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.

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.

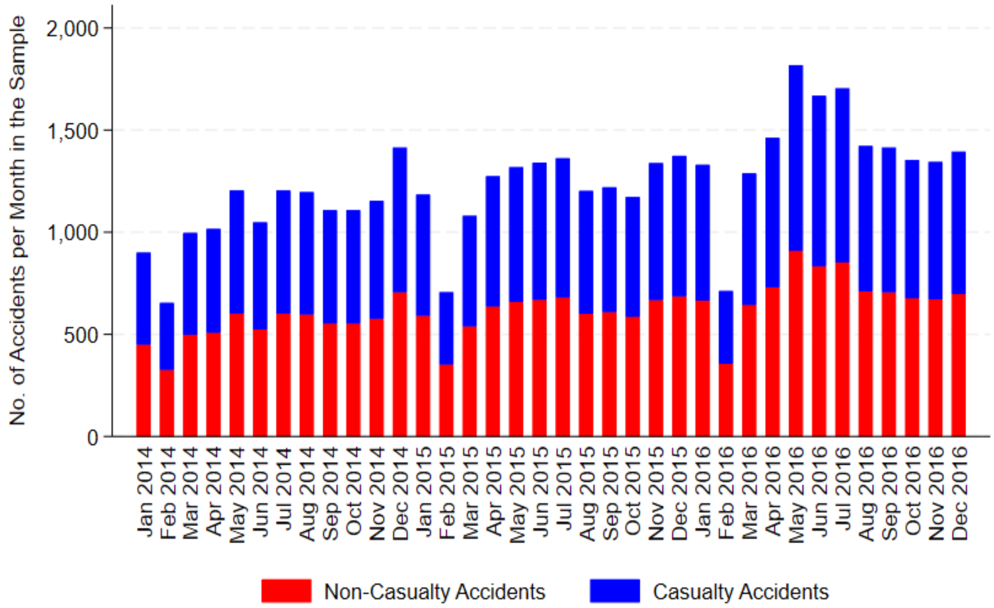


Figure B-2. Number of Accidents per Month, Over Time

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.

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).

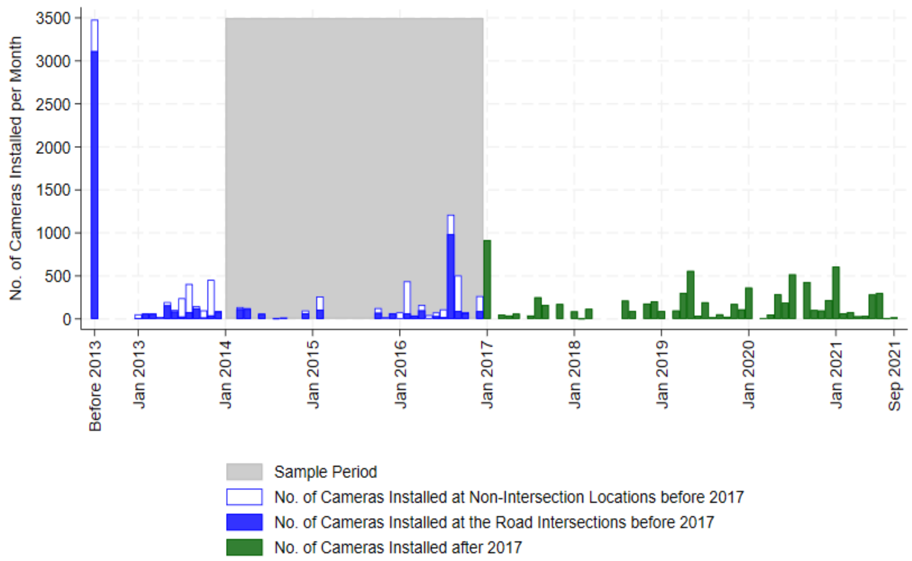


Figure B-4. Temporal Distribution of Road Intersections that were Installed with Traffic Cameras per Month

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.

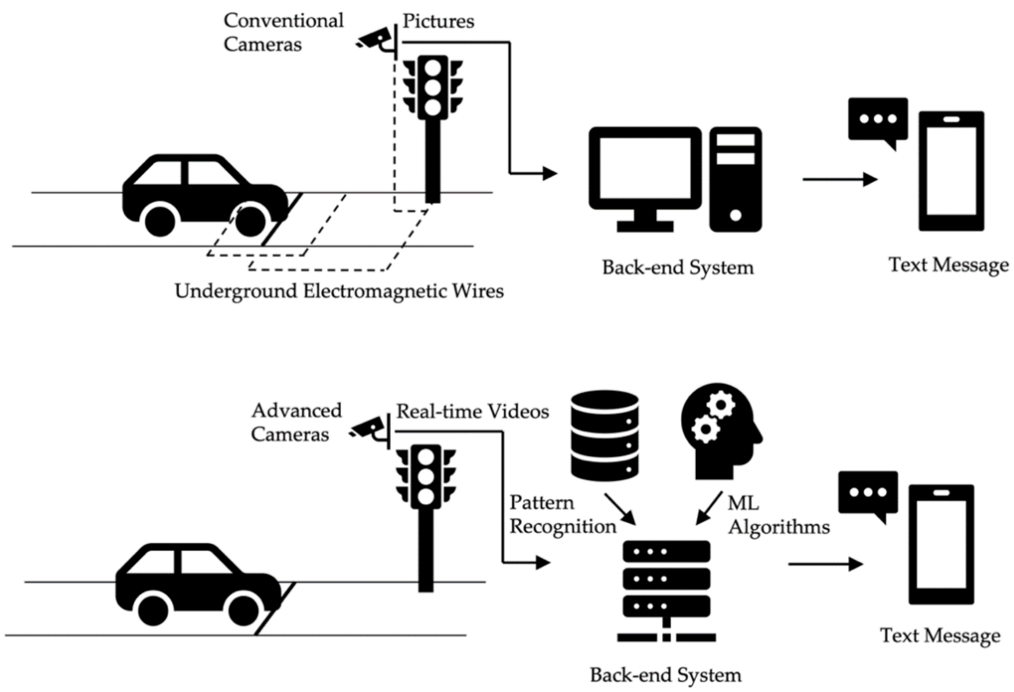


Figure B-5. Graphical Illustration of Conventional and Advanced Camera Enforcement

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.

