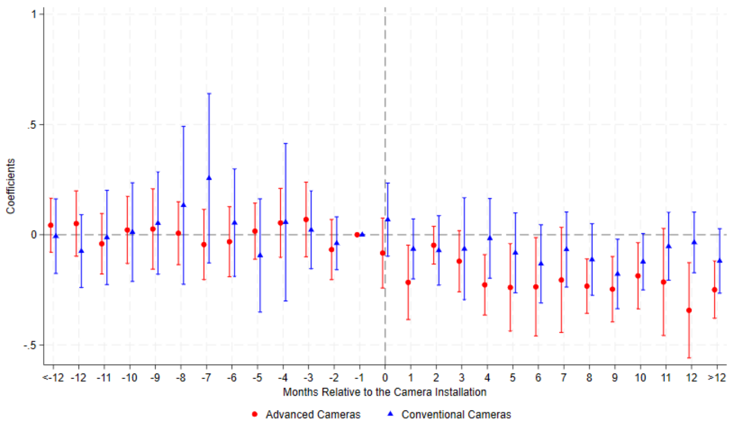


Figure E-6. Intersections *with* Cameras (either new or old) vs. *without* Cameras

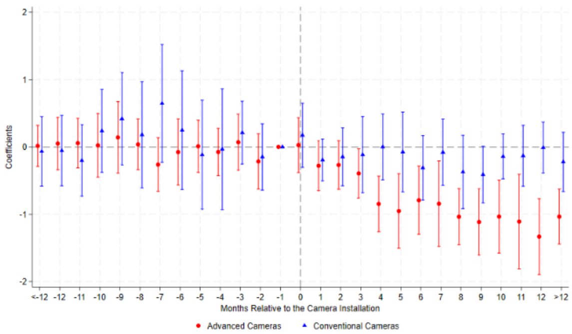
E.8. Automated Enforcement Effect on Traffic Violations (That Led to Accidents)

It is sensible to directly test the deterrent effect of camera installation on traffic violations. We replace the accidents with violation punishment, measured by the penalty points and ticket fines, as the dependent variables and replicated the event study analysis to trace the changes in the punishment near the camera-installed intersections.

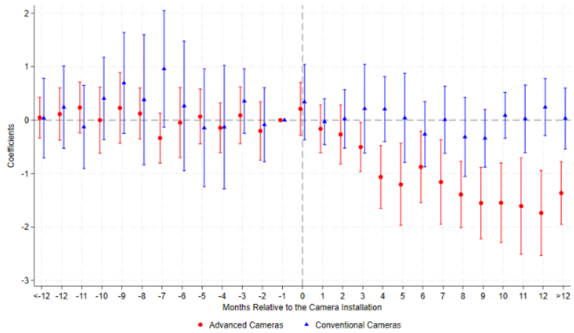
As seen in Figure E-7, there is a significant drop in punishment near the intersections installed with advanced cameras, indicating a decrease in violations as well; however, we do not find any significant change in punishment after the installation of conventional cameras. A note of caution here is that we do not have access to the full dataset of violations, some of which are not associated with any accidents. Still, the observed decrease in the violations serves as the lower bound for, and corroborates, the deterrence of automated enforcement.



(1) # Penalty Points



(2) ¥ Ticket Fines (Min.)



(3) ¥ Ticket Fines (Max.)

Figure E-7. Effects of Camera Installation on the Punishment (Penalty points and Fines) of Traffic Violations (That Led to Accidents) Per Intersection Per Month

Appendix F: More Analyses for Exploring Underlying Mechanisms

F.1. Mapping between Theoretical Mechanisms and Empirical Tests

Table F-1 shows the mapping between theoretical explanations, cameras involved, accidents examined, empirical tests, and their effects. We shade the rows for the key mechanisms (automated detection, real-time recording, and driver learning) we identify that drive the baseline results, with un-shaded rows being the cross-validation or falsification tests.

