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Electric vehicle adoption and transport-sector CO_2 emissions

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Abstract
This study examines whether electric-vehicle (EV) adoption is associated with lower transport-sector carbon dioxide (CO_2) emissions using a balanced panel of 31 countries observed annually from 2010 to 2022. Because EV adoption most directly affects road transport rather than economy-wide emissions, transport-sector CO_2 is used as the primary channel-aligned outcome, with oil-related and total CO_2 providing complementary mechanism and comparison tests. We estimate two-way country and year fixed-effects models and evaluate the robustness of the association using second-period-lag and Bartik battery-metal shift-share instrumental variables, alternative specifications and diagnostics, falsification tests, and a staggered difference-in-differences design around major EV-policy adoption. A 1% increase in new-EV sales is associated with a 0.058% reduction in transport-sector CO_2 and a 0.041% reduction in oil-related CO_2; the corresponding lag-IV (−0.062) and Bartik-IV (−0.071) estimates are similar in magnitude. The transport-sector association is stronger than the corresponding association with total CO_2, consistent with concentration of the relationship in the sector through which EV substitution should operate. The estimated reduction is also stronger when contemporaneous internal-combustion-engine sales are high and in countries with cleaner electricity grids, with a smaller additional amplification observed among high-income countries. EV sales are additionally associated with lower transport-sector CO_2 per unit of GDP, although this estimate is only marginally significant. The difference-in-differences estimate is −0.072 for the full panel and −0.128 among early-adopting cohorts; the association is concentrated among early adopters and strengthens with time since policy adoption. Results remain broadly stable across alternative specifications, while sectoral placebo and pre-EV-period negative-control tests are broadly supportive of the proposed interpretation. Collectively, the convergence of channel-aligned outcomes, fixed-effects, instrumental-variable, heterogeneity, and policy-timing analyses provides robust evidence that greater EV adoption is associated with lower transport-sector emissions, while the observational design does not establish that EV adoption alone caused the observed reductions.

Keywords
Electric vehicles, EV adoption, Transport-sector CO_2 emissions, Carbon emissions, Transportation decarbonization, Electric vehicle policy, Panel data analysis, Difference-in-differences, Instrumental variables, Clean energy transition

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1. Introduction

The rapid pace of global climate change has placed an urgent focus on reducing carbon emissions, particularly in the transportation sector, which is responsible for nearly a quarter of global CO_2 emissions (1). Electric vehicles (EVs) have emerged as a key technological solution, promising to significantly reduce emissions compared to traditional internal combustion engine (ICE) vehicles (2). Governments and industries alike have embraced this shift, promoting EV adoption through subsidies, incentives, and the expansion of charging infrastructure (3). However, despite the growing momentum behind EVs, questions remain about their true environmental impact, particularly when considering the lifecycle emissions from electricity generation, vehicle production, and end-of-life disposal (4).

The environmental benefits of EVs are often touted as a cornerstone of sustainable development, with policymakers pushing for aggressive EV targets to reduce national carbon footprints (5). Yet, the actual emissions reductions achieved by EVs depend heavily on the energy sources used to generate electricity (4). In countries or regions where fossil fuels dominate the energy grid, EVs may still contribute to substantial indirect emissions, undermining their potential environmental benefits (6). Furthermore, the transition to EVs is happening alongside significant economic growth in many regions, which complicates the relationship between vehicle electrification and overall emissions reduction. As economies grow, so too does energy consumption and transportation demand, making it unclear whether EVs can substantially reduce emissions on a per capita or per GDP basis (7).

Current studies have shown mixed results regarding the net environmental benefits of EVs. Research by Gillingham et al. (8) highlights the importance of a decarbonized electricity grid to maximize EVs' emission-reduction potential, while Tessum et al. (9) argue that coal-dominated energy grids may reduce the environmental gains from EV adoption. Moreover, Borenstein and Davis (10) point out that the slow adoption of EVs, particularly in regions with less government support, limits their ability to make a significant dent in overall emissions. Beyond the direct emissions reductions, little research has explored how EVs influence emissions relative to economic growth. This research seeks to fill that gap by exploring not only the direct CO_2 reduction from EV adoption but also how this adoption influences emissions per unit of GDP, a key metric for sustainable development. This is crucial because, even with rapid EV growth, economies continue to rely heavily on fossil fuels, limiting the benefits from cleaner vehicle technologies. The complex interaction between economic growth, energy consumption, and vehicle emissions requires robust empirical analysis. By analyzing transport-sector emissions, oil-related emissions, emissions per GDP, and the role of the energy mix, we provide a comprehensive assessment of the conditions under which EVs contribute to meaningful emissions reductions. Our findings aim to inform policymakers on the effectiveness of current strategies and highlight the critical interplay between EV adoption, energy systems, and broader economic trends in the transition to a low-carbon future.

Total national emissions are dominated by industry, residential heating, and electricity generation, and using total CO_2 as the dependent variable conflates the channel of interest—road transport—with sectors over which the EV transition has no direct mechanism. The mismatch between the dependent variable and the causal claim creates a fundamental identification problem that no amount of econometric refinement can fix. We therefore use the OWID/EDGAR transport-sector emissions series as our main dependent variable and use oil-related CO_2 as a complementary mechanism check. This choice provides a crucial diagnostic: if EVs work by displacing gasoline and diesel consumption, the strongest empirical effect should appear on transport-sector and oil-related emissions, not on total emissions. We therefore report transport CO_2, oil-related CO_2, and total CO_2 side by side in the main results so that the reader can verify the mechanism directly.

We examine the multi-faceted impact of EV adoption on CO_2 emissions across 31 countries from 2010 to 2022. Using panel data covering more than a decade, the study aims to disentangle the effects of EV sales from other key economic factors such as GDP growth, fossil fuel consumption, and energy demand. By assessing the relationship between EV adoption and emissions, this research seeks to provide insights into the extent to which EVs are reducing emissions and contributing to more sustainable economic growth, and to provide evidence-based insights to policymakers on whether the current push for electric vehicles is achieving the intended environmental benefits. Additionally, our study addresses whether the pace of EV adoption is sufficient to offset the ongoing reliance on non-electric vehicles and traditional energy sources. For example, can EVs alone significantly reduce carbon emissions, or is a broader systemic change—such as cleaner energy production and enhanced regulations—needed to fully realize their potential?

1.1 Summary

We find that higher electric-vehicle (EV) sales are consistently associated with lower transport-sector CO_2 emissions. In the preferred country and year fixed-effects specification, a 1% increase in new-EV sales is associated with a 0.058% reduction in transport-sector CO_2 ($p = 0.001$). The corresponding association with oil-related CO_2 is −0.041 ($p = 0.022$), while the association with total national CO_2 is smaller in magnitude at −0.046 ($p = 0.006$). This pattern is consistent with the proposed displacement mechanism because the strongest association appears in the sector most directly affected by vehicle electrification, while the oil-related result provides complementary evidence consistent with reduced petroleum use. These associations, however, should not be interpreted as direct proof that EV adoption alone caused the observed emissions reductions.

The relationship is not uniform across national and vehicle-market contexts. The estimated reduction in transport-sector CO_2 is stronger when contemporaneous internal-combustion-engine (ICE) sales are higher: the EV × ICE-sales interaction is −0.012 ($p = 0.029$), and increasing ICE sales by one standard deviation increases the absolute magnitude of the estimated EV elasticity by approximately 45%. This finding suggests that the environmental significance of EV adoption depends partly on whether electrification substitutes for continued ICE use rather than simply expanding the total vehicle fleet. EV adoption is also associated with lower transport CO_2 per unit of GDP, although this estimate is only marginally significant ($\beta = -0.030$, $p = 0.071$) and should therefore be regarded as suggestive rather than conclusive evidence of declining transport carbon intensity.