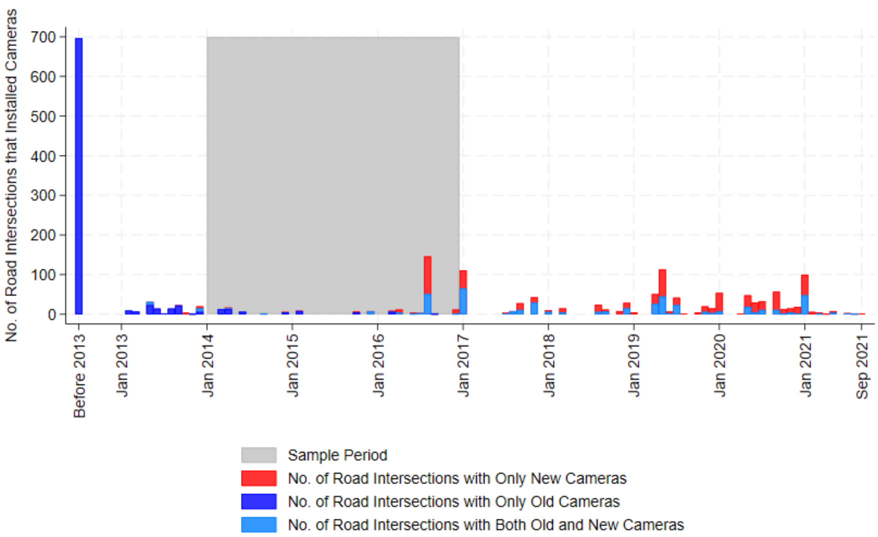


Figure B-6. Temporal Distribution of Road Intersections that Were Installed with Advanced and Conventional Traffic Cameras per Month

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.

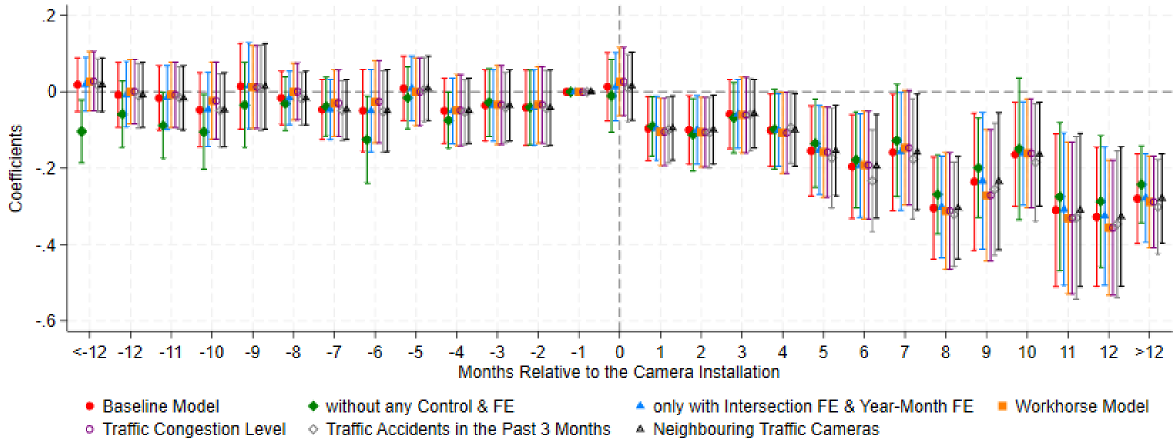
(3) We maintain all covariates in the baseline model and add the interactions between all covariates (except for time fixed-effects) and the year-month fixed-effects (dummies). This specification brings monthly variations of previously time-invariant variables such as road types and distance to district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

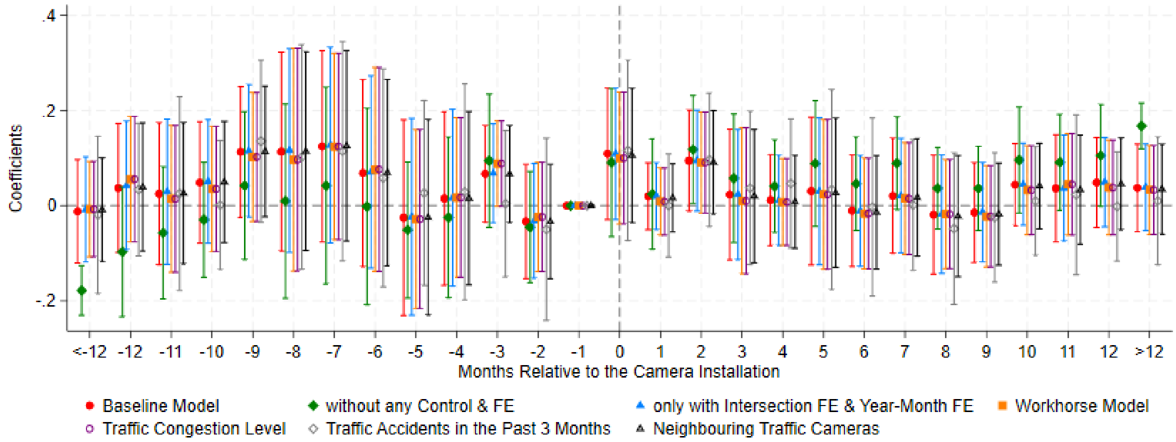
(5) We consider the influence of past accidents on the camera installation and accidents in the current month by additionally controlling for the total accident cases and casualty cases in the past three months (intersection-specific time-varying) to the baseline model