Table F-1. Mapping between Mechanisms, Empirical Tests, and Effects

	Mechanisms	Cameras (location)	Accident (location)	Effect	Figure
Technical Capability	**Automated Detection**	Advanced or conventional cameras (at focal intersections)	Type A accidents (at focal intersections)	Statistically significant reduction in both, but pronounced for advanced cameras	Figure 3, Figure 4, and Table 4
	Real-time Recording	Advanced cameras (at focal intersections)	Type B accidents (at focal intersections)	Statistically significant reduction in advanced cameras only	Figure 5, and Table 4
	Placebo effects for falsification	Advanced or conventional cameras (at focal intersections)	Type C accidents (at focal intersections)	Statistically insignificant for both	Figure F-1 in Appendix F
Driver Cognition	**Driver Learning (of proactive functions)**	Both advanced and conventional cameras (at neighboring intersections), and only conventional cameras (at focal intersections)	Type A accidents (at neighboring intersections)	Statistically significant reduction	Figure 6, and Table 4
	Driver Learning (of passive functions)	Both advanced and conventional cameras (at neighboring intersections), and only conventional cameras (at focal intersections)	Type B accidents (at focal intersections)	Statistically insignificant	Figure F-3 in Appendix F
	Driver Learning (of neither proactive nor passive functions) for falsification	Both advanced and conventional cameras (at neighboring intersections), and only conventional cameras (at focal intersections)	Type C accidents (at focal intersections)	Statistically insignificant	Figure F-4 in Appendix F

Notes: Here we colored it red for the particular camera type that we examine its effect in the corresponding empirical analysis. Additionally, we used shade for the main mechanisms (in bold) proposed and empirically supported that drive the main baseline estimates.

F.2. Effect of Camera Installation on Type C Accidents

We conducted a falsification test to assess the effects of new and old cameras on type C accidents for which the associated violations are neither captured by cameras' proactive functions nor passive functions. Figure F-1 reveals statistically insignificant results for both advanced and conventional cameras, confirming that cameras without the necessary technical capabilities cannot reduce the corresponding accidents.

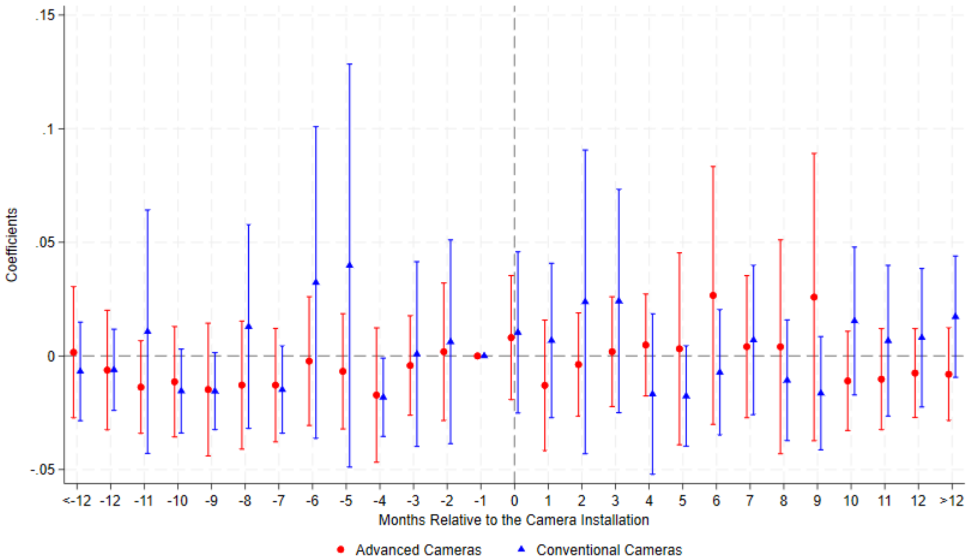


Figure F-1. Effect of Camera Installation on Type C Accidents

Note: Examples of accidents for which the associated violations could have been captured by advanced cameras' passive functions are "drunk driving" or "driving without a license."

F.3. Graphical Illustration of Spillover Effects of Advanced Cameras at the Neighboring Intersection

In the mechanism analysis (§4.2), we study driver learning by estimating the changes in accidents for which the associated violations could have been captured by advanced cameras' proactive functions at focal intersections with conventional cameras installed when an advanced camera was newly installed nearby (100-300 meters away).

Figure F-2 illustrates the spillover effects of advanced cameras at the neighboring intersection on traffic accidents at the focal intersection. We restrict our sample to intersections (e.g., A, B, C) that were installed with conventional cameras prior to the advanced camera installation. In this setting, drivers passing through all intersections are subject to some but limited deterrence (since the conventional cameras only detect two violations). The similar appearance of advanced and conventional cameras may lead drivers to mistakenly believe a conventional camera at a focal intersection (A) is an advanced camera (the latter may, in their memory, be located in the same broader area). This deterrence spillover effect can solely arise from driver learning because: (i) advanced cameras at neighboring intersections (e.g., B) cannot capture violations 100-300 meters away (e.g., A), (ii) conventional cameras at focal intersections (e.g., A in this case) cannot detect violations (e.g., speeding) that can only be captured by advanced cameras, and (iii) the reduction in accidents (i.e., near A) can only be attributed to drivers learning the presence and function of advanced cameras nearby (i.e., at B) and extending their deterrence to the conventional camera they see at the focal intersection (A).