Electricity-grid composition provides a second important source of heterogeneity. The interaction between EV sales and the clean-energy indicator is negative and significant ($\beta = -0.031$, $p = 0.011$), indicating that the estimated reduction in transport-sector CO_2 associated with EV adoption is larger in countries with cleaner electricity grids. EV sales nevertheless remain negatively associated with transport emissions outside the cleanest-grid group. Taken together, these results suggest that transportation electrification and electricity-sector decarbonization are complementary: the potential transport-emissions benefit of replacing petroleum-powered vehicles is greater when the additional electricity required by EVs is supplied by relatively low-carbon generation. A smaller additional interaction with high-income status ($\beta = -0.018$, $p = 0.039$) suggests further heterogeneity across national contexts, although the present analysis cannot identify which infrastructural, institutional, or energy-system characteristics underlying income are responsible for this difference.

The distinction between annual EV sales and accumulated EV-stock penetration also requires caution. New-EV sales capture current adoption flows and are negatively associated with transport-sector CO_2, whereas EV-stock share shows a positive association in some specifications. This positive coefficient should not be interpreted as evidence that larger EV fleets directly increase emissions. Accumulated EV stock is correlated with broader characteristics including total vehicle ownership, electricity demand, economic development, charging infrastructure, market maturity, and grid composition. The available data therefore cannot determine whether the stock association reflects electricity-related offsets or other time-varying characteristics of countries with mature EV markets. EV-specific electricity consumption and marginal-generation data would be required to distinguish these possibilities more directly.

To address concerns that EV adoption may be endogenous to unobserved climate policy or secular transport trends, we use two complementary instrumental-variable approaches: the second-period lag of EV sales and a Bartik-style shift-share instrument constructed from international nickel, copper, and aluminium price shocks interacted with baseline vehicle-market exposure (11,12). The IV estimates of −0.062 for the second-period-lag instrument and −0.071 for the Bartik instrument are close to the preferred fixed-effects estimate of −0.058, while their first-stage Kleibergen–Paap statistics exceed conventional weak-instrument thresholds (13,14). The similarity of these estimates reduces concern that the primary association is entirely attributable to contemporaneous reverse causality or omitted policy ambition, conditional on the identifying assumptions of the instruments.

An alternative identification strategy based on the timing of major EV-policy adoption produces a complementary result. In the difference-in-differences analysis, transport-sector CO_2 is lower following major EV-policy adoption relative to never-treated countries, with an estimated coefficient of −0.072 ($p = 0.003$) in the full policy-analysis sample and −0.128 ($p < 0.001$) among early-adopting cohorts. The association is concentrated among early adopters and strengthens with time since policy adoption. In the balanced event study, the estimated effect is essentially zero in the policy-adoption year and then becomes progressively more negative over the following four years. This temporal pattern is consistent with gradual fleet turnover: EV policies may affect vehicle purchasing relatively quickly, whereas measurable transport-emissions reductions would be expected to accumulate as EV stock increases and existing ICE vehicles are progressively retired.

The principal association also remains negative under alternative specifications, including country-specific linear trends, first-difference estimation, alternative control sets, outlier sensitivity analyses, and rotation of correlated energy controls. Panel diagnostics motivate the use of covariance estimators robust to cross-sectional dependence, serial correlation, and heteroskedasticity (15,16). Falsification tests are broadly supportive of the proposed interpretation: cement and flaring CO_2 do not show significant IV associations, transport CO_2 is not significantly predicted during the pre-EV period, and the cement-CO_2 difference-in-differences placebo is null. The coal placebo is marginal at the 10% level and is therefore less definitive than the other negative controls.

Overall, the contribution of the study lies in the convergence of several complementary patterns rather than in any single coefficient. Higher EV adoption is most strongly associated with lower emissions in the transport sector, the relationship extends in the expected direction to oil-related emissions, it becomes stronger where ICE displacement opportunities are greater and where electricity grids are cleaner, and the policy-associated reduction emerges gradually over time. Fixed-effects, instrumental-variable, difference-in-differences, heterogeneity, robustness, and falsification analyses therefore point in a broadly consistent direction. The results support an interpretation in which transport electrification contributes to lower emissions as part of a broader transition involving vehicle substitution, fleet turnover, cleaner electricity generation, and complementary policy, while the observational design does not establish that EV adoption alone caused the observed emissions changes.

1.2 Literature review

The growing body of literature on electric vehicles and their environmental impact provides a mixed picture of their efficacy in reducing carbon emissions. The general consensus is that EVs, when charged with clean energy, offer significant reductions in tailpipe emissions, making them an essential part of the global strategy to mitigate climate change (8). However, the full lifecycle emissions of EVs, which include manufacturing, charging, and disposal, must be considered to assess their overall impact (4). Gillingham et al. (8) highlight the importance of the electricity mix in determining the environmental benefits of EVs. In countries with coal-heavy energy grids, the emissions associated with EV charging can offset the benefits of zero tailpipe emissions. Similarly, Tessum et al. (9) argue that EV adoption in regions with high fossil fuel dependence may provide only marginal improvements in overall emissions, suggesting that a decarbonized grid is essential for maximizing the environmental gains from EVs.

Borenstein and Davis (10) point out that the slow pace of EV adoption is a significant barrier to achieving meaningful emissions reductions. Despite aggressive policy targets in many regions, EVs still make up a small fraction of total vehicle sales, limiting their immediate impact. Government policies play a crucial role in accelerating EV adoption, but even with subsidies and incentives, adoption rates remain lower than needed to achieve substantial carbon reductions. Beyond the direct emissions reductions, some scholars have explored the broader economic implications of EV adoption, including the cost-effectiveness of greenhouse-gas abatement (20). While EVs can reduce transportation emissions, their effect on overall emissions per unit of GDP is less clear (17,18). As economies grow and industrial activity increases, the demand for energy, including electricity, continues to rise. This may result in higher emissions, even as EVs replace traditional ICE vehicles. To address this, Bataille (19) and Sovacool et al. (17) suggest that EV adoption must be accompanied by decarbonization across the energy and industrial sectors to achieve meaningful reductions in emissions per GDP unit.

In addition to the energy mix, the effectiveness of EV adoption is shaped by factors such as vehicle sales trends and fossil fuel consumption patterns. As noted by Hawkins et al. (4), the sales of non-electric vehicles can offset the environmental benefits of EVs. Countries experiencing rapid economic growth may see increased demand for all vehicle types, making it difficult for EV sales alone to drive down emissions. This dynamic underscores the importance of examining EV adoption within the broader context of economic development and energy consumption. Building on this literature, our study aims to explore not only the direct emissions reduction from EV adoption but also the relationship between EV sales and CO_2 emissions per unit of GDP. By focusing on both absolute and relative emissions metrics, we seek to provide a more comprehensive understanding of the role EVs play in the transition to a low-carbon economy.

Our paper also speaks to a methodological literature on the identification of causal effects in cross-country panels. Bataille (19) and Sovacool et al. (17) caution that aggregate national CO_2 is a noisy proxy for transport-specific decarbonization, because it co-moves with industrial cycles and electricity-sector transitions that EV diffusion does not directly affect in the short run. Holland et al. (21), exploiting U.S. regional grid heterogeneity, document substantial dispersion in the marginal external benefits of EV driving, underlining the importance of using sector-specific outcome measures. We respond to those cautions by switching to transport-sector CO_2 throughout, while using oil-related CO_2 as a mechanism check. On endogeneity, the recent literature has increasingly turned to shift-share or policy-shock instruments. We follow Goldsmith-Pinkham, Sorkin, and Swift (11) and Borusyak, Hull, and Jaravel (12) in constructing a Bartik-style instrument from international battery-metal price shocks, which plausibly affect each country's EV adoption through manufacturing-cost pass-through but have no direct effect on transport CO_2 conditional on country and year fixed effects.