(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

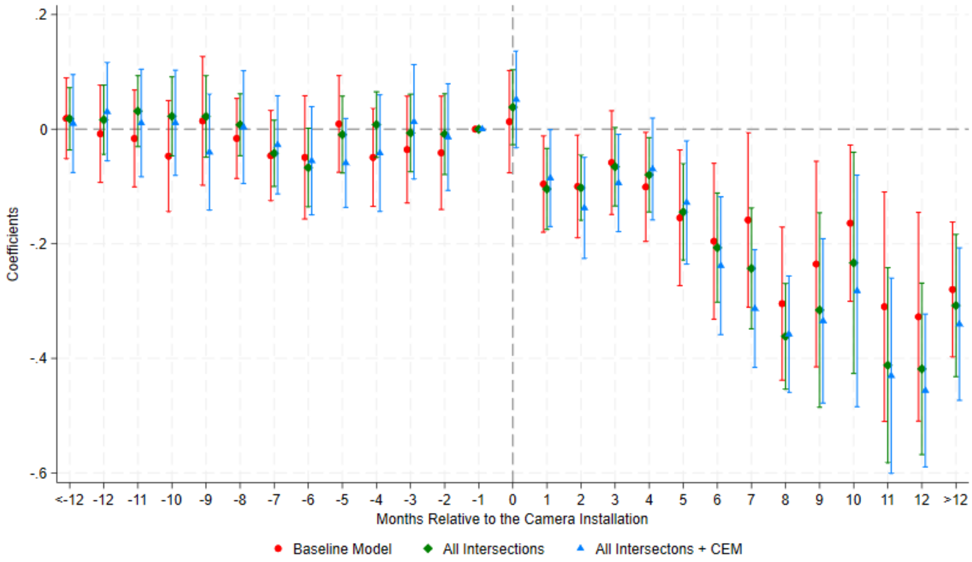
We change the sampling strategy to check the sensitivity of our based estimates of Eq. 1. We take two alternative strategies: (i) use all intersections without camera installation during the sample period as the control group, and (ii) apply the matching technique, specifically Coarsened Exact Matching (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)

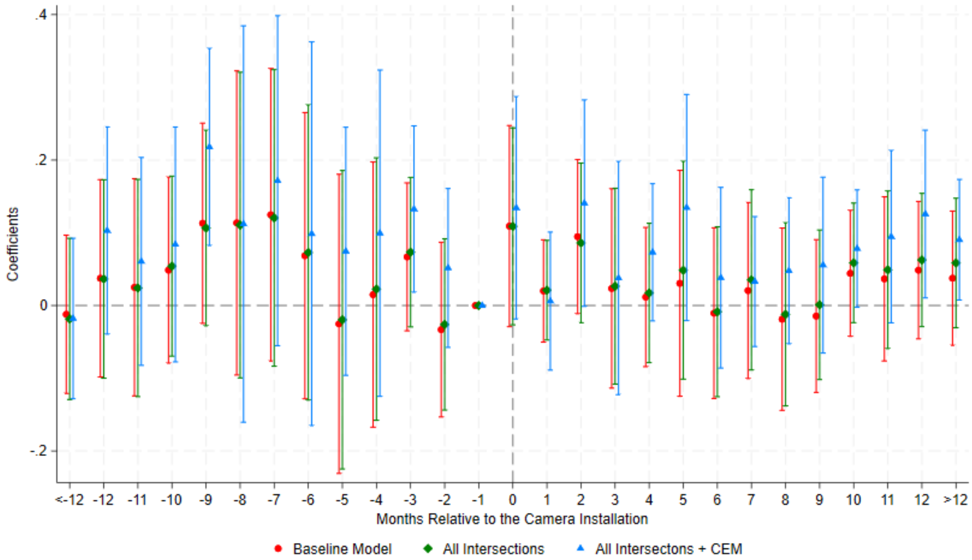
Covariates	Before CEM			After CEM		
Panel A: Advanced vs. No Camera	No Camera	Advanced Camera	Mean Diff	No Camera	Advanced Camera	Mean Diff
	(1)	(2)	(3)	(4)	(5)	(6)
train station_1000m_dum	0.025	0.014	0.011***	0.008	0.008	0
subway station_500m_dum	0.149	0.050	0.099***	0.027	0.027	0
subway station_uc_500m_dum	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

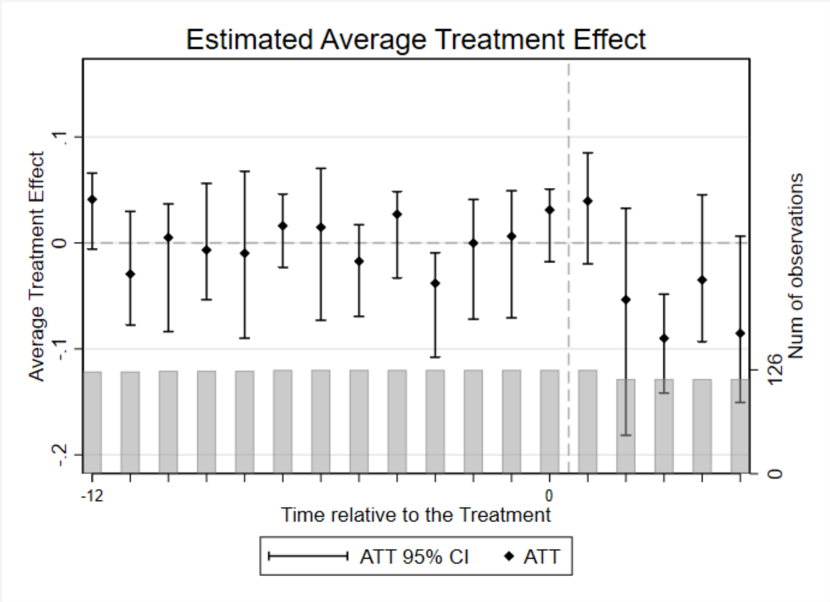
Figure E-2. Event Study Estimates from Alternative Sampling Strategies