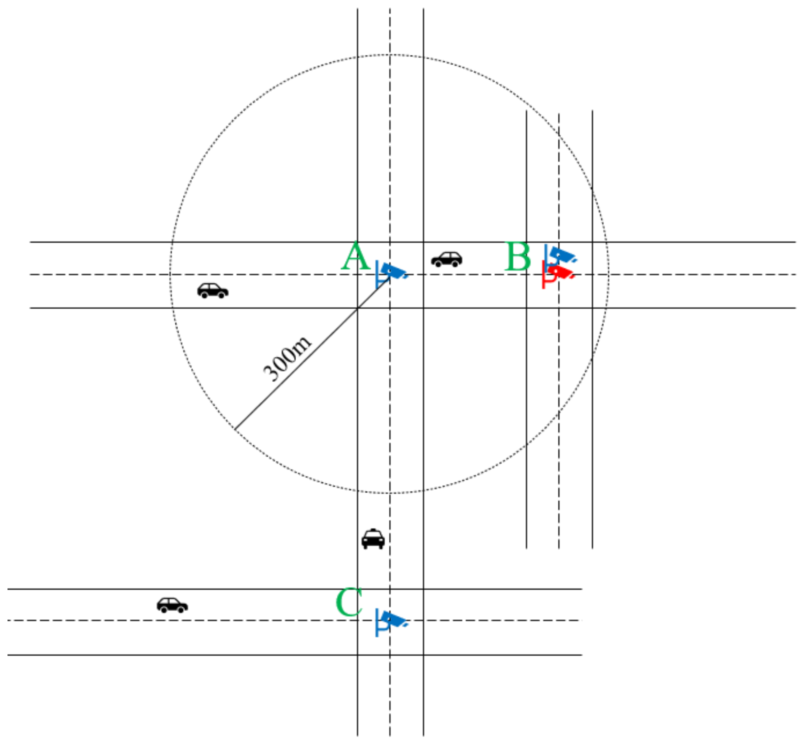


Figure F-2. Graphical Illustration of Spillover Effects of Advanced Cameras at the Neighboring Intersection on Traffic Accidents at the Focal Intersection

F.4. More Analyses for Exploring the Driver Learning Effects.

We examine driver learning by estimating the changes in accidents for which the associated violations could have been captured by advanced cameras' passive functions and not captured by any functions. Figure F-3 and Figure F-4 below present the results, indicating statistically insignificant patterns.

These findings may reveal two points: (i) Drivers who commit violations near passive or non-functional advanced cameras (e.g., at intersection B in Figure F-2) are less likely to be punished (with probabilities around 20% or even 0%) compared to those caught by the proactive functions of advanced cameras (with a 100% probability of punishment). This discrepancy occurs because not all accident victims request video recordings as evidence, allowing some violators (80-100%) to escape punishment. As a result, these drivers do not adequately learn about the capabilities of the advanced cameras. (ii) When these drivers later travel through the same area again (e.g., at intersection A in Figure F-2), their limited learning from previous experiences provides little or no deterrence. Consequently, they do not adjust their behavior, do not feel significantly deterred, and continue to act as usual, which explains the statistically unchanged accident rates near the cameras, regardless of whether they are advanced or conventional, as shown below.

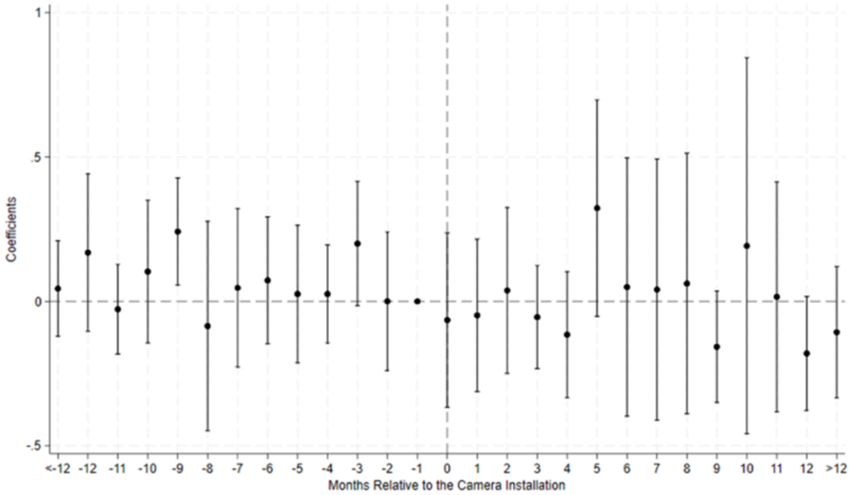


Figure F-3. Effect of Advanced Cameras at Neighboring Intersections on Traffic Accidents (Linked to Violations That Could be Captured by Advanced Cameras' Passive Functions) at the Focal Intersection