2. Methods

2.1 Hypothesis development

EVs are widely recognized as a crucial innovation in the effort to reduce carbon dioxide (CO_2) emissions, primarily due to their zero tailpipe emissions, in contrast to traditional ICE vehicles. The transportation sector is a significant contributor to CO_2 emissions, and replacing ICE vehicles with EVs has the potential to substantially decrease these emissions. This potential is particularly notable in regions where transportation accounts for a significant proportion of CO_2 output (8).

Regulatory bodies have established ambitious targets to accelerate this transition. For instance, the European Union aims to reduce emissions by 55% by 2030, while California has mandated that all new car sales be zero-emission vehicles by 2035. These goals represent broader strategies to mitigate climate change, improve air quality, and foster the adoption of cleaner transportation technologies. Achieving such objectives requires significant advancements in EV technology, infrastructure development, and effective policy enforcement.

Despite the promising outlook, the actual impact of EV adoption on national or global CO_2 emissions depends on multiple factors, including the scale of EV adoption and the pace at which ICE vehicles are phased out. Merely increasing the number of EVs on the road does not guarantee significant reductions in CO_2 emissions if the adoption of EVs is accompanied by continued or even growing sales of ICE vehicles. As demonstrated in previous studies, the environmental benefits of EVs are undermined when non-electric vehicle sales remain high, as the emissions reductions from EVs are offset by the continued contribution of ICE vehicles to total emissions (21). Moreover, the slow replacement of existing ICE vehicles and the increase in overall vehicle ownership exacerbate the issue, leading to a rise in transportation-related emissions. This highlights the critical importance of not only promoting EV sales but also implementing policies to actively phase out ICE vehicles and reduce overall vehicular emissions. Given these complexities and the persistence of ICE vehicles in the global fleet, we posit the following hypotheses:

2.1.1 ***H1***: *Higher EV sales are associated with lower transport-sector CO_2 emissions.*

The proposed mechanism is substitution of electric vehicles for internal-combustion vehicles and the resulting reduction in direct petroleum combustion. Because EV adoption does not necessarily correspond one-for-one with ICE retirement, particularly in expanding vehicle markets, the magnitude of this association may depend on contemporaneous ICE-market conditions.

2.1.2 ***H2:*** *The negative association between EV sales and transport-sector CO_2 is stronger when contemporaneous ICE sales are higher.*

H2 tests whether the EV–emissions relationship varies with the surrounding ICE-market context. A negative EV × ICE-sales interaction would indicate that the association between additional EV sales and lower transport CO_2 becomes stronger as contemporaneous ICE sales increase. Such a pattern would be consistent with greater scope for vehicle substitution, although the aggregate country-level data cannot establish which individual ICE vehicles are displaced by EV purchases.

Economic growth provides a second context in which the EV–emissions relationship should be evaluated. Expanding economies may experience increasing transportation demand even as their vehicle fleets electrify. Absolute emissions reductions therefore do not necessarily imply that transportation is becoming less carbon intensive relative to economic activity. We consequently examine whether EV adoption is associated not only with lower absolute transport emissions but also with lower transport-sector CO_2 per unit of economic output.

2.1.3 ***H3***: *Higher EV sales are associated with lower transport-sector CO_2 per unit of GDP.*

The emissions implications of transportation electrification may also depend on the electricity system supporting it. EVs eliminate direct tailpipe emissions, but the electricity required for charging may be generated from either low-carbon or fossil-fuel sources. Consequently, the net emissions advantage associated with substituting electric for internal-combustion vehicles should be greater where electricity generation is cleaner (4,8,21). This predicts an interaction between EV adoption and grid composition rather than a uniform EV association across countries.

2.1.4 ***H4:*** *The negative association between EV sales and transport-sector CO_2 is stronger in countries with cleaner electricity grids.*

Finally, changes in annual EV sales and changes following EV-policy adoption represent complementary views of the transition. Major EV policies may increase adoption relatively quickly, but aggregate transport emissions may respond more gradually because existing ICE vehicles remain in the fleet for years. If policy-driven electrification contributes to transport decarbonization through fleet turnover, the post-policy association should therefore emerge progressively rather than necessarily appearing in the year of policy adoption.

2.1.5 ***H5:*** *Transport-sector CO_2 declines, on average, following major EV-policy adoption relative to never-treated countries, with the estimated reduction increasing over time as EV penetration rises and ICE fleet turnover proceeds.*

2.2 Data sources

Our data spans from 2010 to 2022, covering 31 countries that represent a diverse range of electric vehicle adoption levels, CO_2 emissions, energy grid compositions, and economic growth trajectories. The primary source for this data is Our World in Data (http://www.ourworldindata.org), a widely recognized platform for global datasets on environmental, energy, and economic metrics. The dataset includes critical variables such as annual electric vehicle sales, market share, and growth rates, along with total CO_2 emissions by sector, including transportation-specific emissions sourced from the EDGAR (Emissions Database for Global Atmospheric Research) sectoral series and cross-checked against IEA country reports. It also incorporates information on energy grid composition, detailing the proportion of renewable versus non-renewable energy sources in electricity generation, as well as economic indicators such as GDP growth rates, per capita income, and industrial output. Transport-oil subsidies for 2010–2024 come from the IEA Subsidy Database. International battery-metal price series (nickel, copper, aluminium) used to construct the Bartik instrument come from the World Bank Pink Sheet and are converted to year-on-year shocks orthogonal to a Hodrick–Prescott trend, following the procedure in Borusyak et al. (12). To ensure data consistency, the sample is restricted to countries with complete and reliable data for all control variables throughout the sample period. Variables that span several orders of magnitude (EV sales, non-EV sales, GDP per capita, population, sectoral emissions) are log-transformed; where necessary we apply the conventional ln(x+1) transformation to handle zero EV sales in early years.

2.3 Sample construction and data cleaning

The unit of observation is the country–year. We begin from the Our World in Data country–year master file and merge, by ISO-3 country code and calendar year, the EDGAR transport-sector emissions series, the IEA electric-vehicle sales and transport-oil subsidy series, the World Bank GDP and population series, and the World Bank Pink Sheet commodity-price series. For the primary transport-CO_2 analysis, we restrict the sample to the 31 countries that have non-missing values for the required explanatory and control variables over 2010–2022, which yields a strongly balanced panel of 31 countries over 13 years. The 31-country balanced panel (403 country-year observations) is the primary analysis sample for the baseline transport-CO_2 specification; secondary analyses use outcome- and design-specific complete-case samples when the required emissions, moderator, instrumental-variable, or policy-timing data are available for a broader set of countries. Consequently, the number of observations and country clusters varies across specifications, with the applicable estimation sample reported separately in each table; lagged-IV specifications additionally lose observations because the required lag periods are unavailable at the beginning of each country series.

Before estimation we sort the data by country and year and drop any duplicate country–year rows so that each country–year appears exactly once, and we declare the panel structure with country as the panel identifier and year as the time identifier. All monetary variables are expressed in constant 2017-PPP US dollars so that levels are comparable across countries and over time. This cleaning sequence is deterministic and is fully reproducible from the variable definitions and data sources reported here.

2.4 Variable construction and measurement

2.4.1 *Dependent variables*

The primary dependent variable, $LnTransportCO_2$, is the natural logarithm of transport-sector CO_2 emissions in metric tons taken from the OWID/EDGAR sectoral series: $LnTransportCO_2(i,t) = \ln(TransportCO_2(i,t))$. We use the transport-sector series rather than total national CO_2 because the EV mechanism operates only on road transport; using total CO_2 would dilute the channel of interest with industry, heating, and power-sector emissions over which EV adoption has no direct mechanism. For the mechanism checks we construct $LnCO_2Total$, $LnCO_2Oil$, and $LnCO_2Gas$ as the natural logs of total, oil-related, and gas-related CO_2 from the same OWID source. For the carbon-intensity test (H3) we construct $CO_2perGDP$ as transport-sector CO_2 in kilograms divided by GDP in constant 2017-PPP dollars, so that the variable measures the carbon intensity of economic output (kg CO_2 per dollar). The natural-log transformation is applied to all emissions levels because the raw series span several orders of magnitude across countries and are strongly right-skewed; logging stabilises the variance, linearises multiplicative relationships, and allows slope coefficients in the log-emissions specifications to be interpreted as elasticities.

