TI 2026-025/VIII
Tinbergen Institute Discussion Paper

Electric vehicles reduce driver injury severity but increase risk for other road users

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Electric vehicles reduce driver injury severity but increase risk for other road users

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Abstract: Electric vehicles (EVs) are typically 20% heavier than conventional internal combustion engine vehicles because of their dense battery packs and reinforced structures. While this additional mass shields EV occupants, it transfers disproportionately greater kinetic energy to other road users during collisions, exacerbating their injury severity. Here, we quantify this critical safety disparity using data from over 300,000 two-vehicle collisions in California. We find that driving an EV reduces the occupant's risk of serious injury or fatality by 18%. However, it significantly elevates the corresponding risk for occupants of colliding vehicles by 13%—an effect driven almost entirely by vehicle weight. Economically, these externalized accident costs offset approximately one-third of the environmental climate benefits of EVs, indicating that while EV adoption still yields a net gain in social welfare, it introduces profound safety inequities. As vehicle electrification accelerates globally to mitigate climate change, our findings highlight an urgent need for policies regulating fleet weight to ensure equitable road safety.

JEL codes: D62, Q54, Q58, R41, R48.

Introduction

Road traffic accidents remain a leading cause of premature death for individuals under 40, resulting in over 5 million injuries, 40,000 fatalities, and an economic burden of $500 billion annually in the United States (US) alone (National Safety Council, 2024). Despite significant policy interventions—such as stricter speed limits and infrastructure investments—and technological advancements like airbags and automatic emergency braking, crash and fatality rates per mile driven have stagnated over the past 25 years (Fig. 1A).

A plausible driver of this plateau is the aggregate increase in automobile weight over the last 15 years (although average vehicle weight in the US started to drop after 2004 due to increasing fuel prices and new regulation standards, it has increased sharply since 2010; these trends also hold for California, Fig. 1D), a trend increasingly fueled by the rising market share of electric vehicles (EVs). Because of their dense battery components and necessary structural reinforcements, EVs are on average 20% (approximately 933 pounds) heavier than their internal combustion engine (ICE) counterparts (Fig. 1B). This weight disparity is starkly reflected in California's two-vehicle collision records. While the average weight of colliding ICE vehicles has plateaued at around 3,800 pounds since 2017, the average weight of colliding EVs has surged by 700 pounds, reaching 4,300 pounds (Fig. 1C). This trend is particularly alarming given that newer EV models continue to grow heavier. Consumer demand for extended driving ranges necessitates larger batteries, and a broader market shift towards large SUVs and trucks further compounds the problem (Tyndall, 2021).

The growing weight disparity fundamentally alters crash dynamics, often at the severe expense of occupants in lighter vehicles (Van Ommeren et al., 2013; Anderson and Auffhammer, 2014). The combination of increased mass and rigid battery enclosures transfers disproportionately high kinetic energy to other vehicles and pedestrians during an impact. Compounded by faster acceleration capabilities and potentially extended braking distances, EVs may further elevate both the frequency and severity of accidents for other road users. Conversely, EVs offer distinct structural advantages for their own occupants—such as a lowered center of gravity from floor-mounted batteries and enhanced energy dissipation provided by engine-free crumple zones. This asymmetry creates a classic market failure: incentivized by lower operating costs, reduced emissions, and enhanced personal safety, consumers will increasingly adopt EVs, inadvertently imposing uninternalized external accident costs on the broader public.

The implications of EV-involved collisions extend far beyond the US. Globally, the market share of EV sales has quintupled from 4% in 2020 to 22% in 2024 (IEA, 2025), propelled by aggressive policy mandates to decarbonize road transport. California mirrors this rapid transition, with EV registrations growing nearly tenfold from 0.4% in 2016 to 4.1% in 2023 (Fig. 2A). Consequently, researchers increasingly warn that the influx of heavier EVs could burden society with substantial accident costs (Shaffer et al., 2021; Rapson and Muehlegger, 2023). These concerns are validated by empirical trends: the proportion of two-vehicle accidents involving EVs in California surged from 1.4% in 2017 to 7.7% in 2024 (Fig. 2B). In these collisions, the average weight disparity between an EV and an ICE vehicle is approximately 800 pounds—nearly double the typical weight difference between two colliding ICE vehicles (Fig. 2C). Preliminary data further indicate that fatality and severe injury rates spike significantly when ICE vehicles collide with EVs (Fig 2D).

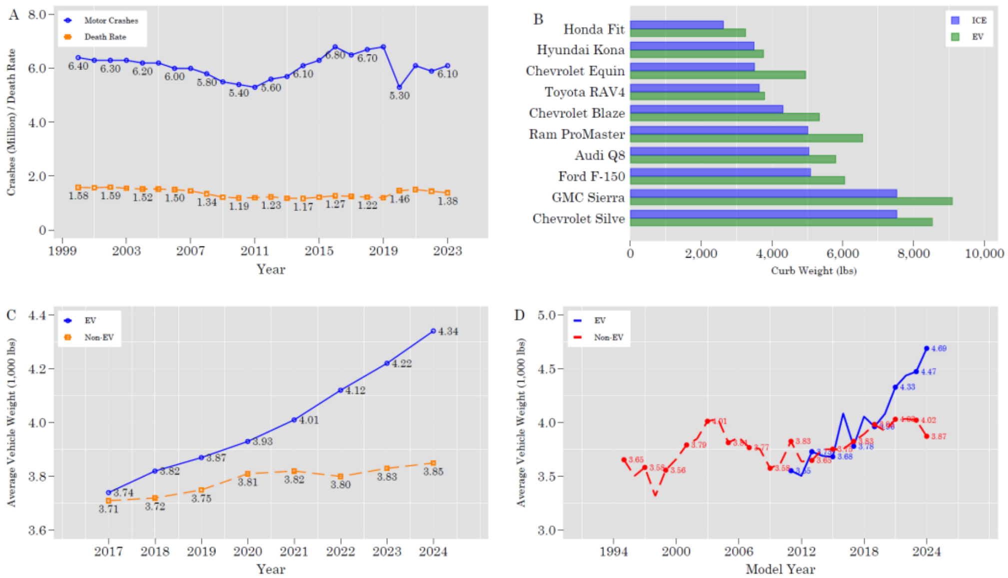

Fig 1. **Annual motor vehicle crash and death rates in United States and vehicle weight disparity between EVs and non-EVs involved in collisions.** (A) Annual motor vehicle crashes and death rates per 100 million miles driven in the US from 2000 to 2023 (in millions) [Source: Motor crashes are from National Safety Council; death rates are from National Highway Traffic Safety Administration]. (B) Vehicle weight (lbs.) between ICE and EV variants of the top 10 most popular models in the US [Source: iSeeCars]. (C) Average weight (1,000 lbs.) of EVs and ICE vehicles involved in collisions by year of collision. (D) Average weight (1,000 lbs.) of EVs and ICE vehicles involved in collisions by production (or model) year [Source for (C) and (D): California Highway Patrol's Statewide Integrated Traffic Records System (SWITRS)].

Motivated by these alarming collision trends, we rigorously examine the bidirectional safety impacts of EVs: whether they protect their own occupants at the cost of exacerbating injuries for opposing drivers. Our analysis of California crash data reveals a stark tradeoff. Driving an EV reduces an occupant's risk of serious injury or fatality by approximately 18%, but colliding with an EV elevates the opposing driver's risk of severe or fatal injury by 13%. Thus, EVs offer substantial internal safety benefits while imposing material external accident costs on other road users. We demonstrate that both these protective benefits and external risks are almost entirely attributable to the EVs' excess weight. Economically, adding an EV to the road imposes an external accident cost of \$0.01 per vehicle mile traveled (VMT). However, because this cost offsets only about one-third of the environmental benefits generated, the broader transition to EVs continues to yield a net positive impact on overall social welfare.

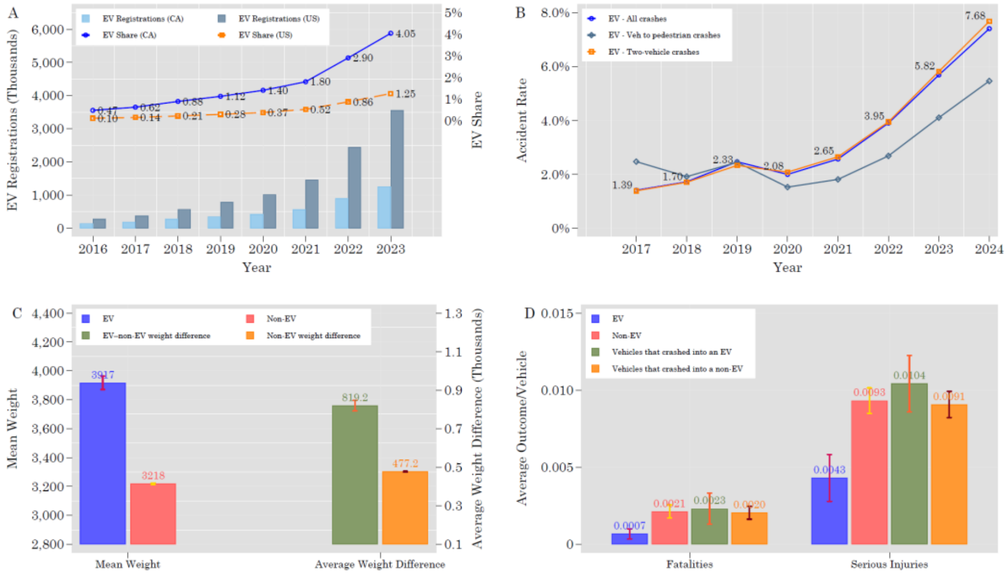

Fig. 2. **Electric Vehicle registrations in California and US, accident rate, mean vehicle weight, and injury outcomes for EVs and non-EVs involved in collisions.** (A) The number of light EV registrations in California and the US, along with the share of light EV registrations in total vehicle registrations in California and nationwide [Source: Alternative Fuels Data Center and Federal Highway Administration]. (B) The share of EV-involved crashes in total crashes, the share of EV-involved crashes in total crashes involving pedestrians, bicycles, or motorcycles, and the share of EV-involved crashes in total two-vehicle crashes. (C) EV and ICE vehicle weights, along with the absolute weight difference in EV–ICE vehicle collisions and in ICE vehicle – ICE vehicle collisions. (D) Fatality and serious injury per vehicle for EVs and ICE vehicles, vehicles that crash into an EV and vehicles that crash into an ICE vehicle. Panels (C) and (D) are based on collisions involving two passenger vehicles with model years after 2007, excluding crashes in which both vehicles are EVs. [Source for (B), (C) and (D): California Highway Patrol's Statewide Integrated Traffic Records System (SWITRS)].