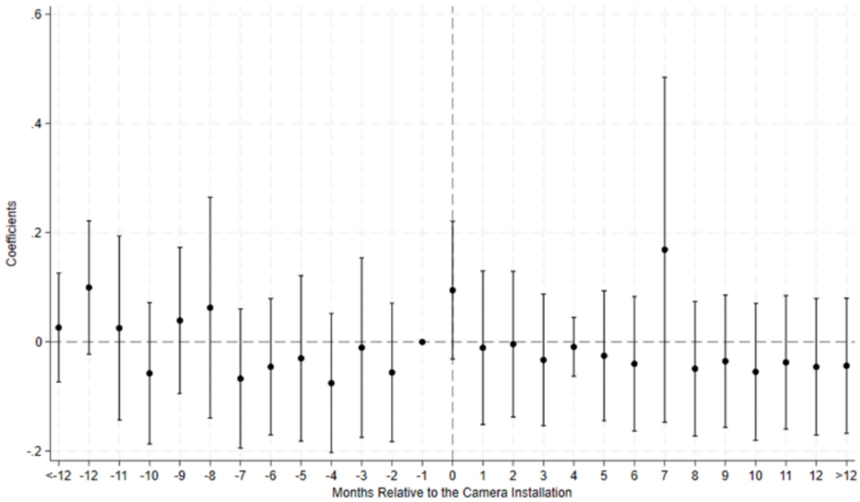


Figure F-4. Effect of Advanced Cameras at Neighboring Intersections on Traffic Accidents (Linked to Violations Not Captured by Any Cameras' Functions) at the Focal Intersection

F.5. Mechanism Analyses on Specific Accidents

Finally, we analyze specific accidents that most frequently occurred in our sample to further test the mechanisms (characterized in Table 3, Section 4.2). The results for the average effect of advanced and conventional cameras on these accidents are in Tables F-2 below. As shown in Column 3, advanced cameras, with their proactive and passive functions, are associated with a decline in accidents linked to specific violations. However, for the accident identified as caused by "other improper operations," which is unaffected by either function, the coefficient is positive but statistically insignificant. Column 4 highlights that conventional cameras, which only detect "running red light" and "retrograde" violations, significantly reduce accidents involving "motor vehicle failing to comply with traffic signal regulations" but show no significant effect on other violations. Overall, the estimates are generally consistent with the results from the analysis using Type A, B, and C accidents in Section 4.2, further corroborating the mechanisms we identified in the main text (see Table 4).

Table F-2. Estimates of Effects on Accidents Linked to Exemplary Violations (Top 5 Accident Types Ranked by Frequency in Our Accident Data)

Accidents identified as caused by the following violations	Functions of cameras in capturing these violations	Effect of Advanced Cameras	Effect of Conventional Cameras
(1)	(2)	(3)	(4)
"Operating a motor vehicle in a manner that otherwise hinders safe driving"	Passive	-0.011** (0.004)	0.018 (0.016)
"Motor vehicle failing to comply with traffic signal regulations"	Proactive	-0.058*** (0.013)	-0.059*** (0.018)
"Changing lanes in a way that affects other normally moving motor vehicles"	Proactive	-0.023*** (0.008)	-0.008 (0.005)
"Failing to maintain the necessary safety distance from the vehicle ahead in the same lane"	Passive	-0.003 (0.006)	-0.004 (0.012)
"Other improper operations"	Neither Proactive nor Passive	0.006 (0.004)	0.004 (0.008)

Notes: Table F-2 presents the top 5 accident types ranked by frequency in our data, along with the effects of advanced and conventional cameras on their incidence. Notably, we also applied TWFE-DiD estimation to accident types beyond the top 5. However, due to their smaller sample sizes, the statistical power of these estimates is limited, and they are not reported here. Robust standard errors (clustered at the block level) are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix G: Alternative Explanations

G.1. Temporal and Spatial Displacement Effects

In line with the scholarly debate on whether deterrence primarily displaces, rather than reduces, crimes (e.g., Banerjee et al. 2019), we empirically test the accident displacement effect in our setting. First, it is clear in Figure G-1 that there is no *temporal displacement* because once cameras are installed at a road intersection, they are rarely withdrawn. Second, *spatial displacement* is likely if drivers become more strategic in driving after learning the locations of cameras. To test this possibility, we replicate the baseline event study estimation but use the number of nearby accidents (that could be at a neighboring road segment or intersection) within the 100-300m range near the focal intersection. However, we find no evidence for such a spatial displacement. Empirically, there are no significant changes in nearby accidents after the traffic camera installation (Figure G-1).