E.3. Generalized Synthetic Control

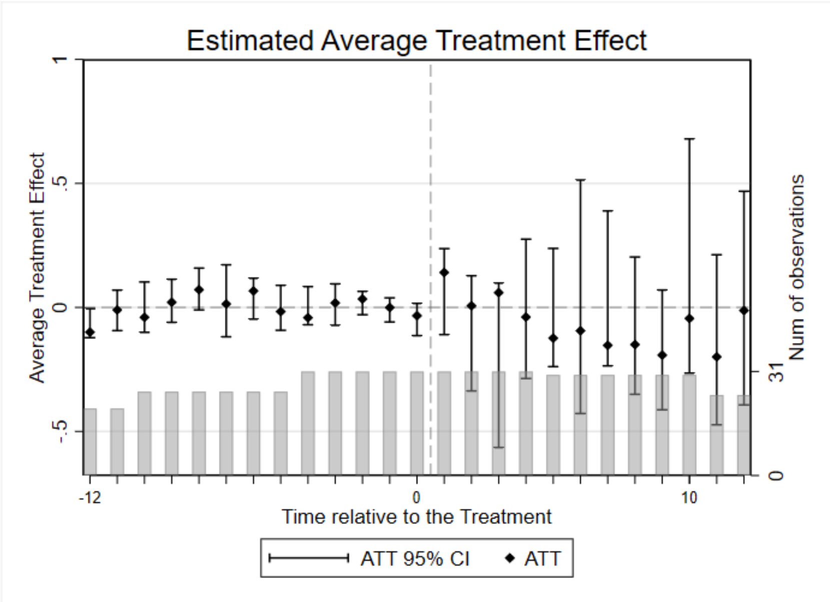
While the event study estimates have shown compelling evidence for the effects of traffic cameras on accidents at the installation intersection, it is possible that such estimates might be biased when unaccounted time-varying confounders influence treated and untreated road intersections differently. 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.

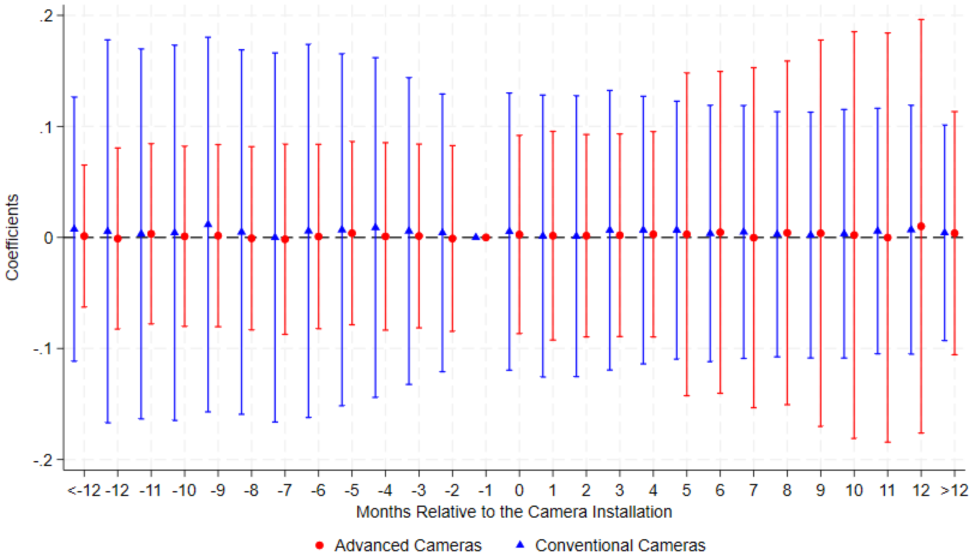


Figure E-4. Permutation Test for Falsification

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.

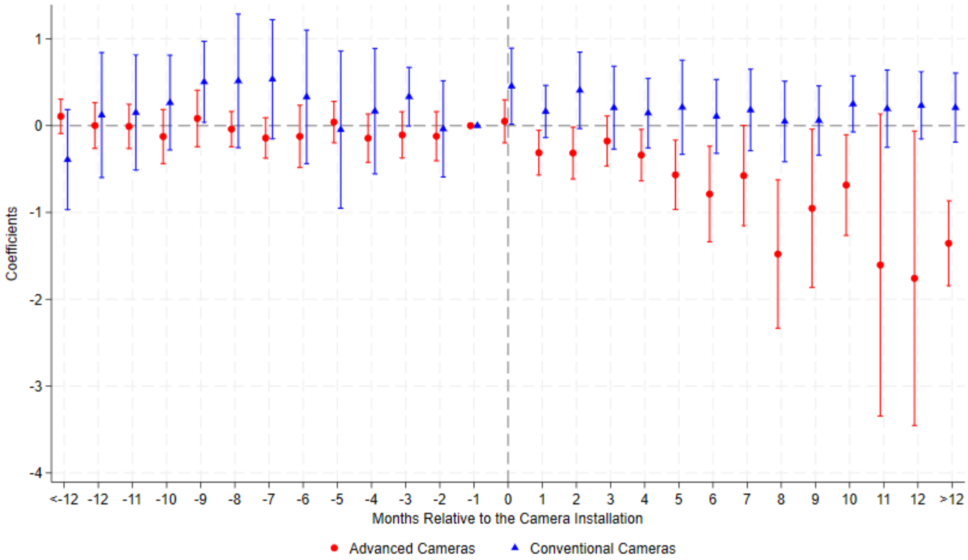


Figure E-5. TWFE-Poisson Estimates on the Dynamic Effects of Automated Enforcement

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).