Methods

To quantify EVs impact on collision outcomes, we focus on two-vehicle collisions involving vehicles weighing up to a threshold of 10,000 pounds. This threshold is much higher than in older literature (Anderson and Auffhammer, 2014), which focused on "light vehicles", i.e. vehicles up to 6,000 pounds. As vehicles nowadays are much heavier, setting a low threshold would exclude more than 30% of accidents (see Fig. 1C and Fig. 1D), rendering our results less representative. Our empirical regression model takes the following form:

$$A^{w}_{ijkct} = \beta^{w} E_i + \gamma^{w} E_j + \eta^{w} \log W_i + \lambda^{w} \log W_j + C_i \delta^{w} + C_j \theta^{w} + X_k \rho^{w} + \mu_c + \tau_t + \varepsilon_{ijkct}, \quad (1)$$

where A_{ijkct} is a binary variable denoting whether driver i involved with another driver j in accident k in jurisdiction c in year-month t is suffering from an injury outcome w where $w = \{injury, serious\ injury, fatality\}$. To facilitate interpretation, *serious injury* also includes fatalities. As the number of serious injuries is much larger than those of fatalities, this has no consequence for the estimates. Similarly, *injury* includes minor injuries, serious injuries, and fatalities.

Our primary interests are in the effects of the variables E_i, which is a binary variable taking the value of 1 if own driver i is driving an EV, 0 otherwise, and E_j, which is a binary variable taking the value of 1 if another driver j is driving an EV, 0 otherwise. β^{w} measures the internal accident effects of driving an EV on the driver's injury outcome w, and γ^{w} measures the external effects of colliding against an EV on the driver's injury outcome w. If driving a heavier EV packed with new technologies enhances safety for drivers, we expect $\beta^{w} < 0$. Conversely, if crashing against a heavier EV heightens the risk of serious injury and death, we expect $\gamma^{w} > 0$.

To ensure that our estimates are not driven by differences between EVs and ICE vehicles, or their drivers, we augment a rich set of driver and vehicle characteristics in equation (1). Specifically, C_i denotes a vector of own-driver characteristics (e.g age, gender and ethnicity) and vehicle characteristics, such as indicator variables for light truck and the model year. For instance, given that the fleet of EVs are, on average, newer than ICE vehicles, reduced severity for EVs could stem from the technological advancements in road safety and better materials for chassis from newer vehicles. Controlling for the model year of vehicles allows us to account for these differences. C_j denotes an analogous set of driver and vehicle characteristics for the other driver involved in the collision. The rationale is that the injuries severity may also be affected by the behaviors, demographics, and vehicle attributes of the driver he or she is crashing onto.

X_k represents a vector of accident-related characteristics such as road type (e.g. interstate highway, intersection) and weather conditions (e.g. rainfall) as these factors could influence collision severity. We also control for jurisdiction fixed effects (μ_c) to partial time-invariant location characteristics, as EV popularity varies between areas and area-specific factors could influence collision outcomes (e.g. access to emergency response teams). τ_t denotes time (hour, day-of-week, month and year) fixed effects that control for seasonal and temporal shocks. ε_{ijkct} represents robust standard errors clustered at accident level.

We further investigate to what extent the internal (β^{w}) and external (γ^{w}) EV effects can be explained by the weight differences between EV and ICE vehicles by controlling for the natural logarithm of the weight of the own, $\log W_i$, and the other vehicle, $\log W_j$. Employing the logarithm transformation of car weight is in line with Newtonian mechanics that highlights that the ratio of weight of the cars involved in the accident determines the collision outcomes. If these effects are entirely explained by weight differences, then β^{w} and γ^{w} must be statistically indistinguishable from zero given weight controls. If driving heavier vehicles enhances driver safety but increases the risk for others, we expect $\eta^{w} < 0$, where marginal increase in own vehicle weight reduces the risk of injuries and deaths for drivers, and $\lambda^{w} > 0$, where marginal increase in weight for the other vehicle heightens the risk of injuries and deaths for drivers.

In order to estimate the annual collision probability (p_t), we utilized state-level collision and vehicle stock data. For instance, in 2023, a total of 483,098 two-vehicle collisions occurred in California, of which approximately 3.54% involved an EV. During the same year, California had roughly 1,256,600 EVs in operation. Accordingly, the probability that an EV was involved in a two-vehicle collision in 2023 is calculated as 483,098 × 3.54% ÷ 1,256,600 = 1.36%. Using the same approach, the annual probabilities (p_t) for the years 2017 to 2023 are estimated to be 2.78%, 2.34%, 2.42%, 1.33%, 1.45%, 1.29%, and 1.36%, respectively.

Results

Table 1 reports the effects of EV on three different injury outcomes from the estimation of equation (1) from methods section: whether drivers suffer from injury, serious injury or fatal injury. We find that drivers colliding with an EV ("Other vehicle is EV") face a markedly higher risk of severe or fatal outcomes. Specifically, crashing into an EV increases the baseline probability of sustaining any injury by 9.2% (1.99 percentage points). More critically, the probability of sustaining a serious injury or fatality rises by 12.6% and 36.0%, respectively, translating to an aggregate 13% increased risk of severe or fatal outcomes for the opposing driver. Conversely, EV drivers enjoy a protective advantage ("Own vehicle is EV"): driving an EV during a two-vehicle collision reduces the risk of any injury, serious injury, and fatality by 16.3%, 18.0%, and 16.0%, respectively. Collectively, these findings illuminate a structural inequity: the heavier mass and advanced safety features of EVs shield their occupants but externalize significant physical risks to others. Left unchecked, this dynamic could drive EV adoption beyond the socially optimal level, underscoring a critical market failure.

Table 1: Effect of electric vehicles (EV) on injury outcomes in two-vehicle crashes

	(1)	(2)	(3)	(4)	(5)	(6)
	Injury		Serious injury		Fatal injury	
Other vehicle is EV $[E_j]$ (γ^w)	0.0199***	0.0121***	0.0014*	-0.0001	0.0009**	0.0004
	(0.0032)	(0.0032)	(0.0008)	(0.0008)	(0.0004)	(0.0004)
Own vehicle is EV $[E_i]$ (β^w)	-0.0353***	-0.0192***	-0.0020***	-0.0004	-0.0004*	0.0002
	(0.0033)	(0.0033)	(0.0006)	(0.0006)	(0.0002)	(0.0002)
Weight of other vehicle $[\log W_j]$ (λ^w)		0.0520***		0.0099***		0.0033***
		(0.0029)		(0.0008)		(0.0004)
Weight of own vehicle $[\log W_i]$ (η^w)		-0.1076***		-0.0106***		-0.0038***
		(0.0028)		(0.0008)		(0.0004)
Sample size	540,865	540,865	540,865	540,865	540,865	540,865
R (Tyndall, 2021)	0.0920	0.0949	0.0201	0.0207	0.0093	0.0097
Mean dependent variable	0.2167	0.2167	0.0111	0.0111	0.0025	0.0025
Percentage change of other EV	+9.2%	+5.6%	+12.6%	-	+36.0%	-
Percentage change of own EV	-16.3%	-8.9%	-18.0%	-	-16.0%	-

Reported estimates are the effects on various injury outcomes when a driver crashes into an EV (γ^w) and when a driver is driving an EV (β^w). Marginal effects of other vehicle weight (λ^w) and own vehicle weight (η^w) on these outcomes are also reported. Dependent variables are binary (1 or 0) denoting whether driver is suffering from injury (columns 1 and 2), serious injury (columns 3 and 4) or fatal injury (columns 5 and 6). Mean dependent variable is the mean value of the respective dependent variables. Percentage change of own and other EV is computed by taking the estimated effects before dividing by the respective mean dependent variable before multiplying by 100. The estimation equation takes the following form: $A^w_{ijkct} = \beta^w E_i + \gamma^w E_j + \eta^w \log W_i + \lambda^w \log W_j + C_i\delta^w + C_j\theta^w + X_k\rho^w + \mu_c + \tau_t + \varepsilon_{ijkct}$. Main variable of interests are binary denoting whether own (E_i) and other vehicle (E_j) are an EV. Weight for own $(\log W_i)$ and other vehicle (og W_j) is in logarithm. Weather (X_k) and time controls (τ_t) include rain, wet, dark, normal road, intersection, Interstate highway, day of week, and month, year, hour fixed effects. Vehicle and driver controls for own (C_i) and other vehicle (C_j) include indicators for whether vehicle is a light truck, vehicle's model-year fixed effects, driver age, quadratics in driver age, indicators for male drivers, young male drivers, and indicators for white drivers, and young white drivers. Standard errors (ε_{ijkct}) reported in parenthesis are clustered at the collision level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

To determine whether this external accident cost is fully explained by the inherent weight disparity between EVs and ICE vehicles (Table S3), we adjust our models for the logarithmic weight of both vehicles. Two notable findings emerge. First, conditional on vehicle weight, colliding with an EV no longer significantly increases the opposing driver's probability of severe or fatal injury. This indicates that the severe external risks posed by EVs are driven almost entirely by their excess mass, rather than other design factors. The sole exception is minor injuries, which remain slightly elevated for drivers colliding with EVs even after accounting for weight. Second, the internal safety benefits of EVs mirror these external costs: adjusting for weight eliminates the protective effect of EVs against serious injuries and fatalities for their own occupants. Collectively, these results suggest that unique EV features—such as a lower center of gravity and reinforced battery frames—may offer slight protective benefits. However, they simultaneously exacerbate minor injury risks for opposing drivers through factors like faster acceleration and extended braking distances. Nonetheless, because the societal cost of minor injuries is dwarfed by that of severe injuries and fatalities, the overall external accident cost of EVs fundamentally stems from their heavier weight.