2.4.2 *Main explanatory variable*

LnNewEV is the natural logarithm of new battery-electric-vehicle sales, computed as $LnNewEV(i,t) = \ln(NewEV(i,t) + 1)$. We add one before taking logs because several countries record zero EV sales in the early years of the sample and ln(0) is undefined; the $\ln(x + 1)$ transformation maps zero sales to zero on the log scale while remaining effectively logarithmic for the large positive values that dominate the panel. Because the dependent variable is also in logs, the coefficient β_1 in Equation 1 is the elasticity of transport-sector CO_2 with respect to EV sales.

2.4.3 *Other vehicle-market and intensity variables*

LnNewNonEV is the natural log of new non-electric (internal-combustion) passenger-car sales, included to absorb the offsetting emissions of contemporaneous ICE sales. ShareNewEV is the ratio of new EVs to new non-EVs sold in a given year, expressed in percent, and ShareEVStock is the ratio of the cumulative EV stock to the total vehicle stock, also in percent. The first captures the flow intensity of adoption and the second the accumulated penetration of the vehicle fleet, allowing contemporaneous adoption and accumulated fleet composition to be examined separately.

2.4.4 *Macroeconomic and energy controls*

The control vector X(i,t) contains GDP per capita (constant 2017-PPP US$) and its annual growth rate, to absorb the level and pace of economic development; annual electricity demand and electricity generation (TWh), to control for the scale of power-sector activity that ultimately supplies EV charging; the annual growth rates of fossil-fuel, gas, and oil consumption, to capture short-run shifts in traditional energy use; the levels of coal, gas, and oil consumption (TWh-equivalent), the most carbon-intensive energy inputs; the natural logs of cumulative CO_2 emissions from gas, oil, and coal (LnCumGas, LnCumOil, LnCumCoal), which capture the path-dependent legacy emission stocks that the year-on-year flow regressors cannot; and the natural log of population together with its annual growth rate, because larger and faster-growing populations raise travel demand and energy use. Each control is included because it is a plausible confounder correlated both with EV adoption and with transport emissions, so that omitting it would bias β_1. Full definitions and sources for every variable are listed in Appendix A.

2.4.5 *Moderator indicators*

High_Clean is a binary indicator equal to one if a country's clean-energy mix — the share of electricity from renewables plus nuclear in total per-capita energy capacity — falls in the top decile of the within-year cross-country distribution, and zero otherwise. High_Income is defined analogously on the top decile of the within-year distribution of GDP per capita. We construct both indicators within each year, rather than pooling across years, so that the cut-off tracks the moving frontier of grid decarbonisation and income and so that the indicators are not mechanically driven by the global upward trend in either variable. These indicators enter the H4 interaction model (Equation 3).

2.4.6 *Instrument construction*

The second-period lag instrument, L2.LnNewEV, is LnNewEV lagged two years within each country, formed after the panel structure is declared. The Bartik shift-share instrument is built in two steps. First, for each country we compute a baseline (2010–2012 average) per-capita vehicle-market exposure share, separately for EVs and for total vehicles. Second, we interact each baseline exposure share with the contemporaneous international price shock for nickel, copper, and aluminium, where each price shock is the year-on-year change in the World Bank Pink Sheet price series after removing a Hodrick–Prescott trend, so that only the transitory, plausibly-exogenous component of the metal price is used. The three resulting metal-specific shift-share terms are the excluded instruments for LnNewEV in the over-identified 2SLS specification. The economic logic is that battery-metal cost shocks shift the marginal cost of producing EVs, and therefore EV sales, but have no direct effect on transport CO_2 once GDP, population, and energy controls and the two-way fixed effects are partialled out.

2.5 EV-policy adoption years

We code each country's first major EV-policy adoption year using the IEA Policies Database (accessed May 2026), the ICCT 2024 Global Passenger-Car ZEV Tracker, European Commission Fit-for-55 country reports, and national transport-ministry releases. Coding: NOR/JPN/USA/FRA = 2010 (in place by the start of the sample, treated as always-treated); NLD/DNK/DEU = 2012; BEL/SWE/FIN = 2013; AUT/CHE = 2014; IND/KOR/ITA = 2015; ESP/IRL/PRT = 2016; CHN/GBR/CAN = 2017; POL/MEX/CHL = 2018; BRA/IDN = 2019; TUR/NZL/THA/ZAF = 2020; AUS = 2022. Country-years with no documented major federal EV policy by 2022 are coded as never-treated.The policy-adoption years listed above correspond to countries in the primary analysis sample; for the broader DiD sample described in Section 2.3, the same coding protocol and sources were applied to all countries with the required policy and outcome data.

2.6 Research design

Our research design follows an identification ladder that begins with conditional associations and then evaluates whether those associations persist under specifications intended to reduce endogeneity concerns. We begin with a two-way fixed-effects (TWFE) panel regression that exploits within-country, over-time variation in EV adoption while holding constant all time-invariant country characteristics and all common annual shocks. This is the natural starting point for a country–year panel because it removes the two largest classes of confounders — fixed national differences such as geography, baseline grid composition, and culture, and global shocks such as oil-price cycles and the COVID-19 demand collapse — without requiring that they be measured. We then address the residual concern that EV adoption is itself a choice correlated with unobserved climate ambition by (i) instrumenting EV sales with their second-period lag and with a Bartik battery-metal shift-share instrument, and (ii) re-casting the question as a difference-in-differences comparison around the timing of each country's first major EV policy. The stability of the estimates across OLS, IV, and DiD specifications provides supporting evidence for the proposed interpretation, but it does not eliminate all threats to causal inference in this observational cross-country setting.

To analyze the impact of EV adoption on annual transport-sector CO_2 emissions (H1), we estimate the following two-way fixed-effects panel regression model,

$$LnTransportCO_2(i,t) = \alpha + \beta_1\, LnNewEV(i,t) + \beta_2\, LnNewNonEV(i,t) + \beta_3\, ShareNewEV(i,t) + \gamma\, X(i,t) + \mu_i + \tau_t + \varepsilon(i,t) \qquad \text{(eq1)}$$

The dependent variable is the natural logarithm of transport-sector CO_2 emissions in year t for country i, and the main independent variable is the natural logarithm of the number of electric vehicles sold. We use log transformation to address the skewness of the data. This approach allows us to interpret β_1 as the elasticity of transport-sector CO_2 emissions with respect to EV sales. A negative coefficient on LnNewEV indicates that higher EV sales are associated with lower transport-sector CO_2, conditional on the included controls and fixed effects. A coefficient of −0.058, for example, indicates that a one-percent increase in EV sales is associated with approximately 0.058 percent lower transport-sector CO_2, holding the other regressors and fixed effects constant.

We include several control variables essential to ensure the analysis accurately isolates the relationship between electric vehicle adoption and CO_2 emissions by accounting for various confounding factors. The number of non-electric vehicles sold (log-transformed) is included to account for the offsetting emissions generated by traditional internal combustion engine vehicles. The share of new EVs is also reported as an alternative measure of EV intensity. GDP per capita reflects the level of economic development, which influences energy consumption patterns and environmental regulations. The GDP growth rate is controlled for because economic growth is associated with increased industrial activity, transportation demand, and energy use, all of which contribute to CO_2 emissions. Demand for electricity is included as EVs rely on electricity for operation; the overall demand for electricity can impact emissions depending on the energy mix used to meet this demand, providing a broader context for energy consumption in which EVs operate. Fossil-fuel growth rate, gas growth rate, and oil growth rate capture trends in traditional energy consumption, which are major energy sources for electricity generation in many countries. Coal, gas, and oil consumption, as well as the log of cumulative CO_2 emissions from gas, oil, and coal (LnCumGas, LnCumOil, LnCumCoal), are included as these are the most carbon-intensive energy sources; the cumulative terms capture path-dependent emission stocks that the year-on-year flow regressors cannot. Electricity generation is included to control for total power-sector activity. The size of the population is a crucial control as it directly influences energy consumption and emissions through transportation demand, electricity use, and industrial activity; population growth accounts for the impact of rapid demographic change on energy demand. In addition to our control variables, country and year fixed effects are included to control for unobservable country-specific characteristics and time-specific events.