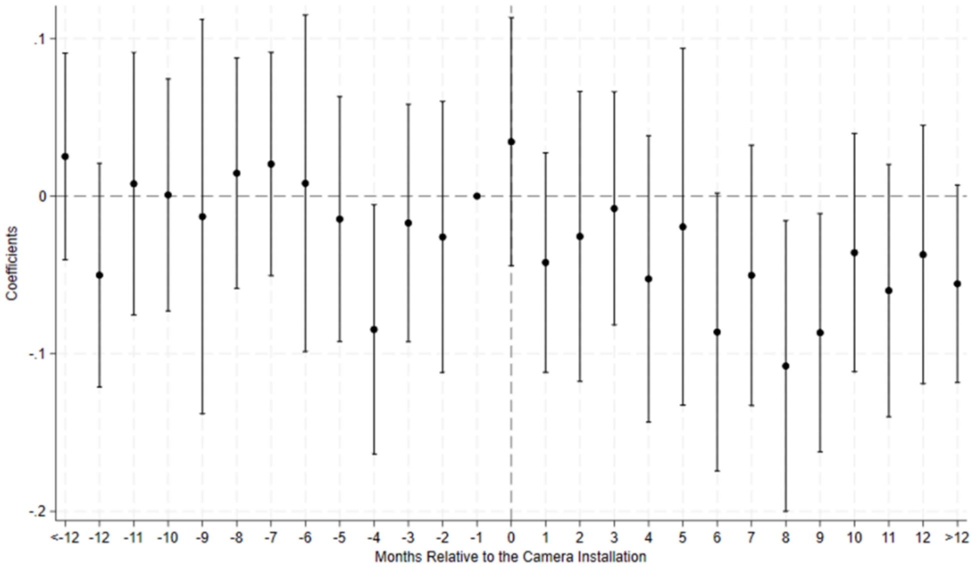
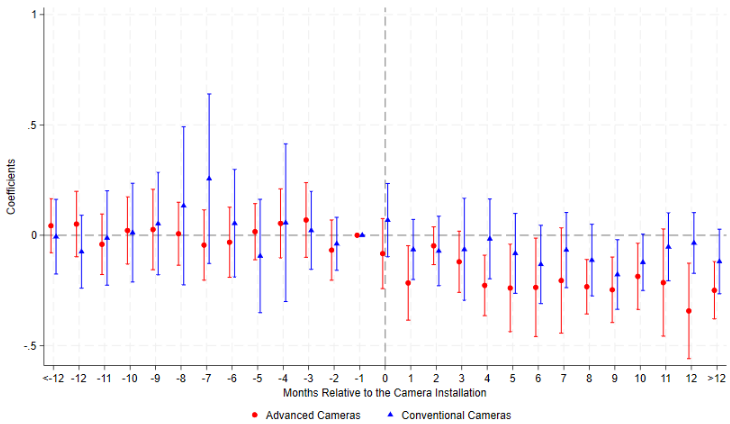


Figure E-6. Intersections *with* Cameras (either new or old) vs. *without* Cameras

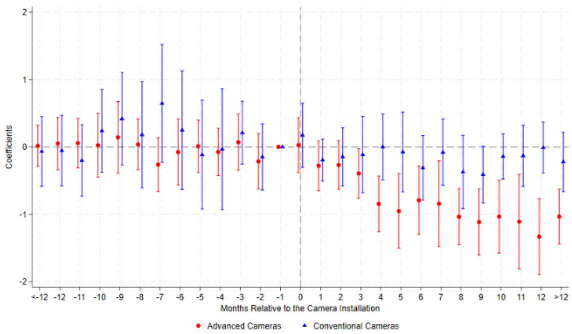
E.8. Automated Enforcement Effect on Traffic Violations (That Led to Accidents)

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.

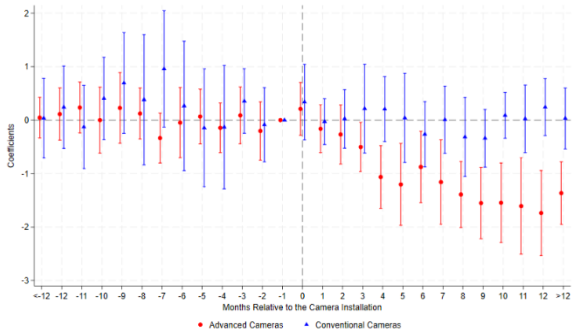
As seen in Figure E-7, there is a significant drop in punishment near the intersections installed with advanced cameras, indicating a decrease in violations as well; however, we do not find any significant change in punishment after the installation of conventional cameras. A note of caution here is 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.

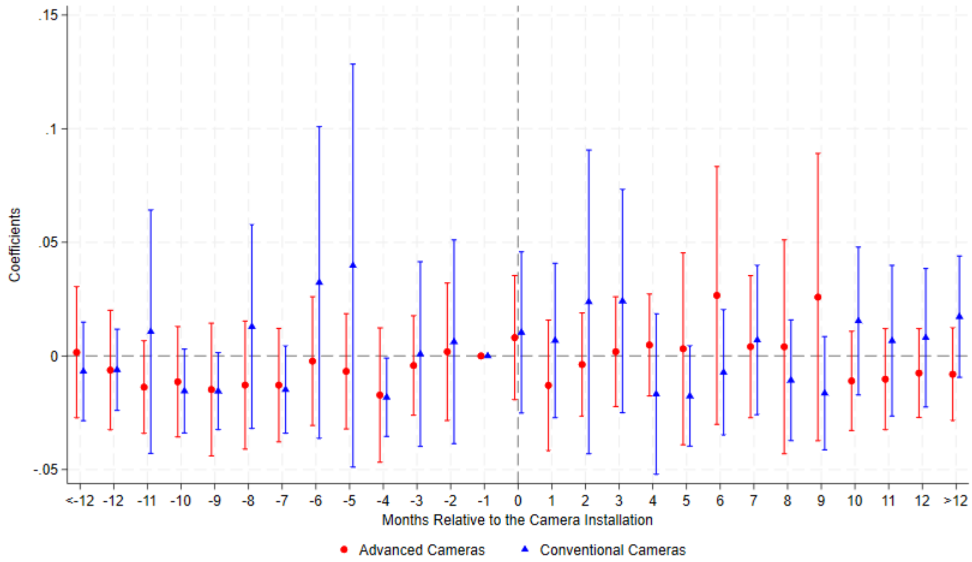


Figure F-1. Effect of Camera Installation on Type C Accidents

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).