Focusing on the marginal effects of weight, we find that a 10% increase in a vehicle's own weight reduces its driver's risk of slight injury, serious injury, and fatality by 1.07, 0.106, and 0.038 percentage points, respectively. Conversely, colliding with a vehicle that is 10% heavier elevates the opposing driver's risk across the same categories by 0.52, 0.099, and 0.033 percentage points. Given that contemporary EVs are on average 20% heavier than equivalent ICE vehicles, switching to an EV reduces the adopter's probability of injury, serious injury, and fatality by 12.4%, 23.9%, and 38.0% (computed by dividing the estimated marginal effects by the mean outcome values before scaling; for instance, the 0.0106 percentage point effect for serious injuries yields an approximate 23.9% change from the baseline mean of 0.0111). However, this same switch simultaneously inflates the corresponding injury risks for an opposing driver in a collision by 6.0%, 22.3%, and 33.0%.

To robustly attribute these safety disparities to EVs rather than confounding factors, we address several potential biases. First, utilizing Oster's coefficient stability tests , we confirm that unobserved demographic or behavioral differences between EV and ICE drivers do not drive our primary findings (Table S5). Second, we rule out collision fault as a confounder by stratifying the analysis by at-fault and not-at-fault drivers, observing no discernible differences in EV effects across subgroups (Tables S6 and S7). Third, to ensure disparities are not merely artifacts of generational improvements in vehicle safety technologies, we restrict our analysis to post-2008 vehicles and matched-age collisions, yielding highly consistent results. Fourth, we verify that our baseline estimates are robust to the choice of functional form; employing a probit model in place of a linear probability model yields strictly comparable marginal effects. Finally, expanding our scope using Poisson regression models demonstrates that these bidirectional safety effects apply to all vehicle occupants, not just drivers, and that all such effects become negligible once vehicle weight is controlled (Table S8).

Environmental consequences

Our results highlight a profound inequity in the safety benefits of technological advancement: EVs enhance occupant safety strictly at the expense of other road users. As fleet electrification accelerates, the net impact of EVs on overall road safety will hinge heavily on the evolving mass distribution of the vehicle fleet. This underscores a critical need for transportation policies to explicitly account for the external safety impacts of new technologies, moving beyond the traditional paradigm of isolated occupant protection.

A central question remains: do the environmental benefits of EVs justify the external accident costs they impose? By integrating our estimated external weight effects with the U.S. Department of Transportation's 2024 Value of Statistical Life ($13.7 million), we estimate the external accident cost at $0.0118 per kilometer per EV annually (Table 2). For California's current EV stock, this translates to an aggregate external accident cost of approximately $122.96 million per year. To benchmark these costs, we calculate the net avoided CO_2 emissions per kilometer, balancing ICE tailpipe reductions against grid emission intensities. Multiplying our estimate of 0.206 kg of net avoided CO_2 per kilometer by the social cost of carbon ($190 per tCO_2), the climate benefit per EV is approximately $0.0391 per kilometer.

Table 2: Electric Vehicles external accident cost and environmental benefits per kilometer driven

	(1)	(2)	(3)	(4)
Panel A: Annual external accident cost per EV/km/year ($) [$EAC(EV)_t$]				
	Fatal injury	Serious injury	Minor injury	Total cost
Standard estimates	0.0083	0.0026	0.0009	0.0118
Lower bound	0.0050	0.0016	0.0005	0.0071
Upper bound	0.0116	0.0037	0.0012	0.0166
			Standard estimates	Lower/upper bound
EV accident costs in California per year ($): $EAC(EV)_t \times VMT \times$ EV stocks per year				
			122.9591 million	[73.8, 172] million
Panel B: Environmental benefits per EV/km/year ($) [$EB(EV)_t$]				
Per-kilometer annual climate benefit per EV			0.0391	[0.0247, 0.0699]
EV climate benefits in California per year: $Benefit_{EV} \times VMT \times$ EV stocks per year				
			406.490 million	[256.8, 727] million
Panel C: Net social benefits per EV/km/year ($) [$EB(EV)_t - EAC(EV)_t$]				
Per-kilometer annual social benefits per EV			0.0273	[0.0081, 0.0628]
Average annual social benefits			283.531 million	[84.6, 653] million

The U.S. Department of Transportation assigns a value of statistical life (VSL) of $13.7 million for the year 2024, along with a set of relative disutility factors for different injury classes. Conversion factors for minor injury and serious injury are 0.003 (0.003 × $13.7 million = $41,100) and 0.105 (0.105 × $13.7 million = $1.439 million) of VSL respectively. Alternative VSLs are set at ±40% of the baseline value ($13.7 million). Standard estimates are obtained from column (2), (4), and (6) of Table 1 for injury, serious injury, and fatal injury, respectively, based on the baseline VSL, while the lower and upper bounds are based on the alternative VSLs. Environmental benefits are calculated using carbon costs, where the EPA**Error! Reference source not found.** sets the price of CO_2 at $190 per tCO_2, with a lower bound of $120 and an upper bound of $340 per tCO_2. Net social benefits are obtained by subtracting the standard estimates of external accident costs from the standard estimates of environmental benefits, while the lower bound is calculated as the environmental benefits' lower bound minus the accident costs' upper bound, and the upper bound as the environmental benefits' upper bound minus the accident costs' lower bound.

Subtracting the external accident costs from these climate benefits yields a net social benefit of $0.0273 per kilometer per EV annually, indicating that environmental gains currently offset the externalized accident costs by more than a factor of two. Boundary simulations further show that EVs would only generate a net negative social benefit if they were over 83% heavier than ICE counterparts—a threshold unlikely to be breached given current sedan weight disparities (Fig 3A).

Looking forward, applying a logistic growth model to California's EV adoption projects a fleet of 12.7 million EVs by 2035 (Fig 3B). While the present value (PV) of cumulative external accident costs would surge to $2.17 billion, the PV of environmental benefits scales proportionately to $7.18 billion, securing a projected net social benefit of approximately $5.01 billion by 2035.

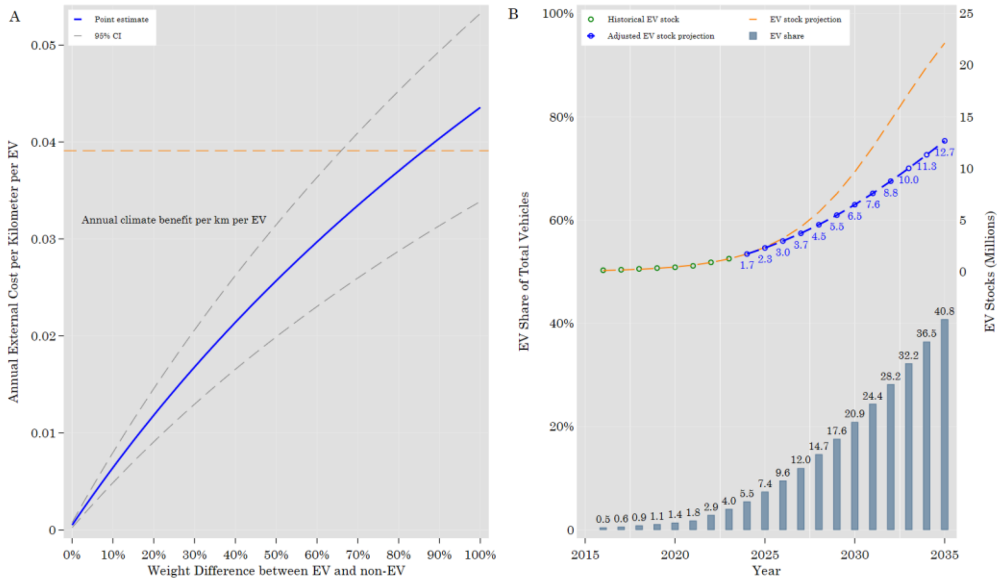

Fig. 3 Annual external accident cost and environmental benefit from Electric Vehicles, Historical and Projected Stock of EVs in California. (A) The orange horizontal dashed line represents the annual climate benefit per kilometer per EV. The blue solid line shows the point estimate of the annual external cost per kilometer per EV, derived from equation (S3) across varying levels of the weight difference ratio between non-EVs and EVs. The gray dashed lines denote the 95% confidence interval around the estimate. (B) The green hollow circles represent California's EV stock from 2016 to 2023, the orange line depicts the EV stock projections generated from the logistic growth model following (**Error! Reference source not found.**), the blue line shows the projections based on the adjusted logistic growth model, and the bar chart illustrates the share of EVs in the total vehicle stock. [Source: Alternative Fuels Data Center and Federal Highway Administration].

Conclusion

Driven by global mandates to mitigate climate change, the rapid proliferation of EVs represents a fundamental shift in the composition of the vehicle fleet. While the environmental merits of this transition are well-documented, the secondary implications for traffic safety have remained critically underexplored (Shaffer et al., 2021; Holland et al., 2016). We provide compelling empirical evidence that the transition to EVs introduces a severe safety asymmetry: the inherent mass of EVs shields their occupants while simultaneously endangering other road users during collisions. Because this risk is almost entirely a function of vehicle weight, manufacturers must prioritize the development of lighter battery technologies and structural materials, rather than exclusively pursuing extended driving ranges.

Although the environmental benefits of EVs currently more than offset their external accident costs, these societal costs are substantial and will escalate rapidly as aggressive EV adoption targets are met. Ignoring this externality risks embedding profound physical inequities into our transportation systems. To foster a fairer and more efficient transition, policymakers must integrate external accident costs into vehicle safety standards, tax incentives, and road usage regulations. Adjusting vehicle taxation or reducing purchase subsidies for heavier EVs to reflect these externalized costs would directly address the safety imbalances caused by this weight disparity. Such holistic governance will ensure that the sustainable future promised by EVs is not only environmentally clean but also equitably safe for all road users.