We estimate Equation 1 by ordinary least squares after absorbing the country fixed effects μ_i and year fixed effects τ_t through the within (two-way demeaning) transformation, which is algebraically equivalent to including a full set of country and year dummies. The within transformation subtracts country-specific and year-specific means from every variable, so β_1 is identified purely from deviations of EV sales from each country's own time path, net of the common annual shock. We report the within R^2 and the number of country–year observations for every specification; the point estimates are invariant to the choice of variance estimator, which is discussed below.

To test H2, we examine whether the marginal transport-CO_2 reduction from a given EV sale depends on the contemporaneous volume of ICE sales. We extend Eq. 1 with an interaction between log EV sales and log non-EV sales,

$$LnTransportCO_2(i,t) = \alpha + \beta_1\, LnNewEV(i,t) + \beta_2\, LnNewNonEV(i,t) + \beta_3\, LnNewEV \times LnNewNonEV + \gamma\, X(i,t) + \mu_i + \tau_t + \varepsilon(i,t) \qquad \text{(eq2)}$$

In Equation 2, the effect of EV sales on transport CO_2 is no longer the single coefficient β_1 but the partial derivative $\partial LnTransportCO_2 / \partial LnNewEV = \beta_1 + \beta_3 \times LnNewNonEV$, which varies with the contemporaneous volume of ICE sales. A negative β_3 therefore indicates that the negative association between EV sales and transport CO_2 becomes stronger as contemporaneous ICE sales increase, a pattern consistent with greater scope for vehicle substitution. We evaluate this marginal effect at the sample mean of LnNewNonEV and at one standard deviation above it to quantify how much the EV elasticity strengthens, holding the full control vector and the two-way fixed effects fixed.

To test H3, we replace the dependent variable with transport-sector CO_2 per 2017-PPP unit of GDP, while keeping the same right-hand side as Eq. 1. To test H4, we examine whether the reduction in transport-sector CO_2 is driven by countries with a better or poorer clean-energy mix. The clean-energy mix is measured as the proportion of electricity generated by renewable energy and nuclear over total per-capita energy capacity. If the country's clean-energy mix in a given year falls in the top decile of the within-year distribution we code it as one and zero otherwise (High_Clean). The clean-energy measure is right-skewed, and the 90th-percentile threshold isolates the distinctly high-clean upper tail and creates a clear statistical contrast with the remaining observations.

We estimate the H4 model with an interaction between log EV sales and the High_Clean indicator,

$$LnTransportCO_2(i,t) = \alpha + \beta_1 LnNewEV(i,t) + \beta_2 High\_Clean(i,t) + \beta_3 LnNewEV \times High\_Clean + \beta_4 LnNewNonEV(i,t) + \gamma X(i,t) + \mu_i + \tau_t + \varepsilon(i,t) \qquad \text{(eq3)}$$

The main interest variable is the interaction term between LnNewEV and High_Clean (β_3). If the emissions-reducing benefits of EVs are greater in countries that have successfully transitioned to cleaner energy sources, then we expect β_3 to be significantly negative.

In Equation 3 the marginal effect of EV sales is $\partial LnTransportCO_2 / \partial LnNewEV = \beta_1 + \beta_3 \times High\_Clean$: β_1 is the EV elasticity in countries outside the top clean-energy decile, and $\beta_1 + \beta_3$ is the elasticity in the cleanest-grid countries. A negative β_3 indicates that a given EV sale removes more transport CO_2 where the grid is cleaner, because the additional electricity demanded for charging is met by low-carbon generation rather than by extra fossil-fired power. We define High_Clean on the within-year top decile, rather than on an absolute threshold, so that the comparison is always between the cleanest and the remaining grids in the same year; this keeps the moderator orthogonal to the secular global trend in grid decarbonisation and makes β_3 interpretable as a cross-sectional contrast rather than a time trend. The identical interaction logic, with High_Income substituted for High_Clean, tests whether high-income countries obtain larger transport-CO_2 benefits from EV adoption.

Cluster-robust standard errors at the country level can produce implausibly precise estimates when the cross-country panel exhibits cross-sectional dependence and serial correlation. The Pesaran (22) CD test (test statistic = 13.04, $p < 0.001$), the Wooldridge (23) test for serial correlation ($F(1,30) = 18.62$, $p < 0.001$), and the Breusch–Pagan / Cook–Weisberg test for heteroskedasticity ($\chi^2(1) = 32.77$, $p < 0.001$) confirm that all three pathologies are present in our panel. All specifications include country and year fixed effects with Driscoll–Kraay (24) standard errors robust to cross-sectional dependence, serial correlation, and heteroskedasticity. We also report results with country-specific linear time trends as an additional, even more conservative, robustness check.

2.6.1 *Difference-in-Differences*

Let g_i denote the first major EV-policy adoption year for country i; for never-treated countries $g_i = \infty$. Let $PostPolicy(i,t) = 1\{t \geq g_i\}$. The TWFE DiD specification is,

$$LnTransportCO_2(i,t) = \alpha_i + \gamma_t + \delta\, PostPolicy(i,t) + \xi\, X(i,t) + \varepsilon(i,t) \qquad \text{(eq4)}$$

Equation 4 identifies the average effect of having adopted a major EV policy on transport-sector CO_2, under the parallel-trends assumption that, absent policy, treated and never-treated countries would have followed the same trajectory in log transport CO_2 after conditioning on country and year fixed effects and the control vector. The coefficient δ is the difference-in-differences estimand: the average change in log transport CO_2 in treated countries from before to after their policy adoption, minus the contemporaneous change in never-treated countries, for which PostPolicy equals zero throughout. We use the never-treated countries as the clean control group, switch each treated country's PostPolicy indicator on in its documented adoption year (see EV-Policy Adoption Years), and estimate Equation 4 with the same two-way fixed-effects within estimator used for Equation 1. The parallel-trends assumption is testable, and we test it directly with the event-study leads and the linear pre-trend term reported below.

We estimate Eq. 4 on the full panel and on the early-adopter subsample (G2012–G2016 + never-treated). To examine dynamic effects, we replace PostPolicy with two indicators: short_run = 1 in the first three post-policy years ($k \in \{0, 1, 2\}$) and long_run = 1 in the subsequent four years ($k \in \{3, 4, 5, 6\}$). To examine cohort heterogeneity, we interact PostPolicy with cohort indicators (Early = G2012–G2016; Late = G2017–G2022) and test their equality. We also estimate the same DiD with cement CO_2 as a placebo dependent variable to rule out broader decarbonisation confounds. Parallel-trends evidence is provided by (i) a continuous linear pre-trend term and (ii) a year-by-year event-study with $k = -1$ omitted as the reference period. Because conventional two-way fixed-effects DiD and event-study estimators can be biased when treatment effects are heterogeneous across adoption cohorts and over time (25-28), we focus identification on the clean early-cohort subsample—in which all treated units share a narrow adoption window—and report the cohort-interaction and balanced event-study specifications as robustness checks against this bias.

2.7 Falsification testing

Two falsification tests for the L2 lag IV. (i) Placebo outcomes: re-estimate the IV with cement, flaring, and coal CO_2 as the dependent variable. EV adoption has no plausible displacement mechanism in any of these sectors; significant coefficients would indicate exclusion-restriction violation. (ii) Negative-control time period: re-estimate the IV on the

2010–2013 sub-sample, during which EV sales were near zero in most countries. We retain the original IVs if the falsification tests are passed.