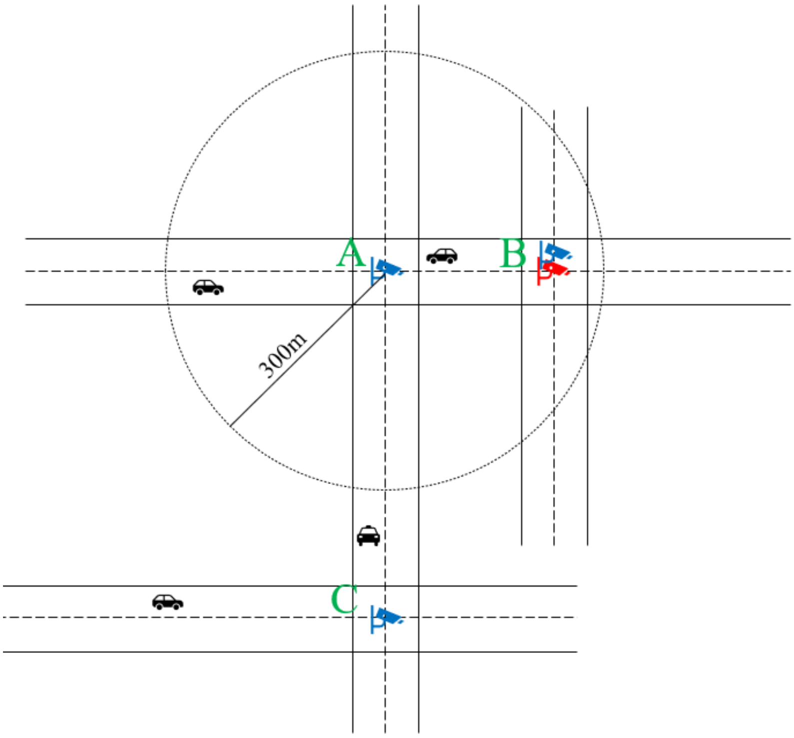


Figure F-2. Graphical Illustration of Spillover Effects of Advanced Cameras at the Neighboring Intersection on Traffic Accidents at the Focal Intersection

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.

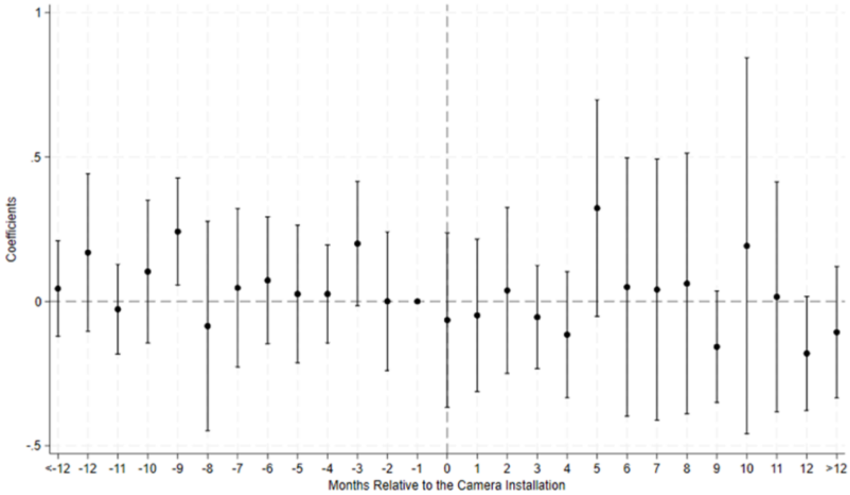


Figure F-3. Effect of Advanced Cameras at Neighboring Intersections on Traffic Accidents (Linked to Violations That Could be Captured by Advanced Cameras' Passive Functions) at the Focal Intersection

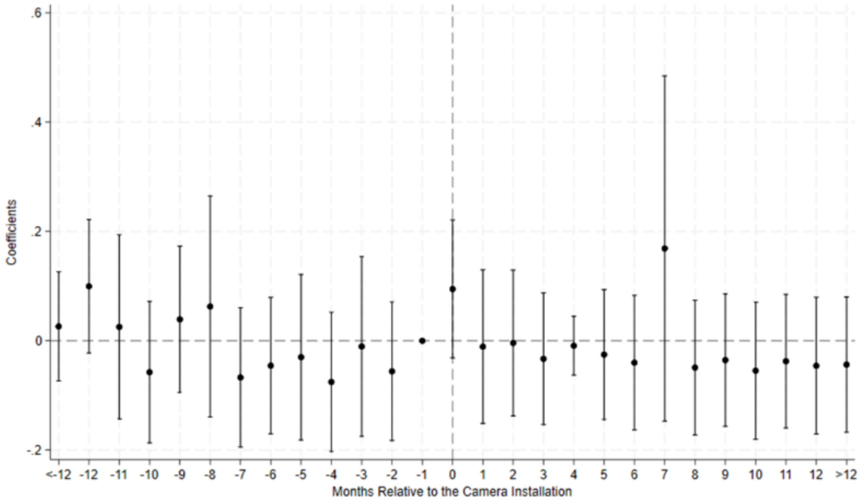


Figure F-4. Effect of Advanced Cameras at Neighboring Intersections on Traffic Accidents (Linked to Violations Not Captured by Any Cameras' Functions) at the Focal Intersection

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).