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SUPPLEMENTARY INFORMATION

Electric vehicles reduce driver injury severity but increase risk for other road users

1. Data

We collect collision-level accident characteristics and injury outcomes (minor injuries, serious injuries and fatalities) between January 2017 and December 2024 from the California Highway Patrol's Statewide Integrated Traffic Records System (SWITRS). SWITRS is a database maintained by the California Highway Patrol that collects and processes traffic accident scene data, covering traffic accidents recorded by law enforcement agencies in California. It includes information on individuals, vehicles, locations, environmental conditions, and injuries. The SWITRS database comprises three fact tables: *accident*, *party*, and *victim*. The *accident* table refers to unintended events involving motor vehicles in motion that result in damage or injury, containing information such as accident date, location, and environmental conditions. The *party* table typically refers to motor vehicles but may also include pedestrians, cyclists, or other entities, and contains details such as driver characteristics, vehicle make, and fault determination. The *victim* table refers to individuals injured or killed in the accident, including their category and injury severity. SWITRS is arguably the most comprehensive micro-level traffic accident database in California and serves as the core data source for our study of the internal benefits and external costs of EVs.

Approximately 20% of vehicles in this dataset provided Vehicle Identification Numbers (VINs). To address concerns of selection bias regarding this subsample, we provide descriptives of observable drivers' and collision characteristics for both the VIN sample and the full sample (Table S1). These descriptives are almost identical, suggesting there are no salient differences between accidents that report VINs and those that do not. We employ the National Highway Traffic Safety Administration's (NHTSA) VIN Decoder to identify the car make for vehicles involved in collisions based on VIN and ascertain if they are EV or not. The NHTSA VIN Decoder is an official, free tool provided by the U.S. Department of Transportation's NHTSA, designed to decode VINs to ensure transparency of vehicle information. A VIN is a globally standardized 17-character code, akin to a vehicle's "identification card." The first three characters form the world manufacturer identifier, indicating the vehicle's manufacturer and country of origin; characters 4–9 constitute the vehicle descriptor section, describing key vehicle characteristics such as model, body type, and engine type; and characters 10–17 form the vehicle identifier section, indicating the model year, assembly plant, and production sequence number. We used the NHTSA VIN Decoder's vehicle API to batch-query VIN data for accident-involved vehicles, obtaining information such as engine type, model year, gross vehicle weight rating, and curb weight. We identified vehicles as EVs if their primary fuel type was electricity. Curb weight data were available for only a small proportion of vehicles.

In Figure S1, we plotted the distribution of accidents involving vehicles with VINs from the SWITRS data. Due to the lack of geographic boundary data for jurisdictions, we mapped these to city-level geographic boundaries. However, some jurisdictions are unincorporated and thus cannot be directly matched to cities. For jurisdictions that could not be accurately matched, we first identified their corresponding county and then matched them to the "Unincorporated" category in the city geographic boundary data. As shown in Figure S1, accidents involving vehicles with VINs cover the entirety of California, though they are somewhat less prevalent in the southern regions. However, since we matched unincorporated jurisdictions to the "Unincorporated" category in the city geographic boundary data, the actual distribution of these accidents may be broader but sparser. Our data is unlikely to cause selection bias due to their wide spatial coverage. Additionally, the driver and collision characteristics in our sample are nearly identical to those in the full sample (see Table S1 below). Furthermore, in our econometric analysis, we control for jurisdiction fixed effects to mitigate potential selection bias.

We further collect weight from publicly available sources including CARSPECS.US and iSeeCars based on car make. CARSPECS.US (https://www.carspecs.us/) is an open vehicle specifications database, primarily providing data on cars sold in the U.S. market, covering most models from 1990 to the present. iSeeCars (https://www.iseecars.com/car-finder) is an automotive search and data analysis platform that aggregates large-scale used car transaction and manufacturer data, including models predating 1990. We used Python to scrape vehicle information from CARSPECS.US and iSeeCars, including make, model, model-year, curb weight, and trim specifications such as transmission and body class. We first identified vehicles for which curb weight data could not be obtained from the NHTSA VIN Decoder and matched them based on make, model, model year, and trim specifications with vehicle data from CARSPECS.US and iSeeCars to obtain the curb weights of accident-involved vehicles. The weights of some rare models could not be retrieved from CARSPECS.US or iSeeCars. We manually supplemented these data from other online sources, such as Edmunds, automobile-catalog, VinCheck, and automobile manufacturer webpages.

Information on vehicle characteristics and variables employed in the analysis is summarized in Table S5. We focus on California for three reasons. It is a large state (about 40 million inhabitants) with a high EV adoption rate, accounting for over one-third of the national total. Second, collision data is of high quality and encompasses the necessary information to identify EVs. Third, detailed information is available not only on collision outcomes for drivers including injuries, serious injuries and fatalities, but also on drivers (e.g., gender, age, whether at fault) and road conditions (e.g., location, road type). The rich data allows us to isolate other factors that could drive a spurious relationship between EVs and collision severity, providing more reliable estimates.

2. Summary statistics

We use collision-level data from the California Highway Patrol's Statewide Integrated Traffic Records System (SWITRS), covering the period from 2017 to December 2, 2024. Approximately 20% of vehicles in this dataset provided Vehicle Identification Numbers (VINs), which we use as the basis for our main analysis. To check data quality and representativeness, we compared collision characteristics across the full sample of all two-vehicle collisions in California (column 1), the subsample without VINs (column 3), and the subsample with VINs (column 5) in Table S1. Here, "with VINs" refers to vehicles with provided VIN, but not necessarily valid VINs, such as those with fewer than 17 characters. So, Table S1 presents descriptive statistics for the raw two-vehicle collision data before sample selection. We found no systematic differences between these samples.

We then select vehicles with valid VINs, complete basic vehicle information (e.g., make, model, model year, engine type) and driver information (e.g., gender) for either vehicle involved in the collision. We include small to medium-sized motor vehicles, pickup trucks, SUVs, and minivans with a curb weight below 10,000 pounds. Motorcycles are excluded. Tables S2 and S3 report the descriptive statistics of our final sample, which are broadly similar to those in Table S1.

Our main outcome of interest is the injury and fatality outcomes of drivers in each vehicle. Table S2 presents the distribution of injuries of drivers. In two-vehicle collisions, the fatality rate for EV drivers (0.06%) is substantially lower than that for ICE vehicle drivers (0.25%). The proportion of severe injuries among EV drivers is 0.36%, half that of ICE vehicle drivers, and the likelihood of minor injuries for EV drivers (19.24%) is slightly lower than for ICE vehicle drivers (20.60%).

Table S2 also presents the specific characteristics of vehicles involved in two-vehicle collisions. Among these vehicles, over half of the EVs are manufactured by Tesla (48.89%), with nearly half of the EV models being Tesla's Model 3 and Model Y (43.55%). For ICE vehicles, vehicles produced by Toyota and Honda account for 41.45%, with the top five models, all produced by these manufacturers, comprising 26.42% of the total. EVs are manufactured more recently than ICE vehicles, with 78.61% of EVs produced between 2017 and 2023, compared to 42.90% of ICE vehicles manufactured between 2013 and 2019, the period with the highest share for ICE vehicles.

Table S3 reports descriptive statistics for the control variables used in the main analysis. EVs are, on average, 364 pounds heavier than ICE vehicles but are less likely to be light trucks. The average model year for EVs is 2019, compared to 2012 for ICE vehicles. EV drivers differ from ICE vehicle drivers in several ways: they are more likely to be male, older, and white, and they are less likely to be at fault in collisions. The likelihood of EVs being involved in accidents during rain, on wet roads, in dark conditions, on normal roads, at intersections, or on Interstate highways is like that of ICE vehicles. Column (5) of Table S3 reports descriptive statistics for the control variables of ICE vehicles in accidents involving EVs, with the mean of each variable being similar to those in column (3). Definitions and sources of all variables included in the analysis are provided in Table S4.

3. Robustness checks

We conduct a series of tests and alternative model specifications to verify the robustness of our findings.

3.1 Oster test

To assess whether our estimates are sensitive to omitted-variable bias, we implement the coefficient stability test of Oster (California Energy Commission, 2023), which evaluates how changes in the EV coefficients and the accompanying R (Shaffer et al., 2021) values between models with and without driver characteristics inform the potential influence of unobservables. The resulting delta parameter (δ) measures how much stronger selection on unobservables would need to be, relative to observables, to fully eliminate the estimated effect. Table S5 shows that the deltas for being struck by an EV are large—112.35 for overall injury and 5.21 for fatal injury—indicating strong robustness, as unobservables would have to be many times more influential than observed controls to overturn these estimates. The delta for serious injury (1.35) suggests moderate robustness, while the negative deltas for the "own EV" coefficients reflect that adding controls reduces the coefficient but does not imply sensitivity that would invalidate the estimates. Overall, the Oster results indicate that the main findings are unlikely to be driven by omitted-variable bias.

3.2 Restricted to own-driver or other-driver no-fault collisions

Drivers may have unobservable characteristics that affect accident severity. However, our Oster test and sensitivity analysis have shown that the impact of omitted driver variables is negligible. To further validate this, we leveraged California's insurance law, which requires police to determine the at-fault driver in an accident (in nearly all cases, only one driver is identified as the at-fault party). For no-fault EVs, the likelihood of colliding with an at-fault driver is random under certain conditions, and the unobservable characteristics of the no-fault party are unlikely to affect the injury outcomes of the at-fault party. To identify the internal effect of EVs, our primary analysis focuses on the injury outcomes of struck no-fault drivers.