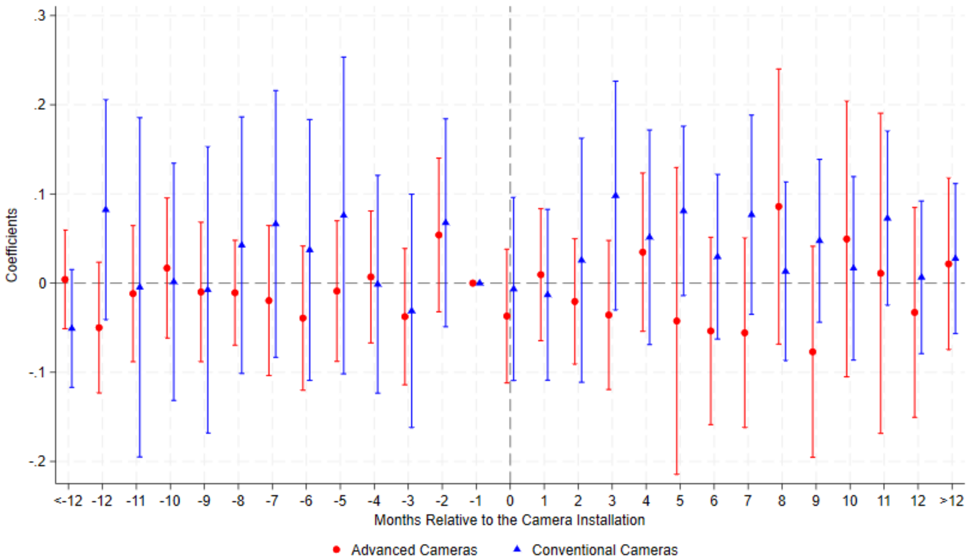


Figure G-1. Spatial Replacement (Radius: 100-300m)

G.2. Distraction Effect

Newly installed cameras would present as a distraction to drivers when they pass the operated road intersections. If a driver suddenly notices the cameras and slams on the break, the vehicles behind would have to follow suit. If the latter cannot respond as promptly as possible, rear-end collisions will happen. These cases would increase the number of accidents immediately after the camera installation. To empirically test this possibility, we replicate the event study estimates but only focus on rear-end collision accidents as the dependent variable. However, no evidence suggests such a distraction effect (Figure G-2).

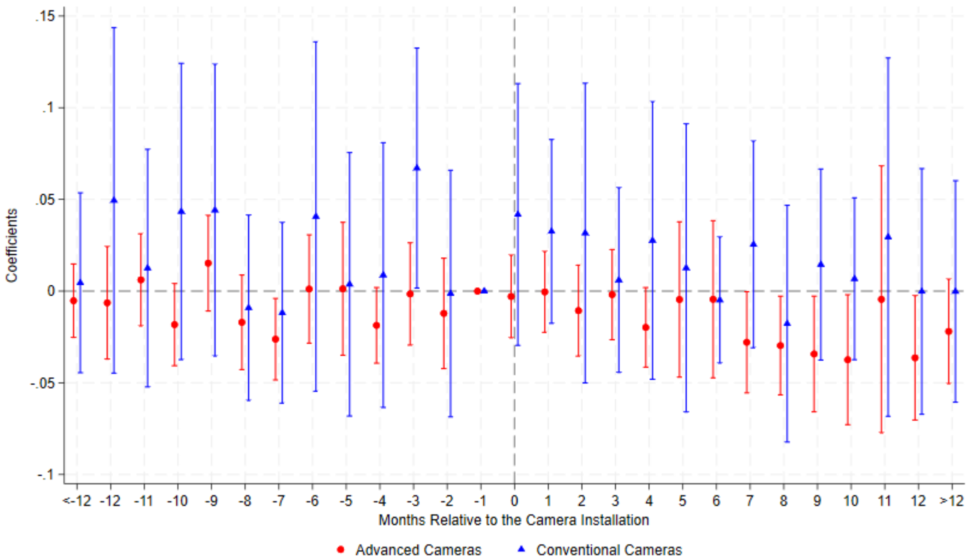


Figure G-2: Distraction Effect

G.3. Risk Compensation Effect

Despite the existence of deterrence, there are still cases where the decline in accidents is not seen. It may be explained by the risk compensation effect. Because only drivers, but not pedestrians or cyclists, are deterred by the traffic cameras, drivers may be more careful than others on the road. In this setting, the main effect may be explained only by the decline of motor-and-motor accidents, but not the pedestrian-and-motor accidents or single motor accidents (non-motor accidents thereafter). It is likely that accident risk is transferred from those who are under the deterrence (drivers) to—or compensated by—those who are not (pedestrians or cyclists), thereby increasing the accident incidences of the latter. If so, such a risk compensation effect would offset the negative deterrent effects. To check this possibility, we replicate the analyses but only focus on the changes in non-motor accidents. However, no statistically significant evidence supports the risk compensation explanation (Figure G-3).