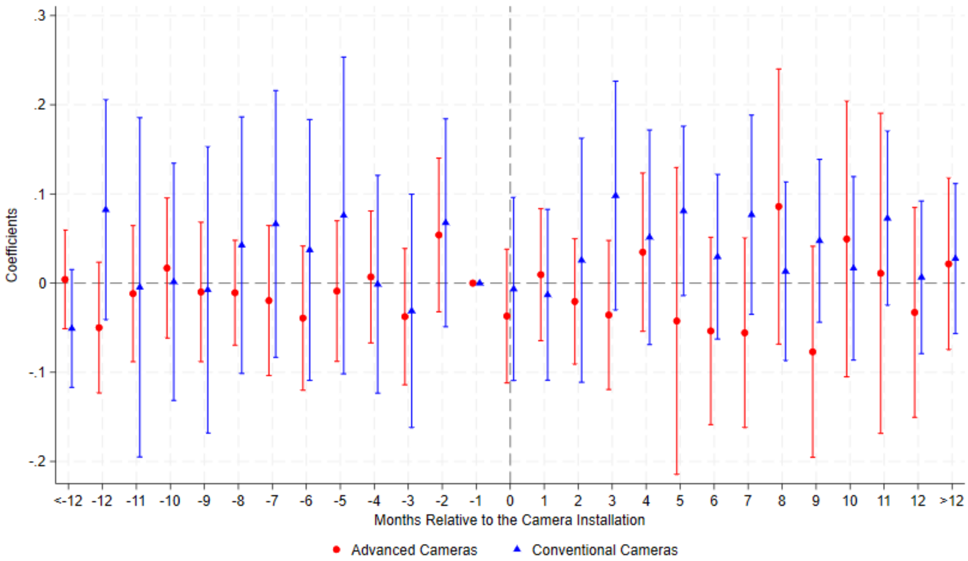


Figure G-1. Spatial Replacement (Radius: 100-300m)

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).

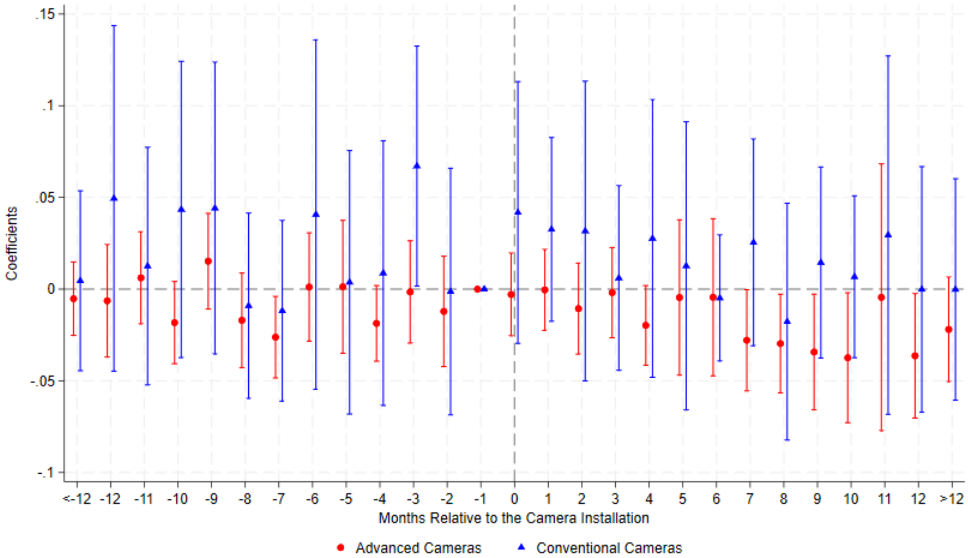


Figure G-2: Distraction Effect

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).

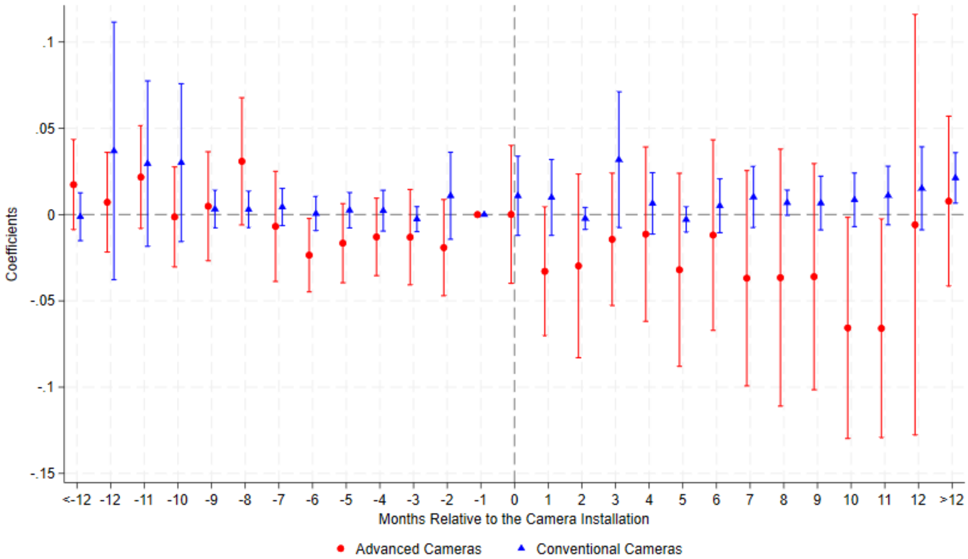


Figure G-3: Risk Compensation Effect

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.