Column (1) shows that, after restricting the sample to collisions where the own driver is not at fault, our regression results remain nearly unchanged in both statistical and substantive significance. When the own vehicle is an EV, the probability of injury (Panel A of Table S6), serious injury (Panel B of Table S6), and fatality (Panel C of Table S6) for the own vehicle's driver decreases significantly. After controlling for weight, the effect of "own EV" on injury (Panel A of Table S7) remains significantly negative, but there is no significant effect on serious injury (Panel B of Table S7) or fatality (Panel C of Table S7).

Similarly, to identify the external effect of EVs, our primary analysis focuses on the injury outcomes of struck drivers where the striking driver is not at fault. As shown in Column (2) of Tables S6 and S7, after restricting the sample to collisions where the other driver is not at fault, our results remain similar. When the other vehicle is an EV, the probability of injury, serious injury, and fatality for the own vehicle's driver increases significantly (Table S6). After controlling for weight (Table S7), the likelihood of injury remains higher for vehicles struck by an EV, but there is no significant difference in the probability of serious injury or fatality.

3.3 Probit estimation

We also estimated a probit version of the baseline model to ensure that our findings are not dependent on the choice of functional form. The probit model is specified as follows:

$$\Pr\left(A_{ijkct}^{w}=1\right)=\Phi\left(\beta^{w}E_i+\gamma^{w}E_j+\eta^{w}\log W_i+\lambda^{w}\log W_j+C'_i\delta^{w}+C'_j\theta^{w}+X'_k\rho^{w}+\mu_c+\tau_t\right), \qquad \text{(S1)}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. The dependent variable A_{ijkct} is defined as an indicator equal to 1 if driver i experiences an injury outcome w (injury, serious injury, or fatality) in accident k, which involves another driver j and occurs in jurisdiction c at time t, and 0 otherwise. The core explanatory variables and control variables are the same as in the LPM.

As shown in column (3) of Tables S6 and S7, the effect of "own EV" remains negative and significant, and the effect of "other EV" remains positive and significant. When conditioned on vehicle weight, the effects of "own EV" and "other EV" on injury persist, indicating consistency across different estimation methods.

3.4 Potential confounding effects from hybrid or dual-fuel vehicles

We focus on the impact of pure EVs on road traffic safety. To isolate potential confounding effects from hybrid or dual-fuel vehicles, we included an indicator variable for whether electricity is the vehicle's secondary fuel type. Column (4) of Tables S6 and S7 reports the results. The relationships between "own vehicle is EV" and "other vehicle is EV" with injury, serious injury, and fatality risks are consistent with the baseline findings, reinforcing the robustness of our results.

3.5 Differences in model year

Although our analysis includes model year fixed effects to control for technological differences related to vehicle age, we further restricted the sample to collisions where the absolute difference in model year between the two vehicles is no more than 16 years (in our sample, the earliest model year for EVs is 2008, resulting in a maximum absolute model year difference of 16 years between the newest and oldest EVs) to reduce the impact of potential technological heterogeneity from biasing the results. This approach enhances the comparability of the vehicles involved by excluding collisions with large model year disparities, thereby strengthening the robustness of the estimation results. We then re-estimated the model using specification (3) from the main text on this restricted sample, and the results show that the main conclusions are consistent with the baseline regression (column 5 of Tables S6 and S7), indicating that our findings are not driven by collisions involving vehicles with extreme model year differences.

In addition, we further restrict the sample by excluding collisions in which both vehicles were manufactured before 2008, the earliest model year in which EVs appear in our data. This restriction removes pairs of older gasoline vehicles that could introduce mechanical or structural differences unrelated to EV status, thereby improving the comparability between EV–ICE vehicle and ICE vehicle–ICE vehicle collisions. We re-estimated specification (3) from the main text using this filtered sample (column 6 of Tables S6 and S7), and the results remain highly consistent with our baseline estimates. This provides additional evidence that our findings are not driven by crashes involving exclusively older gasoline vehicles.

4. Effects of EVs on occupant safety

Here, we used Poisson regression to examine the impact of EVs on occupant safety outcomes. The Poisson model is suitable for count-dependent variables and is specified as follows:

$$\mathbb{E}(Y_{ijkct}) = \exp\left(\beta E_i + \gamma E_j + \eta \log W_i + \lambda \log W_j + C'_i \delta + C'_j \theta + X'_k \rho + \mu_c + \tau_t\right), \qquad \text{(S2)}$$

where Y_{ijkct} represents the count of injuries or fatalities for driver i in accident k, which involves another driver j and occurs in jurisdiction c at time t, specifically including the number of fatalities, the sum of serious injuries and fatalities, and the sum of minor injuries, serious injuries, and fatalities in the own vehicle. The core explanatory variables and control variables are consistent with specification (3) in the main text.

Table S8 summarizes the estimation results. We find that when the own vehicle is an EV, the number of minor injuries (column 1), serious injuries (column 3), and fatalities (column 5) in the own vehicle decreases significantly. When the other vehicle is an EV, the number of injuries (column 1) in the own vehicle increases significantly, as do the number of serious injuries (column 3) and fatalities (column 5), though the latter two are not statistically significant. After controlling for weight, EVs continue to reduce the number of injuries in their own vehicle and increase the number of injuries in the struck vehicle (column 2), but there is no significant effect on serious injuries (column 4) or fatalities (column 6).

5. Cost-benefit analysis

Does environmental benefit of EVs outweigh the external accident cost imposed? We provide answers by quantifying the external accident costs and environmental benefits in monetary terms. The external accident cost per kilometer per EV per annum at year t ($EAC(EV)_t$) is expressed as follows:

$$EAC(EV)_t = \frac{\sum_n (\gamma^n \times \Omega^n \times p_t + \lambda^n \times \Omega^n \times d \times p_t)}{VMT} \qquad \text{(S3)}$$

where n represents different types of injury outcomes (1 = injury, 2 = serious, 3 = fatality); γ^n denotes the estimated external effects of EVs on outcome n; Ω^n is the monetary cost of outcome n (e.g., economic cost of injury, serious injury and Value of Statistical Life (VSL)). According to U.S. Department of Transportation (DOT), in 2024, VSL is estimated to be \$13.7 million, and the estimated costs of slight and serious injury are at \$41,100 (0.003 × VSL) and \$1.439 million (0.105 × VSL) respectively. p_t is the probability that an ICE vehicle crashes into an EV, set between 1.29% and 2.78% based on the stock of EVs and ICE vehicles registered from 2017 to 2023 (see Methods); d is the ratio of the weight difference between ICE vehicles and EVs at 20% (we do not add a fixed weight difference, e.g., 700 kg as assumed by Shaffer et al. (Drupp and Hänsel, 2021), because as vehicles become heavier, the battery must also be more powerful and heavier to ensure comparable acceleration, gradeability, and range performance); λ^n is the estimated external effect of log weight on outcome n; and VMT is the average annual vehicle miles traveled (VMT) for EVs, set at 18,362 km, based on the 2022 National household travel survey.

The estimated external costs of EVs computed based on equation (S3) are summarized in Table 2. The external accident cost per kilometer per EV per year is \$0.0118/km/year. Given the stock of EV (3.96 million) and the average annual VMT for EVs (18,362.62 km), we estimate the aggregate annual accident cost in California to be approximately \$122.96 million based on 2024 values.

Next, we compute the environmental benefits associated with EVs. EVs replacing ICE vehicles can reduce carbon emissions on the road, but EV charging generates local pollutants[Error! Reference source not found.]. Following Shaffer et al. (Drupp and Hänsel, 2021), we estimate the environmental benefits per kilometer per EV per year from avoided emissions using the following formula:

$$EB(EV)_t = \left(\frac{CO_{2_{ICE,per\ km}} - CO_{2_{EV,per\ km}}}{1000}\right) \times Price_{CO_2,per\ ton} \qquad \text{(S4)}$$

where $CO_{2_{ICE,per\ km}}$ is the tailpipe emissions avoided by an ICE vehicle traveling 1 kilometer, assuming a fuel efficiency of 20 miles per gallon; $CO_{2_{EV,per\ km}}$ is the power sector emissions generated from the electricity required to charge an EV to travel 1 kilometer; and $Price_{CO_2,per\ ton}$ is the price per ton of CO_2. Following EPA[12], we set $Price_{CO_2,per\ ton}$=\$190 per tCO_2 (with a lower bound of \$120 and an upper bound of \$340 per tCO_2). Since CO_2 emissions from a gallon of gasoline are 8.887 kg CO_2/gallon based on estimates from US Environmental Protection Agency (EPA), $CO_{2_{ICE,per\ km}} = \frac{8.887\ \text{kg CO}_2\text{/gallon}}{20\ miles/gallon \times 1.61\ \text{km/mile}} = 0.2760\ \text{kg CO}_2\text{/km}$[13]. Similarly, for power sector emissions, we use California's 2022 average emission intensity of 0.2265 kg CO_2/kWh based on EPA estimates[14]. Assuming an EV fuel economy of 2 miles per kWh, $CO_{2_{EV,per\ km}} = \frac{0.2265\ \text{kg CO}_2\text{/kWh}}{2\ miles\text{/kWh} \times 1.61\ \text{km/mile}} = 0.0703\ \text{kg CO}_2\text{/km}$.

The net avoided CO_2/kg/km of 0.206 (0.2760 – 0.0703) is comparable to the estimates provided by Rapson and Muehlegger[Error! Reference source not found.] and Holland et al.[15]. Multiplying this estimate by the social cost of CO_2, the climate benefit from net avoided emissions per kilometer per EV ($EB(EV)_t$) based on equation (3) is approximately \$0.0391, with a range from \$0.0247 to \$0.0699.

The net social benefit per kilometer per EV per year, which is the difference between $EB(EV)_t$ and $EAC(EV)_t$, is approximately \$0.0273 (\$0.0391 - \$0.0118), suggesting that the environmental benefits of EVs are sufficient to offset the external accident cost induced by EVs. Even our most conservative estimate suggests that the environmental benefits are at least twice external accident costs (\$0.0391÷ \$0.0166). The annual social benefits per km are equal to \$0.0247. In this calculation, we exclude internal safety benefits for EV drivers, which is reasonable given the assumption that the latter benefits are internalized by drivers who pay for the additional costs associated with driving EVs.