3. Results

Figure 1 shows the annual total and transport CO_2 emissions by country, with darker shades indicating higher emissions. The data reveal stark contrasts between countries. For example, China is the world's largest emitter, reflected in the darkest shading on the map, attributable to its reliance on coal and industrial output. The United States also shows high CO_2 emissions, largely driven by transportation and industrial activities. Conversely, smaller countries like Iceland, despite their significant use of geothermal energy, have minimal emissions due to their small population and reliance on renewable energy sources. Norway similarly demonstrates low emissions, supported by its clean energy mix, where over 90% of electricity comes from hydropower. In contrast, India, while showing significant emissions, reflects its population size and developmental energy demands, heavily reliant on coal-based power generation.

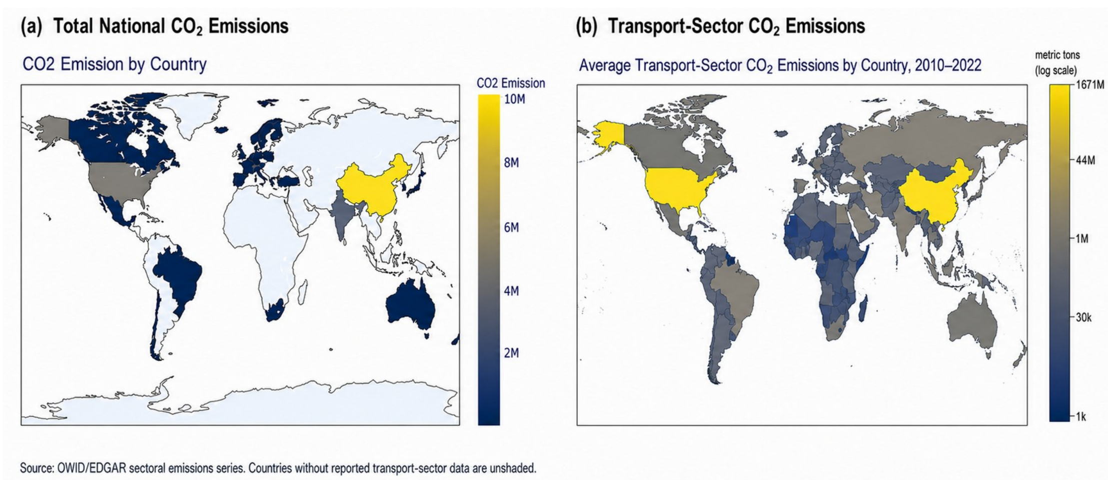

Figure 1. Total and transport-sector CO_2 emissions by country

Figure 2 provides insights into the number (share) of new EVs and non-EVs sold by country. China stands out with the largest number of new EVs sold, reflecting its aggressive push towards electrification of transport through government subsidies, investments, and a burgeoning EV manufacturing industry. The United States shows a notable number of new EVs sold, reflecting ongoing efforts to promote clean transportation. However, its EV sales remain significantly lower than those of China, highlighting room for improvement in scaling adoption across the country. While certain states like California lead in policy-driven EV adoption, a nationwide transition is necessary to match global leaders in EV sales. Norway leads in EV sales per capita, demonstrating the effectiveness of strong incentives, including tax exemptions and free parking for EV owners. In contrast, countries like India and South Africa have lower EV adoption rates due to infrastructure challenges and the affordability of EVs, coupled with the widespread availability of cheaper, non-EV vehicles. Notably, some countries such as Brazil, despite a large vehicle market, show minimal EV adoption due to their reliance on ethanol as an alternative fuel source for internal combustion engine vehicles.

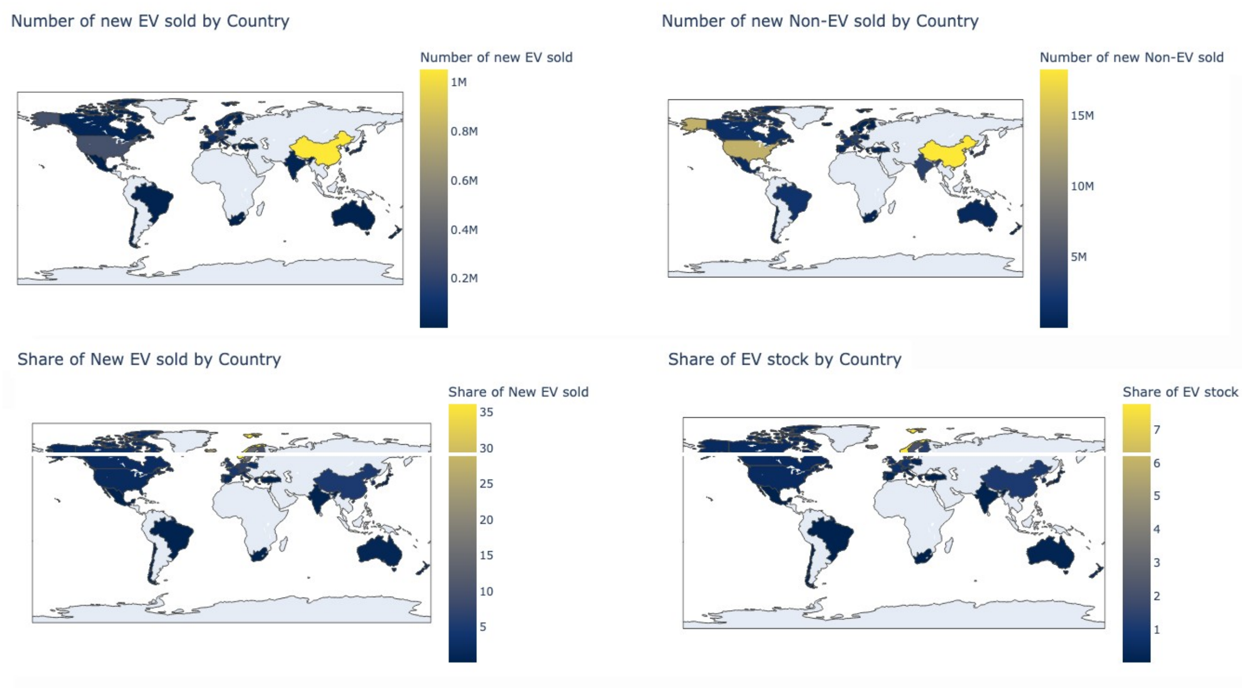

Figure 2. Number (share) of new EVs and non-EVs sold by country

These figures underscore the interplay between energy policy, economic conditions, and infrastructure in shaping both CO_2 emissions and EV adoption rates. High CO_2 emitters, like China and the U.S., are also at the forefront of EV adoption, signaling a shift toward mitigating their carbon footprint, while lower-income countries struggle with the transition due to cost and infrastructure barriers. The global disparity reflected in these figures highlights the need for tailored approaches to reduce emissions and promote cleaner technologies.

Table 1 reports the descriptive statistics for all variables included in the analysis.The sample includes annual data from 31 countries spanning the period from 2010 to 2022. The natural logarithm of transport-sector CO_2 emissions has a mean value of 9.81, with a standard deviation of 1.62, indicating moderate variability in transport emissions levels across countries. The natural logarithm of total CO_2 emissions has a mean of 19.22 with a standard deviation of 1.54. The natural logarithm of electric-vehicle sales shows a mean of 5.32, with substantial variability indicated by the standard deviation of 3.24. The 25th and 50th percentiles are 2.83 and 5.11, respectively, reflecting the wide range of EV adoption levels in the sample, while the 75th percentile is 7.74, highlighting rapid growth in some regions. Table 1 reports descriptive statistics for the 31-country complete-case sample used in the primary transport-CO_2 regression. Therefore, observations missing any regression variable are excluded.