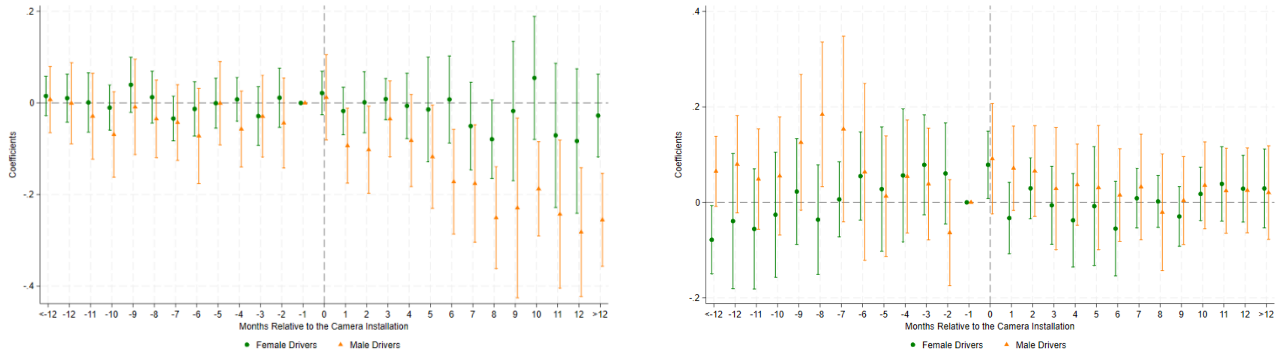
Our average treatment effects estimates are shown in Table I-1 and the event study estimates are presented in Figure I-1 below. In Table I-1, we also present to what extent the estimates between the two subsamples differ statistically significantly. For example, the installation of advanced cameras is 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

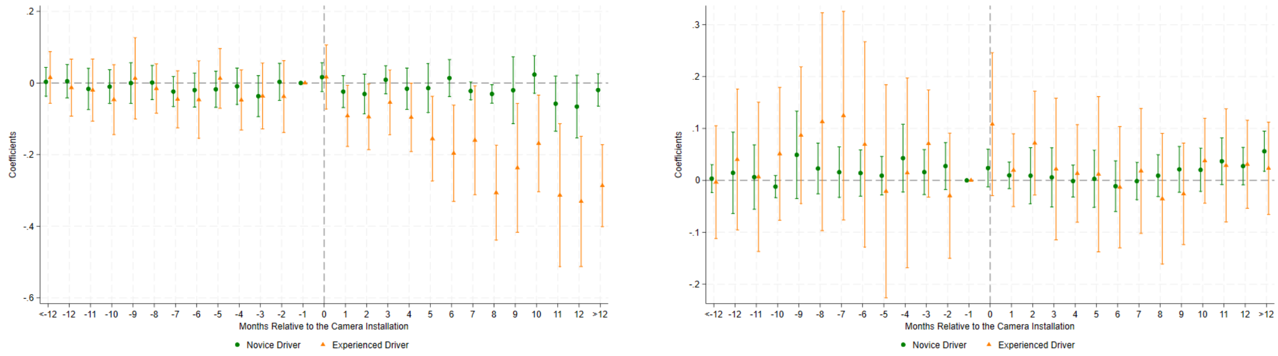
Driver Characteristics	Effect of Advanced Cameras		Effect of Conventional Cameras	
# female driver cases	-0.009	(0.012)	0.003	(0.017)
# male driver cases	-0.063***	(0.015)	-0.011	(0.021)
chi-squared	6.93***		0.16	
# novice driver cases	-0.005	(0.007)	0.011	(0.010)
# experienced driver cases	-0.078***	(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

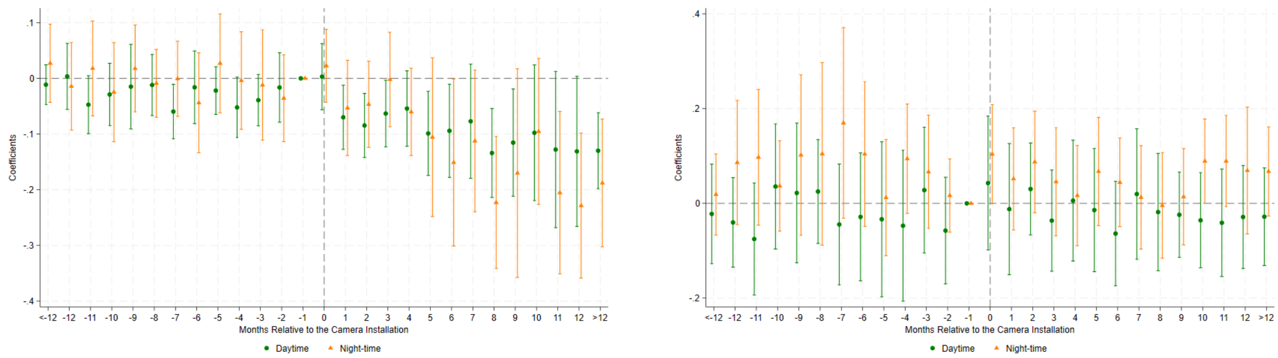
I.2 Event Study Estimates of Effects on Accidents by Driver Characteristics



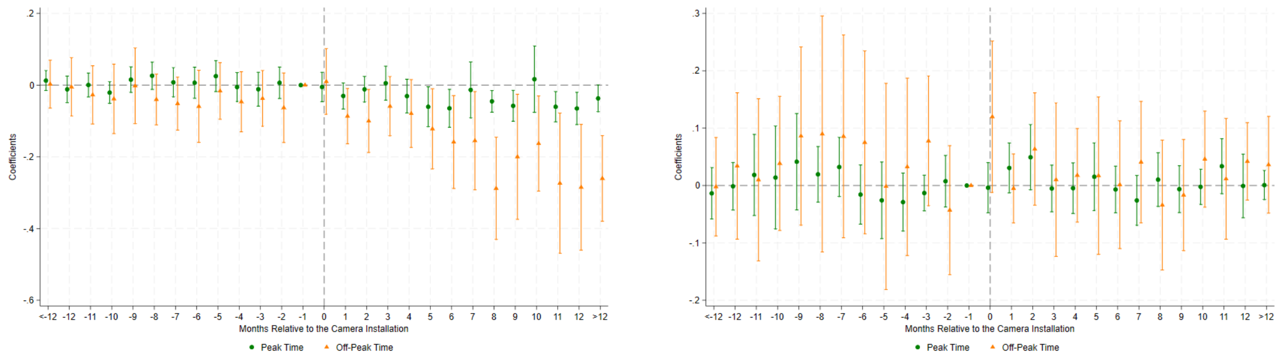
(1) #Female Driver Cases (green) vs. # Male Driver Cases (orange)



(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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