Probing further, we allow the external accident cost per kilometer per EV per annum ($EAC(EV)_t$) to vary based on the ratio of the weight difference between ICE vehicles and EVs (d) in Fig 3A. Benchmarking this with the environmental benefits, $EB(EV)_t$, we observe that EVs will only produce a net negative social benefit when the weight difference ratio between ICE vehicles and EVs exceeds 83%. This is unlikely to be the case since, on average, the weight disparity between ICE and EV variants is approximately 20% to 40% for sedans.

To understand how the external accident cost and environmental benefits could evolve in the future, we forecast the growth of EVs in California based on a logistic model following Rietmann et al.[Error! Reference source not found.] (See S6 of Supplementary Materials for more details). Based on our projections (see Fig 3B), the number of EVs could reach 12.7 million by 2035, constituting 40% of the total vehicle stock[Error! Reference source not found.]. This adjusted projection is slightly lower than that of the CEC[Error! Reference source not found.], which forecasts an EV stock of 13.68 million in 2035. Assuming a social discount rate of 2% following Drupp and Hänsel[Error! Reference source not found.], the present value (PV) of the external accident costs amounts to \$2.17 billion, which is almost 18 times the external accident cost we currently incur. Nevertheless, the incremental PV of environmental benefits amounting to \$7.18 billion meant that EVs are likely to confer net PV of social benefits close to \$5.01 billion by 2035.

6. EVs projection model

Following Rietmann et al.[Error! Reference source not found.], we adopt a logistic growth model to forecast EV stocks (see Equation S5) as EV growth exhibits an accelerating trend from 2016 to 2023 (refer to Fig 3B). We conservatively assume constant emission intensity of the power sector and external accident costs. As time goes on, a cleaner grid will be bolstered by the adoption of EVs, and the path to a net-zero electricity system will become increasingly clear, likely leading to a decline in the average emission intensity of the power sector. If the weight of EVs is controlled, advancements in automotive technology may stabilize the external costs of EVs, leading our social benefit predictions to represent a lower bound. The logistic growth model takes the following form:

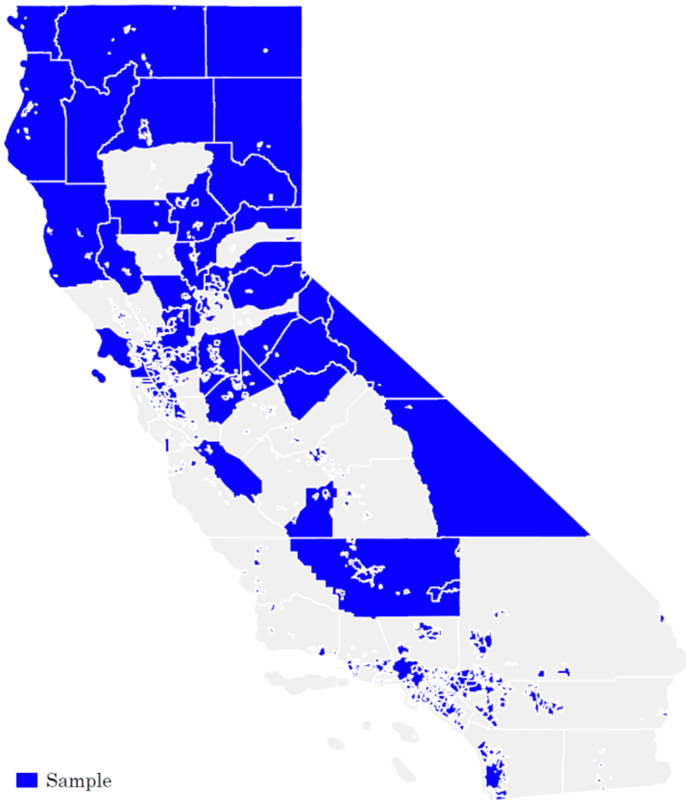
$$EV_t = \frac{K}{\left(1 + \left(\frac{K}{EV_0} - 1\right) \times e^{-r \times K \times t}\right)}, \qquad \text{(S5)}$$

where EV_t = EV stock at time t, K = Saturation limit (the upper limit of the total vehicle stock in California, assuming all vehicles in California are EVs in the future), EV_0 = EV stock at the beginning (t = 0), r = growth factor. Predictions from our model align with actual EV stock trends (refer to Fig 3B), confirming the reliability of the model. Applying the EV and total vehicle stock data from 2016 to 2023 to Equation (S5), we obtain $K = 31{,}040{,}976$ and $r = 1.099 \times 10^{-8}$. However, the model yields excessively rapid growth after 2024, resulting in unrealistically high projections for 2035. Following the adjustment strategy proposed by Rietmann et al.[Error! Reference source not found.], we replace the original EV stock function with a more gradually sloped specification. Specifically, we define a growth function $EV_{adjusted,t}$ with an elevated saturation limit of $K + c$ and subtract c from its values (Equation S6). In this formulation, $EV_{adjusted,t}$ begins below zero at $t = 0$ but eventually converges to the original saturation limit K. Moreover, EV_t and $EV_{adjusted,t}$ are constructed to yield the same projected stock and the same growth rate in 2024.

In our implementation, we set $c = 2{,}000{,}000$, which results in $EV_{adjusted,0} = -939{,}738.11$ and new $r = 5.067 \times 10^{-9}$.

$$EV_{adjusted,t} = \frac{K + c}{1 + \left(\frac{K + c}{EV_{adjusted,0}} - 1\right) \times e^{-r\times(K+c)\times t}} - c \qquad \text{(S6).}$$

Fig. S1. Spatial distribution of accident samples



Notes: This figure presents the geographic distribution of crashes in the SWITRS data for which vehicle VINs are available. Due to the unavailability of geographic boundary data for crash-location jurisdictions, we map the crashes to city-level boundaries. Some jurisdictions are unincorporated and thus cannot be matched one-to-one with cities. For jurisdictions that cannot be accurately matched, we first identify their corresponding counties and then align them with the "Unincorporated" areas within the city-level boundary data.
Sources: SWITRS and California Department of Tax and Fee Administration.

Table S1–S8

Table S1. Summary statistics for accident data set

	Full sample		Without VIN		With VIN	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.621	3,149,471	0.605	2,151,339	0.657	998,132
Age	40.336	3,069,368	40.261	2,080,069	40.494	989,299
The square of age	1.892	3,069,368	1.892	2,080,069	1.891	989,299
Young male	0.050	3,062,133	0.052	2,075,377	0.047	986,756
White	0.318	3,051,341	0.327	2,061,520	0.301	989,821
Young white	0.024	2,984,077	0.026	2,003,601	0.022	980,476
At fault in the crash	0.463	3,746,536	0.475	2,680,441	0.431	1,066,095
Light truck	0.296	3,746,536	0.282	2,680,441	0.331	1,066,095
Model year	2010.811	3,405,923	2010.262	2,347,202	2012.028	1,058,721
Rain	0.025	3,733,768	0.026	2,669,850	0.021	1,063,918
Wet	0.063	3,727,722	0.063	2,661,829	0.064	1,065,893
Dark	0.278	3,735,880	0.283	2,669,902	0.264	1,065,978
Normal road	0.969	3,730,900	0.975	2,664,917	0.955	1,065,983
Intersection	0.248	3,720,888	0.284	2,660,534	0.160	1,060,354
Interstate highway	0.209	3,746,536	0.163	2,680,441	0.323	1,066,095
Fatality	0.002	3,746,536	0.001	2,680,441	0.003	1,066,095
Serious injury	0.012	3,746,536	0.010	2,680,441	0.015	1,066,095
Injury	0.199	3,746,536	0.207	2,680,441	0.180	1,066,095

*This table reports the descriptive statistics of the raw two-vehicle collision cases. Full sample refers to cases where all information is available (except for VIN). With VIN refers to the sample of vehicles for which a VIN is provided, although these VINs are not necessarily valid. The square of age is the driver's age squared divided by 1,000. The definitions of the variables are provided in Table S4.

Table S2. Crashes outcomes and vehicle types of two-vehicle accident

	EV (Percentage) (1)		ICE vehicle (Percentage) (2)
Fatal injury	0.06		0.25
Serious injury	0.36		0.88
Minor injury	19.24		20.60
No injury	80.35		78.27
Company			
Tesla	48.89	Toyota	21.65
Chevrolet	10.08	Honda	14.17
Toyota	9.35	Ford	10.73
Ford	7.43	Chevrolet	8.37
BMW	4.70	Nissan	8.27
Others	19.55	Others	36.81
Model			
Tesla-Model 3	26.27	Honda-Civic	6.26
Tesla-Model Y	17.28	Toyota-Camry	6.14
Chevrolet-Volt	7.13	Honda-Accord	6.11
Tesla-Model S	6.95	Toyota-Corolla	5.02
Toyota-Prius Prime	5.58	Toyota-Tacoma	2.89
Ford-Fusion	4.37	Nissan-Altima	2.75
Others	32.42	Others	70.84
Model year			
2017	8.47	2013	5.19
2018	12.73	2014	5.43
2019	8.27	2015	6.82
2020	7.00	2016	6.97
2021	10.97	2017	7.26
2022	13.77	2018	6.18
2023	17.40	2019	5.04
Others	21.39	Others	57.10
Obs.	15,855		525,010

*This table presents collision outcomes and vehicle attributes for EVs and ICE vehicles involved in two-vehicle crashes used in the main analysis, including manufacturer, model, and model year. The definitions of the variables are provided in Table S4.