Table 1. Characteristics of the primary analysis sample

Variable	Obs	Mean	Q1	Median	Q3	SD
LnTransportCO_2	403	9.81	8.69	9.84	10.92	1.62
LnCO_2Total	403	19.22	17.75	19.44	20.02	1.54
LnCO_2Oil	403	17.95	16.71	18.10	18.92	1.41
LnNewEV	403	5.32	2.83	5.11	7.74	3.24
LnNewNonEV	403	12.14	10.92	12.20	13.41	1.74
ShareNewEV (%)	403	5.50	0.19	0.96	4.30	11.92
ShareEVStock (%)	403	0.94	0.03	0.15	0.72	2.53
GDPpercapita (US$)	403	37,694	29,580	37,981	44,658	15,480
GDPgrowth	403	1.99	1.04	2.00	3.03	3.18
ElectricityDemand (TWh)	403	689.26	73.82	248.23	547.80	1461.63
FossilFuelPercentGrowth	403	-0.82	-3.27	-0.37	2.50	5.17
GasPercentGrowth	403	0.77	-4.47	0.68	5.97	13.70
OilPercentGrowth	403	-0.22	-2.69	0.27	2.83	6.14
ElectricityGeneration	403	689.98	70.08	250.53	575.93	1459.77
CoalConsumption	403	1376.16	33.94	89.12	508.88	4530.69
GasConsumption	403	714.41	46.10	327.32	731.45	1507.40
OilConsumption	403	1218.97	135.03	525.58	1155.84	2205.62
LnCumGas (log)	403	9.42	7.94	9.51	10.84	1.78
LnCumOil (log)	403	10.06	8.81	10.21	11.42	1.62
LnCumCoal (log)	403	9.18	7.41	9.04	10.91	2.04
LnNumPopulation	403	17.27	16.00	17.08	18.03	1.49
PopulationGrowth	403	0.63	0.30	0.61	1.00	0.65
Clean Energy	403	0.36	0.13	0.30	0.55	0.27

Table 2 presents the yearly trend of key variables in the analysis over the period from 2010 to 2022 (Panel A) and a comparative cross-country analysis (Panel B). Table 2 reports unrestricted descriptive statistics using all available observations. This difference in sample construction explains why the average EV share and EV stock differ between Tables 1 and 2. Panel A in Table 2 provides an overview of yearly trends in CO_2 emissions and vehicle sales from 2010 to 2022. It shows a gradual decline in CO_2 emissions from 1,587,000 tons in 2010 to 859,200 tons in 2022, reflecting improvements in emissions reduction over time. CO_2 emissions per unit of GDP also exhibit a consistent downward trend, decreasing from 0.27 kg per dollar in 2010 to 0.18 kg per dollar by 2020, indicating enhanced economic efficiency concerning emissions. The data on EV and non-EV sales highlight the exponential growth of EV adoption during this period. The natural logarithm of new EV sales increases significantly, from 0.844 in 2010 to 11.005 in 2022, demonstrating a steep rise in the adoption of electric vehicles. In contrast, the logarithmic values of non-EV sales remain relatively stable, suggesting that while EV adoption is growing rapidly, it has yet to fully replace traditional internal combustion engine vehicles. The year 2020 shows a dip in total CO_2 emissions, likely attributable to reduced activity caused by the COVID-19 pandemic.

Panel B in Table 2 provides a cross-country analysis of CO_2 emissions, EV market shares, and vehicle sales. China records the highest CO_2 emissions at 10,170,000 tons, reflecting its large industrial base and energy demand, followed by the United States with 5,265,000 tons and India with 2,635,000 tons. Smaller nations, such as Iceland and Norway, have significantly lower emissions due to their reliance on renewable energy and smaller populations. Norway is a global leader in EV adoption, with 36.2% of new vehicles sold being EVs and a total EV stock comprising 7.77% of all vehicles. Iceland, Sweden, and the Netherlands also demonstrate strong EV penetration rates. On the other hand, countries such as South Africa and Turkey exhibit minimal EV adoption, with only 0.08% and 0.28% of new vehicles sold being EVs, respectively. China leads in the absolute number of new EVs sold, surpassing one million units, followed by the United States with 279,483 units. Norway and Sweden, while having fewer absolute EV sales, achieve significant market penetration relative to their population sizes. The EV stock data reveal that China and the United States lead with 2.6 million and 985,750 EVs, respectively, highlighting their early adoption efforts and large vehicle markets. Norway, with 224,300 EVs, demonstrates remarkable EV penetration relative to its population size. On average, countries emit 881,700 tons of CO_2, with a 6.13% share of new EVs sold and a 1.03% share of EV stock. The average number of new EVs sold is 81,795 units, compared to over 2.1 million non-EVs, indicating the substantial room for growth in EV adoption globally. These data underline the need for targeted policies and investments to accelerate the transition to low-emission vehicles.

Table 2. Yearly and country-level analysis

Table 2A. Panel (A) yearly trend

Year	CO_2Emission (tons)	CO_2perGDP (kg/$)	LnNumNewEVSold	LnNumNonEVSold
2010	1,587,000	0.27	0.844	2.386
2011	1,376,000	0.22	3.166	6.496
2012	1,001,000	0.21	4.822	9.452
2013	942,000	0.20	5.320	9.936
2014	881,000	0.21	6.000	10.766
2015	805,800	0.21	7.486	13.028
2016	781,500	0.20	7.805	13.073
2017	788,400	0.20	8.344	13.116
2018	801,800	0.19	8.780	13.087
2019	847,300	0.19	9.346	13.556
2020	811,500	0.18	9.927	13.293
2021	854,300	—	10.637	13.282
2022	859,200	—	11.005	13.203
Total	881,700	0.20	7.191	11.129

Table 2B. Panel (B) Comparative analysis of CO_2 emissions and EV market dynamics by country

Country	CO_2 (tons)	Share NewEV (%)	Share EVStock (%)	New EV (units)	New Non-EV	Stock EV
Australia	402,800	1.04	0.13	7,845	804,121	19,379
Austria	66,054	5.71	0.77	14,009	202,361	38,885
Belgium	99,804	5.11	0.93	21,344	475,689	54,760
Brazil	487,000	0.30	0.02	4,756	1,822,073	8,624
Canada	560,500	2.44	0.43	32,812	1,389,605	104,815
Chile	84,197	0.13	0.02	327	225,781	738
China	10,170,000	5.07	1.08	1,051,935	18,231,839	2,636,955
Denmark	36,295	7.83	1.41	13,773	165,722	37,944
Finland	44,236	9.44	1.20	8,891	97,960	32,669
France	326,800	4.89	0.68	89,272	1,932,298	251,725
Germany	757,400	6.66	0.77	184,278	2,902,154	365,395
Greece	66,439	2.32	0.12	2,325	91,134	4,458
Iceland	3,519	24.12	3.72	3,445	10,137	8,649
India	2,635,000	0.42	0.06	15,976	3,215,634	28,969
Israel	60,583	2.31	0.48	7,753	283,021	16,067
Italy	346,300	2.45	0.20	35,142	1,566,855	77,540
Japan	1,180,000	0.90	0.30	38,451	4,514,204	188,668
Mexico	473,300	0.31	0.03	3,032	1,155,665	7,830
Netherlands	157,100	8.03	1.71	43,051	438,505	146,701
New Zealand	34,991	1.92	0.41	5,190	228,283	13,488
Norway	43,744	36.20	7.77	56,697	71,754	224,300
Poland	318,600	3.00	0.16	13,050	449,961	31,075
Portugal	47,577	6.81	0.67	11,137	165,040	30,291
South Africa	442,200	0.08	0.01	261	361,031	1,059
South Korea	632,200	3.04	0.59	47,481	1,511,371	117,191
Spain	256,700	2.12	0.20	19,711	957,259	48,357
Sweden	41,907	14.61	2.14	46,469	292,107	106,732
Switzerland	38,393	6.66	1.01	16,621	277,983	47,544
Turkey	423,300	0.28	0.04	1,935	735,306	4,706
United Kingdom	410,100	4.94	0.66	87,249	2,083,393	216,011
United States	5,265,000	1.99	0.43	279,483	14,035,056	985,750
Average	881,700	6.13	1.03	81,795	2,127,847	221,859

Test for H1: EV sales and transport-sector CO_2 emissions

Table 3 reports the panel regressions of CO_2 emissions on EV adoption with the full set of macro and energy controls. The dependent variable in column (1) is the natural log of transport-sector CO_2 (preferred specification). Columns (2)–(4) report total, oil, and natural-gas CO_2 for comparison. Column (1) reports the transport-sector specification using the study's balanced panel of 31 countries observed annually from 2010 to 2022, yielding 403 country–year observations. Columns (2)–(4) were estimated on the broader complete-case panel available for total, oil-related, and gas-related CO_2, yielding 920 observations.