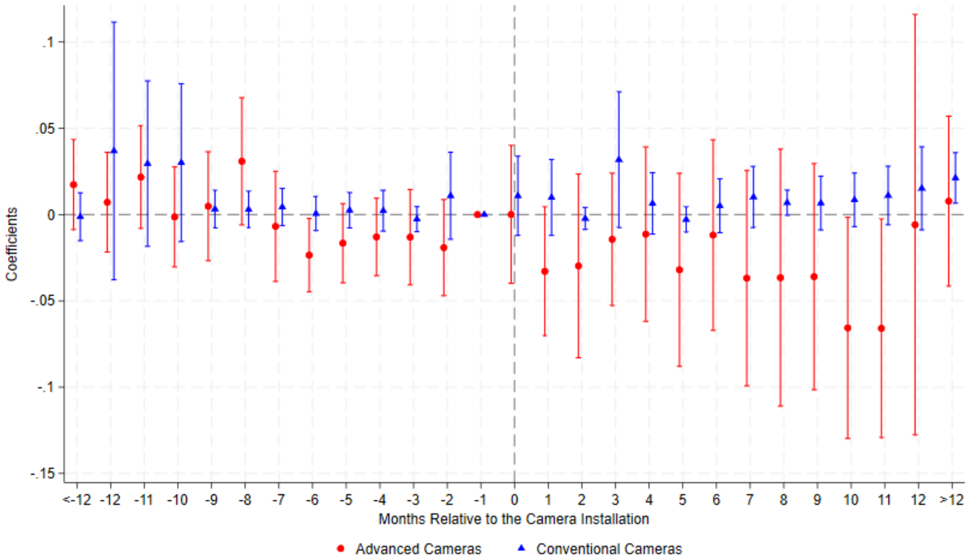


Figure G-3: Risk Compensation Effect

Appendix H. Welfare Analysis

Based on the estimates from Table 2, we herein do a conservative estimation on the incremental economic savings and human cost savings associated with the advanced traffic cameras. Economic savings are calculated using the property loss that could be avoided, and human cost savings are calculated using saved costs for bodily injuries and the loss of lifetime income thanks to the installation of advanced cameras.

For the road intersection *i*, its total social welfare gain (*W*) from a reduction in a specific type of accident outcome *c* (i.e., deaths, serious injuries, minor injuries, and property loss) since the installation of advanced cameras at time t_0 up to the post-treatment period *t* are estimated by the following equation:

$$W_i^c = \sum_{k=1}^{t-t_0} (\bar{Y}_i^c \times M^c \times \gamma^c),$$

where γ^c is the average camera enforcement effects that are obtained from the TWFE-DiD estimates of Table 2, measuring the percentage reduction in accident outcome *n* due to camera enforcement. M^c denotes the average monetized cost from an additional count of accident outcome *n*. $\bar{Y}_i^c$ is the average level for accident outcome *n* within the 0-100m range at road intersection *i* before the installation of advanced cameras. We then sum up the multiplication of these terms to quantify the monetized total social welfare gain associated with camera enforcement for collision type *n*, W_i^c, up to the post-treatment period *t*.

For human cost savings, based on China's standards of compensation for personal damage, where a death occurs, the total compensation is around ¥1,024,369.5, which mainly includes the lump-sum compensation for death (¥893,060) and for a funeral (¥31,309.5), as well as the mental damage compensation for bereaved families (¥100,000); hence, the average human cost savings of one death from the traffic camera per month at road intersection *i* is estimated by $\bar{Y}_i \times ¥1{,}024{,}369.5 \times 0.005$.

The compensation for bodily injury mainly covers the lump-sum compensation for injury based on the degree of disability ranging from Level 1 (the mildest) to Level 10 (the most severe), for mental damage, and for the loss of lifetime income. Specifically, for a serious injury, the total compensation is around ¥106,024, including the highest-level disability compensation (¥89,306), the mental damage compensation (¥10,000), the compensation for the 1-month lifetime income loss (¥5,218), and the 1-month in-hospital food subsidy (¥1,500); for a minor injury, as we do not have specific information about the average compensation, we conservatively impute the monetized human costs as ¥10,602.4, assuming that the average compensation for a minor injury amounts to 10% of a serious injury. As a result, the total human costs saved per month at intersection *i* associated with severe injuries and minor ones are imputed by $\bar{Y}_i \times ¥106{,}024 \times 0.001$ and $\bar{Y}_i \times ¥10{,}602.4 \times 0.068$, respectively.