Table S3. Summary statistics for control variables

	EV		ICE vehicle		ICE vehicle in EV-involved accidents	
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)	Mean (5)	S.D. (6)
Weight (lbs)	4162.629	664.437	3798.497	1069.092	3786.531	1053.399
Weight (in log)	8.321	0.158	8.208	0.255	8.206	0.252
Male	0.608	0.488	0.598	0.490	0.626	0.484
Age	42.192	14.330	39.653	16.222	38.765	16.328
The square of age	1.986	1.325	1.836	1.481	1.769	1.491
Young male	0.027	0.163	0.055	0.229	0.064	0.245
White	0.329	0.470	0.300	0.458	0.291	0.454
Young white	0.017	0.131	0.026	0.160	0.031	0.172
At fault in the crash	0.292	0.454	0.480	0.500	0.666	0.472
Light truck	0.223	0.416	0.398	0.489	0.392	0.488
Model year	2019.520	3.127	2011.664	7.114	2012.052	7.182
Rain	0.026	0.158	0.021	0.144	0.026	0.158
Wet	0.065	0.246	0.065	0.246	0.065	0.246
Dark	0.210	0.407	0.236	0.424	0.210	0.407
Normal road	0.956	0.206	0.960	0.197	0.956	0.206
Intersection	0.149	0.356	0.196	0.397	0.149	0.356
Interstate highway	0.386	0.487	0.313	0.464	0.386	0.487
Obs.	15,855		525,010		15,207	

*This table presents the descriptive statistics of the control variables in two-vehicle collisions used in the main analysis. The square of age is the driver's age squared divided by 1,000. The number of observations for EV is 15,855, while the number of observations for ICE vehicle is 525,010, and the number of ICE vehicle observations in EV-involved accidents is 15,207. The definitions of the variables are provided in Table S4.

Table S4. Variable definitions

Variable name	Description	Source
Panel A: Dependent variables and key independent variable		
Injury	Binary variable indicating whether the driver in own vehicle sustained a minor, serious, or fatal injury (1) or not (0).	SWITRS
Serious injury	Binary variable indicating whether the driver in own vehicle sustained a serious or fatal injury (1) or not (0).	SWITRS
Fatal injury	Binary variable indicating whether the driver in own vehicle sustained a fatal injury (1) or not (0).	SWITRS
EV	Binary indicator equal to 1 if the vehicle's primary fuel type is electricity, and 0 otherwise.	NHTSA VIN Decoder
Panel B: Control variables		
Weight (lbs)	Curb weight of the vehicle, measured in pounds.	NHTSA VIN Decoder, CARSPECS.US, and iSeeCars
Weight (in log)	Natural logarithm of the vehicle's curb weight.	NHTSA VIN Decoder, CARSPECS.US, and iSeeCars
Male	Driver's gender; equals 1 if male, 0 if female.	SWITRS
Age	Driver's age (in years).	SWITRS
The square of age	Square of the driver's age / 1,000.	SWITRS
Young male	Interaction between the indicator for drivers younger than 21 and gender.	SWITRS
White	Indicator equal to 1 if the driver is White, and 0 otherwise.	SWITRS
Young white	Interaction between the indicator for drivers younger than 21 and White.	SWITRS
At fault in the crash	Indicator equal to 1 if the driver was at fault in the collision, and 0 otherwise.	SWITRS
Light truck	Indicator equal to 1 if the vehicle is a light truck (including sports utility vehicle, pickup, or minivan), and 0 otherwise.	SWITRS
Model year	Vehicle model year.	SWITRS
Rain	Indicator equal to 1 if it was raining, and 0 otherwise.	SWITRS
Wet	Indicator equal to 1 if the road was wet, and 0 otherwise.	SWITRS
Dark	Indicator equal to 1 if it was dark (street lights / no street lights / street lights not functioning), and 0 otherwise.	SWITRS
Normal road	Indicator equal to 1 if the road has no unusual condition, and 0 otherwise.	SWITRS
Intersection	Indicator equal to 1 if the crash occurred at an intersection, and 0 otherwise.	SWITRS
Interstate highway	Indicator equal to 1 if the roadway is an interstate highway, and 0 otherwise.	SWITRS
Year	Year of the collision.	SWITRS
Month	Month of the collision.	SWITRS
Day of week	Day of the week when the collision occurred.	SWITRS

Hour	Hour of the day when the collision occurred (24-hour format).	SWITRS
Panel C: Figure variables		
EV registrations (CA)	Number of registered light-duty EVs in California.	Alternative Fuels Data Center
EV registrations (US)	Number of registered light-duty EVs in US.	
EV Share (CA)	Share of registered light-duty EVs in California relative to the total registered motor vehicles in the state.	Alternative Fuels Data Center, and Federal Highway Administration
EV Share (US)	Share of registered light-duty EVs in the US relative to the total registered motor vehicles nationwide.	Alternative Fuels Data Center, and Federal Highway Administration
EV - All crashes	Proportion of crashes involving EVs relative to the total number of crashes.	NHTSA VIN Decoder, and SWITRS
EV - Veh to non-motor crashes	Proportion of collisions involving pedestrians, bicycles, or motorcycles that also involve EVs relative to the total number of collisions involving pedestrians, bicycles, or motorcycles.	NHTSA VIN Decoder, and SWITRS
EV - Two-vehicle crashes	Proportion of two-vehicle collisions involving EVs relative to the total number of two-vehicle collisions.	NHTSA VIN Decoder, and SWITRS
EV	Binary indicator equal to 1 if the vehicle's primary fuel type is electricity, and 0 otherwise.	NHTSA VIN Decoder, and SWITRS
ICE vehicle	Binary indicator equal to 1 if the vehicle's primary fuel type is non-electricity, and 0 otherwise.	NHTSA VIN Decoder, and SWITRS
Vehicles that crashed into an EV	Indicator equal to 1 if the vehicle crashed into an EV, and 0 otherwise.	NHTSA VIN Decoder, and SWITRS
Vehicles that crashed into a ICE vehicle	Indicator equal to 1 if the vehicle crashed into a ICE vehicle, and 0 otherwise.	NHTSA VIN Decoder, and SWITRS
EV mean weight	Average curb weight of EVs, measured in pounds.	NHTSA VIN Decoder, CARSPECS.US, iSeeCars, and SWITRS
ICE vehicle mean weight	Average curb weight of ICE vehicles, measured in pounds.	NHTSA VIN Decoder, CARSPECS.US, iSeeCars, and SWITRS
EV–ICE vehicle weight difference	Difference in curb weight (in pounds) between vehicles involved in collisions between EVs and ICE vehicles.	NHTSA VIN Decoder, CARSPECS.US, iSeeCars, and SWITRS
ICE vehicle weight difference	Difference in curb weight (in pounds) between vehicles involved in collisions between ICE vehicles.	NHTSA VIN Decoder, CARSPECS.US, iSeeCars, and SWITRS

*SWITRS = California Highway Patrol's Statewide Integrated Traffic Records System; NHTSA = National Highway Traffic Safety Administration.

Table S5. Oster test

	(1)	(2)	(3)	(4)	(5)	(6)
	Injury		Serious injury		Fatal injury	
Other vehicle is EV	0.0199***	0.0199***	0.0015*	0.0014*	0.0010**	0.0009**
	(0.0032)	(0.0032)	(0.0008)	(0.0008)	(0.0004)	(0.0004)
Own vehicle is EV	-0.0371***	-0.0353***	-0.0017***	-0.0020***	-0.0002	-0.0004*
	(0.0033)	(0.0033)	(0.0006)	(0.0006)	(0.0002)	(0.0002)
Driver characteristics	No	Yes	No	Yes	No	Yes
Sample size	540,865	540,865	540,865	540,865	540,865	540,865
R (Shaffer et al., 2021)	0.0808	0.0920	0.0192	0.0201	0.0087	0.0093
Mean of dependent variable	0.2167	0.2167	0.0111	0.0111	0.0025	0.0025
Oster δ of other EV		112.3465		1.3490		5.2066
Oster δ of own EV		7.5958		-1.1433		-0.6473

*Each column represents a separate regression estimating equation (3), without including the natural logarithm of vehicle weight. All models are estimated using a linear probability model (LPM). All columns include weather and time controls, vehicle controls, an indicator for driver fault, and jurisdiction fixed effects. The dependent variable in columns (1) and (2) is whether the driver in the own vehicle was injured; in columns (3) and (4), whether the driver sustained a serious injury; and in columns (5) and (6), whether the driver sustained a fatal injury. Parentheses contain standard errors clustered at the collision level. All regressions include as right-hand-side indicators for whether each vehicle is an EV. Weather and time controls include rain, wet, dark, normal road, intersection, Interstate highway, day of week, and month, year, hour fixed effects. Vehicle controls include indicators for whether each vehicle is a light truck and each vehicle's model year fixed effects. Driver characteristic controls include driver age, quadratics in driver age, indicators for male drivers, young male drivers, and indicators for white drivers, and young white drivers. Mean dependent variable is the mean value of the respective dependent variables. Oster's δ measures how much stronger selection on unobservables would need to be, relative to observables, to fully explain away the estimated effect. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table S6. Robustness checks (without weight)

	(1) Own not at fault	(2) Other not at fault	(3) Probit	(4) Consider elec. 2nd fuel	(5) |Δ Model year| ≤ 16	(6) Model year ≥ 2008
Panel A: Dependent variable: driver in own vehicle was injury						
Other vehicle is EV	0.0206***	0.0209***	0.0723***	0.0201***	0.0210***	0.0198***
	(0.0059)	(0.0035)	(0.0127)	(0.0032)	(0.0034)	(0.0032)
Own vehicle is EV	-0.0352***	-0.0288***	-0.1270***	-0.0355***	-0.0350***	-0.0353***
	(0.0041)	(0.0047)	(0.0126)	(0.0033)	(0.0035)	(0.0033)
Mean of dependent variable	0.2645	0.1638	0.2167	0.2167	0.2177	0.2147
R (Shaffer et al., 2021)	0.0884	0.0790		0.0920	0.0932	0.0938
Sample size	284,448	289,421	540,851	540,865	485,976	497,593
Panel B: Dependent variable: driver in own vehicle sustained a serious injury						
Other vehicle is EV	0.0017	0.0013	0.0366	0.0013*	0.0017**	0.0011
	(0.0013)	(0.0009)	(0.0360)	(0.0008)	(0.0008)	(0.0008)
Own vehicle is EV	-0.0013*	-0.0028***	-0.1814***	-0.0020***	-0.0021***	-0.0021***
	(0.0007)	(0.0010)	(0.0466)	(0.0006)	(0.0006)	(0.0006)
Mean of dependent variable	0.0102	0.0117	0.0112	0.0111	0.0108	0.0104
R (Shaffer et al., 2021)	0.0209	0.0205		0.0201	0.0194	0.0190
Sample size	284,448	289,421	538,177	540,865	485,976	497,593
Panel C: Dependent variable: driver in own vehicle sustained a fatal injury						
Other vehicle is EV	0.0012*	0.0009*	0.1515**	0.0010**	0.0012***	0.0008**
	(0.0007)	(0.0005)	(0.0665)	(0.0004)	(0.0004)	(0.0004)
Own vehicle is EV	-0.0005***	-0.0000	-0.2104*	-0.0004*	-0.0003	-0.0004*
	(0.0002)	(0.0005)	(0.1074)	(0.0002)	(0.0002)	(0.0002)
Mean of dependent variable	0.0020	0.0028	0.0027	0.0025	0.0024	0.0022
R (Shaffer et al., 2021)	0.0095	0.0106		0.0093	0.0090	0.0090
Sample size	284,448	289,421	500,101	540,865	485,976	497,593