For the economic savings from property loss, the average damaged property saved per month at road intersection *i* associated with the advanced camera installation in the post-treatment period can be directly calculated by $\bar{Y}_i \times 0.318$.

With these imputed savings, we can infer the total societal benefits from the *actual* installation of advanced cameras. In our sample, 128 intersections were installed with advanced cameras before 2017, and the resultant total social welfare gain is ¥426,003 (≈$65,538). In the year 2017, 80 other intersections were installed with advanced cameras, and all traffic cameras (including those installed before 2017) are estimated to save ¥1,438,508 (≈$221,308) total economic and human costs until the end of this year. Subsequently, 155 extra intersections were progressively installed with new cameras in 2019, and all cameras are estimated to produce ¥2,727,687 (≈$419,644) societal benefits in total until the end of that year.

Appendix I. Heterogeneous Effects of Camera Installations

I.1 TWFE-DiD Estimates of the Average Effects on Accidents by Driver Characteristics

We examine the varying effects of contextual factors to understand *for whom* and *when* advanced cameras improve traffic safety. Specifically, we replicate the TWFE-DiD and our baseline event study estimates within several subsamples of our accident data, including (1) female and male driver accident cases, (2) novice and experienced driver accident cases, (3) daytime and night-time accident cases, and (4) peak and off-peak hour accident cases.

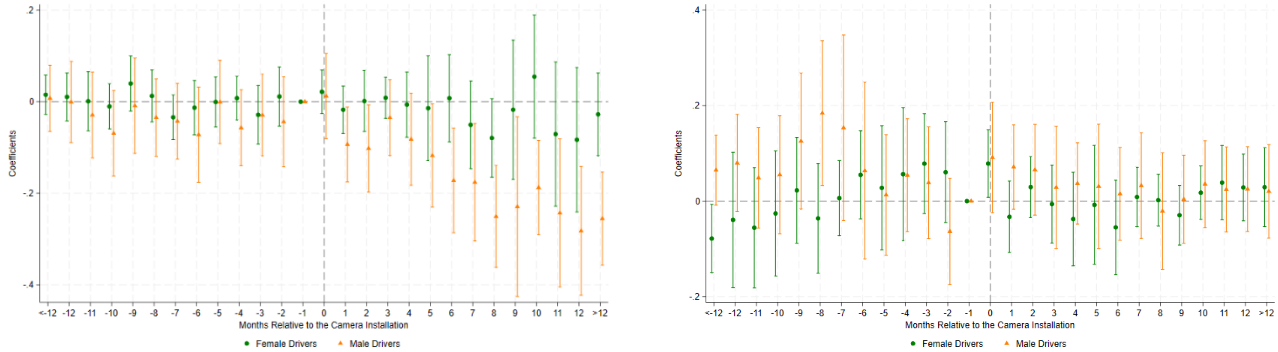
Our average treatment effects estimates are shown in Table I-1 and the event study estimates are presented in Figure I-1 below. In Table I-1, we also present to what extent the estimates between the two subsamples differ statistically significantly. For example, the installation of advanced cameras is statistically significantly ($p < 0.01$) more likely to reduce accidents involving male drivers than female drivers.

Table I-1. Estimates of Effects on Accidents by Driver Characteristics

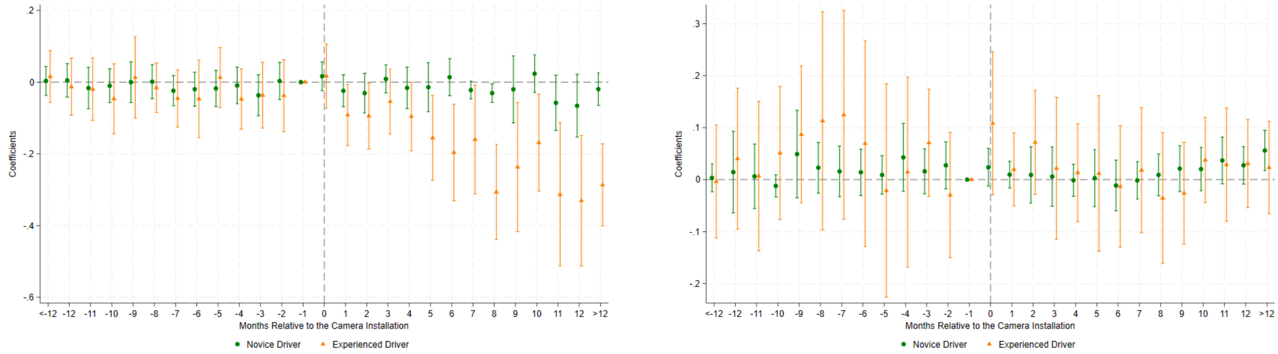
Driver Characteristics	Effect of Advanced Cameras		Effect of Conventional Cameras	
# female driver cases	-0.009	(0.012)	0.003	(0.017)
# male driver cases	-0.063***	(0.015)	-0.011	(0.021)
chi-squared	6.93***		0.16	
# novice driver cases	-0.005	(0.007)	0.011	(0.010)
# experienced driver cases	-0.078***	(0.016)	-0.002	(0.024)
chi-squared	14.68***		0.17	
# daytime cases	-0.041***	(0.012)	0.002	(0.018)
# night-time cases	-0.052***	(0.014)	0.006	(0.021)
chi-squared	0.58		0.02	
# peak hour cases	-0.025***	(0.008)	0.006	(0.012)
# off-peak hour cases	-0.063***	(0.016)	0.006	(0.023)
chi-squared	6.02**		0.00	