*Each column in each panel represents a separate regression. All columns include weather and time controls, vehicle controls, driver characteristics, an indicator for driver fault, and jurisdiction fixed effects. Column (1) limits the estimation sample to collisions involving two vehicles in which the own driver is not at fault. Column (2) limits the estimation sample to collisions involving two vehicles in which the other driver is not at fault. Column (3) uses a Probit estimation method. Column (4) adds an indicator for vehicles whose secondary fuel type is electricity. Column (5) restricts the estimation sample to collisions in which the absolute difference in model years between the two vehicles is less than or equal to 16, corresponding to the range from 2008 (the earliest model year of EVs in the sample) to 2024. Column (6) excludes collisions in which both vehicles were manufactured before 2008, the earliest model year in which EVs appear in the sample. Parentheses contain standard errors clustered at the collision level. All regressions include as right-hand-side indicators for whether each vehicle is an EV. Weather and time controls include rain, wet, dark, normal road, intersection, Interstate highway, day of week, and month, year, hour fixed effects. Vehicle controls include indicators for whether each vehicle is a light truck and each vehicle's model year fixed effects. Driver characteristic controls include driver age, quadratics in driver age, indicators for male drivers, young male drivers, and indicators for white drivers, and young white drivers. Mean dependent variable is the mean value of the respective dependent variables. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table S7. Robustness checks (with weight)

	(1) Own not at fault	(2) Other not at fault	(3) Probit	(4) Consider elec. 2nd fuel	(5) |Δ Model year| ≤ 16	(6) Model year ≥ 2008
Panel A: Dependent variable: driver in own vehicle was injury						
Other vehicle is EV	0.0145**	0.0124***	0.0451***	0.0125***	0.0132***	0.0123***
	(0.0059)	(0.0035)	(0.0128)	(0.0032)	(0.0034)	(0.0032)
Own vehicle is EV	-0.0178***	-0.0146***	-0.0622***	-0.0199***	-0.0191***	-0.0190***
	(0.0041)	(0.0048)	(0.0127)	(0.0033)	(0.0035)	(0.0033)
Weight of other vehicle (in log)	0.0432***	0.0563***	0.1853***	0.0522***	0.0519***	0.0503***
	(0.0043)	(0.0036)	(0.0105)	(0.0029)	(0.0031)	(0.0030)
Weight of own vehicle (in log)	-0.1161***	-0.0978***	-0.4220***	-0.1080***	-0.1067***	-0.1095***
	(0.0041)	(0.0034)	(0.0108)	(0.0028)	(0.0029)	(0.0029)
Mean of dependent variable	0.2645	0.1638	0.2167	0.2167	0.2177	0.2147
R (Shaffer et al., 2021)	0.0911	0.0822		0.0950	0.0960	0.0967
Sample size	284,448	289,421	540,851	540,865	485,976	497,593
Panel B: Dependent variable: driver in own vehicle sustained a serious injury						
Other vehicle is EV	0.0005	-0.0004	-0.0119	-0.0001	0.0003	-0.0002
	(0.0013)	(0.0009)	(0.0363)	(0.0008)	(0.0008)	(0.0008)
Own vehicle is EV	0.0004	-0.0014	-0.1209**	-0.0005	-0.0006	-0.0005
	(0.0007)	(0.0010)	(0.0469)	(0.0006)	(0.0006)	(0.0006)
Weight of other vehicle (in log)	0.0084***	0.0114***	0.3303***	0.0099***	0.0096***	0.0086***
	(0.0010)	(0.0011)	(0.0268)	(0.0008)	(0.0008)	(0.0008)
Weight of own vehicle (in log)	-0.0108***	-0.0096***	-0.3941***	-0.0106***	-0.0100***	-0.0106***
	(0.0010)	(0.0010)	(0.0291)	(0.0008)	(0.0008)	(0.0008)
Mean of dependent variable	0.0102	0.0117	0.0112	0.0111	0.0108	0.0104
R (Shaffer et al., 2021)	0.0215	0.0212		0.0207	0.0200	0.0196
Sample size	284,448	289,421	538,177	540,865	485,976	497,593
Panel C: Dependent variable: driver in own vehicle sustained a fatal injury						
Other vehicle is EV	0.0008	0.0003	0.0956	0.0005	0.0007	0.0004
	(0.0007)	(0.0005)	(0.0673)	(0.0004)	(0.0004)	(0.0004)
Own vehicle is EV	0.0000	0.0005	-0.1233	0.0001	0.0003	0.0001
	(0.0002)	(0.0005)	(0.1080)	(0.0002)	(0.0003)	(0.0002)
Weight of other vehicle (in log)	0.0028***	0.0039***	0.4112***	0.0033***	0.0033***	0.0029***
	(0.0004)	(0.0006)	(0.0483)	(0.0004)	(0.0004)	(0.0004)
Weight of own vehicle (in log)	-0.0037***	-0.0037***	-0.5756***	-0.0038***	-0.0038***	-0.0036***
	(0.0005)	(0.0005)	(0.0559)	(0.0004)	(0.0004)	(0.0004)
Mean of dependent variable	0.0020	0.0028	0.0027	0.0025	0.0024	0.0022
R (Shaffer et al., 2021)	0.0099	0.0110		0.0097	0.0094	0.0093
Sample size	284,448	289,421	500,101	540,865	485,976	497,593

*Each column in each panel represents a separate regression. All columns include weather and time controls, vehicle controls, driver characteristics, an indicator for driver fault, and jurisdiction fixed effects. Column (1) limits the estimation sample to collisions involving two vehicles in which the own driver is not at fault. Column (2) limits the estimation sample to collisions involving two vehicles in which the other driver is not at fault. Column (3) uses a Probit estimation method. Column (4) adds an indicator for vehicles whose secondary fuel type is electricity. Column (5) restricts the estimation sample to collisions in which the absolute difference in model years between the two vehicles is less than or equal to 16, corresponding to the range from 2008 (the earliest model year of EVs in the sample) to 2024. Column (6) excludes collisions in which both vehicles were manufactured before 2008, the earliest model year in which EVs appear in the sample. Parentheses contain standard errors clustered at the collision level. All regressions include as right-hand-side indicators for whether each vehicle is an EV. Vehicle weight is expressed in logarithmic form. Weather and time controls include rain, wet, dark, normal road, intersection, Interstate highway, day of week, and month, year, hour fixed effects. Vehicle controls include indicators for whether each vehicle is a light truck and each vehicle's model year fixed effects. Driver characteristic controls include driver age, quadratics in driver age, indicators for male drivers, young male drivers, and indicators for white drivers, and young white drivers. Mean dependent variable is the mean value of the respective dependent variables. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table S8. Effect of electric vehicle on crash outcomes in two-vehicle accident

	(1)	(2)	(3)	(4)	(5)	(6)
	# ≥ Minor inj.		# Severe + fatal		# Fatalities	
Other vehicle is EV	0.0820***	0.0472**	0.0853	-0.0305	0.2377	0.0951
	(0.0185)	(0.0187)	(0.0906)	(0.0913)	(0.1835)	(0.1857)
Own vehicle is EV	-0.1706***	-0.0952***	-0.3679***	-0.2428*	-0.5980*	-0.3948
	(0.0184)	(0.0186)	(0.1234)	(0.1239)	(0.3117)	(0.3118)
Weight of other vehicle (in log)		0.2381***		0.7973***		1.0825***
		(0.0145)		(0.0648)		(0.1321)
Weight of own vehicle (in log)		-0.4844***		-0.7948***		-1.2836***
		(0.0154)		(0.0695)		(0.1491)
Sample size	540,853	540,853	538,519	538,519	503,325	503,325
Mean of dependent variable	0.2682	0.2682	0.0153	0.0153	0.0036	0.0036

*Each column represents a separate regression of the estimation of equation (S2). All models are estimated using a Poisson regression. All columns include weather and time controls, vehicle controls, driver characteristics, an indicator for driver fault, and jurisdiction fixed effects. The dependent variable in columns (1) and (2) is the number of occupants in the own vehicle who was injured (i.e., minor, serious, or fatal injury); in columns (3) and (4), the number of severely injured and killed occupants in the own vehicle; and in columns (5) and (6), the number of fatalities in the own vehicle. Parentheses contain standard errors clustered at the collision level. All regressions include as right-hand-side indicators for whether each vehicle is an EV. Vehicle weight is expressed in logarithmic form. Weather and time controls include rain, wet, dark, normal road, intersection, Interstate highway, day of week, and month, year, hour fixed effects. Vehicle controls include indicators for whether each vehicle is a light truck and each vehicle's model year fixed effects. Driver characteristic controls include driver age, quadratics in driver age, indicators for male drivers, young male drivers, and indicators for white drivers, and young white drivers. Mean dependent variable is the mean value of the respective dependent variables. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.