Note: Robust standard errors (clustered at the block level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

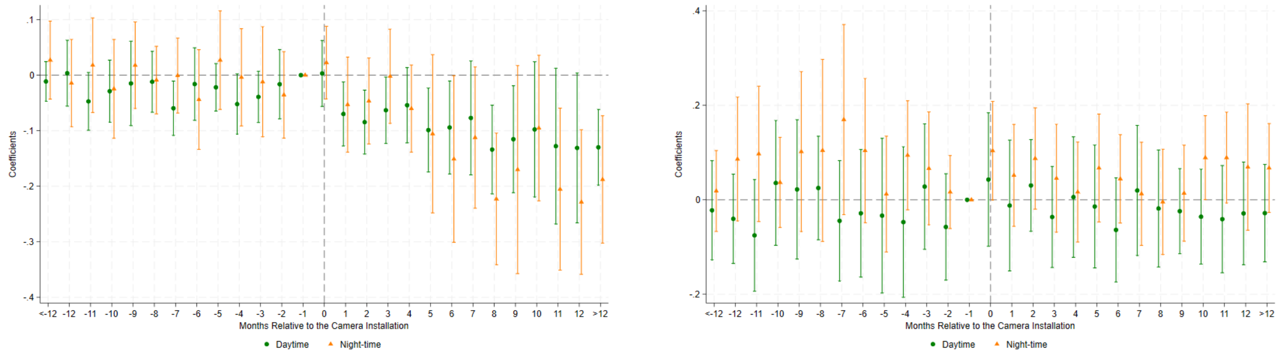
I.2 Event Study Estimates of Effects on Accidents by Driver Characteristics



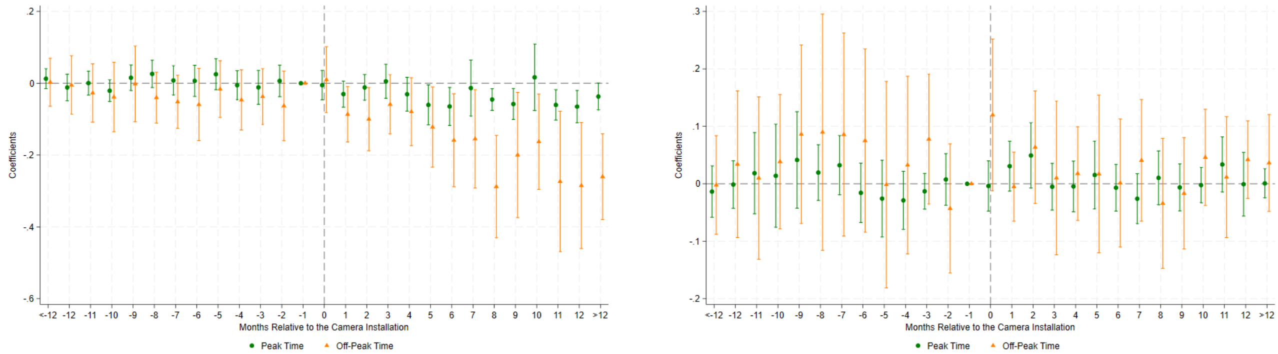
(1) #Female Driver Cases (green) vs. # Male Driver Cases (orange)



(2) #Novice Driver Cases (green) vs. # Experienced Driver Cases (orange)



(3) #Daytime Cases (green) vs. # Night-time Cases (orange)



(4) #Peak Hour Cases (green) vs. # Off-Peak Hour Cases (orange)

Figure I-1. Event Study Estimates of Effects on Accidents by Driver Characteristics

Note: the left panel is new vs. null, and the right panel is old vs. null.

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