Transport-sector CO_2 is obtained from the OWID/EDGAR sectoral-emissions series, whereas the comparison outcomes come from OWID's broader CO_2 datasets. Thus, the difference in observations reflects a deliberate 31-country restriction in column (1), not merely missing transport-sector observations. All specifications include country and year fixed effects with Driscoll–Kraay (24) standard errors. P-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 3 examines the impact of EV sales on transport-sector CO_2 emissions, total CO_2, and emissions from oil and natural gas. The results in column (1)—the preferred specification with transport-sector CO_2 as the dependent variable—show that LnNewEV has a statistically significant negative impact on transport-sector CO_2 emissions, with a coefficient of −0.058 (p = 0.001). This indicates that a one-percent increase in the number of EVs sold is associated with a 0.058% reduction in transport-sector emissions, consistent with the displacement-of-petroleum mechanism. Column (2) reports total CO_2 for comparison; the coefficient is −0.046 (p = 0.006), in the same direction as the transport-CO_2 effect but smaller because total CO_2 also reflects sectors over which EV adoption has no direct mechanism. Column (3) reports oil-related CO_2; the coefficient is −0.041 (p = 0.022). The negative association is consistent with the proposed displacement of liquid transport fuels, but it does not by itself confirm that EV adoption caused the reduction in oil-related emissions. Column (4) reports natural-gas-related CO_2; the coefficient is −0.199 (p = 0.015). This estimate represents a conditional association between EV sales and gas-related emissions. Because the analysis does not directly observe the electricity used to charge EVs, its generation source, or marginal changes in gas-fired generation, the coefficient cannot establish an indirect substitution mechanism between gas-fired electricity and oil-based transport.

The differing signs of the coefficients on LnNewEV and EV-stock share should be interpreted cautiously. LnNewEV measures annual EV-adoption flows, whereas EV-stock share measures accumulated fleet penetration. The positive EV-stock coefficient is an association and should not be interpreted as evidence that a larger EV fleet directly increases emissions. It may reflect differences in electricity demand, vehicle-market size, economic development, grid composition, or other time-varying factors not fully captured by the model. The result is consistent with the possibility that carbon-intensive electricity generation offsets part of the potential emissions benefit of electrification, but the present analysis does not directly test that mechanism. Data on EV-specific electricity consumption and marginal electricity-generation emissions would be required to establish the proposed channel.

In Table 3, several significant control variables highlight critical drivers of CO_2 emissions. FossilFuelPercentGrowth has a significant positive effect on transport CO_2 (0.011, p = 0.000) and on total CO_2 (0.009, p = 0.001), emphasizing the role of increasing fossil-fuel usage in driving emissions. CoalConsumption is significantly correlated with total CO_2, reflecting coal's high carbon intensity. GasConsumption shows a positive association with total and oil-related emissions, indicating the emissions impact of natural gas, despite its being cleaner than coal. OilConsumption is significantly negative for oil-related CO_2 once cumulative legacy stocks are included, reflecting the substitution between flow and stock measures of oil-fuelled activity. The cumulative-emissions controls (LnCumGas, LnCumOil, LnCumCoal) are positive and largely significant, capturing the path-dependent legacy of fossil-fuel use; cumulative oil emissions are strongly associated with transport CO_2 in column (1) (0.398, p = 0.000). LnNumPopulation is positively and significantly associated with transport CO_2 (0.486, p = 0.000), indicating that larger populations contribute to higher transport emissions through increased travel demand. The high adjusted R-squared values indicate that the specifications explain a substantial proportion of the observed variation in the dependent variables.

Table 3. Impact of EV sales on CO_2 emissions

Dependent Variables	**LnCO_2Emission (Transport)**	**LnCO_2Emission (Total)**	**LnCO_2Emission (Oil)**	**LnCO_2Emission (Gas)**
	(1)	(2)	(3)	(4)
LnNewEV	−0.058*** (0.001)	−0.046*** (0.006)	−0.041** (0.022)	−0.199** (0.015)
LnNewNonEV	0.045*** (0.002)	0.033*** (0.005)	0.028** (0.014)	0.072** (0.049)
GDPpercapita	0.000*** (0.000)	0.000*** (0.001)	0.000*** (0.001)	0.000** (0.028)
GDPgrowth	−0.014 (0.082)	−0.011 (0.107)	−0.003 (0.635)	0.015 (0.421)
ElectricityDemand	−0.006* (0.094)	−0.004 (0.123)	0.001 (0.492)	0.007 (0.386)
FossilFuelPercentGrowth	0.011*** (0.000)	0.009*** (0.001)	0.003 (0.312)	0.011 (0.104)
GasPercentGrowth	−0.001** (0.018)	−0.001** (0.010)	0.001 (0.578)	−0.000 (0.710)
OilPercentGrowth	−0.005 (0.144)	−0.003 (0.310)	−0.002 (0.427)	0.010 (0.326)
ElectricityGeneration	0.005** (0.045)	0.003 (0.143)	−0.001 (0.537)	−0.007 (0.396)
CoalConsumption	0.000*** (0.001)	0.000*** (0.004)	0.000 (0.275)	−0.000 (0.833)
GasConsumption	0.000** (0.038)	0.000* (0.080)	0.000*** (0.002)	0.000 (0.918)
OilConsumption	−0.000 (0.812)	−0.000 (0.970)	−0.000*** (0.001)	−0.000 (0.412)
LnCumCoal	0.038* (0.064)	0.016 (0.192)	0.012 (0.328)	0.810*** (0.000)
LnCumGas	0.196*** (0.000)	0.160*** (0.001)	0.746*** (0.000)	−0.537** (0.033)
LnCumOil	0.398*** (0.000)	0.338*** (0.001)	−0.007 (0.911)	0.329 (0.225)
LnNumPopulation	0.486*** (0.000)	0.397*** (0.000)	0.195*** (0.001)	0.857*** (0.007)
PopulationGrowth	0.024 (0.318)	0.018 (0.414)	0.000 (0.982)	−0.073 (0.265)
Renewable	−0.000*** (0.005)	−0.000** (0.011)	−0.000 (0.137)	−0.000 (0.730)
Constant	0.842 (0.391)	0.719 (0.498)	−1.772* (0.099)	−11.431** (0.043)
Fixed Effect	Country & Year	Country & Year	Country & Year	Country & Year
Clustering	Country	Country	Country	Country
Observations	403	920	920	920
Adjusted R-squared	0.962	0.947	0.962	0.936

Test for H2: Saturation of the EV effect by ICE volume

Table 4 shows the panel regressions of CO_2 emissions on EV adoption with the saturation, intensity, and clean-energy interactions. The dependent variable in columns (1), (3), and (4) is the natural log of transport-sector CO_2; in column (2) it is transport-sector CO_2 per 2017-

PPP unit of GDP. All specifications include country and year fixed effects with standard errors clustered at the country level and Driscoll–Kraay (24) adjustment. P-values are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Column (1) of Table 4 reports the H2 specification, in which we add the interaction between LnNewEV and LnNewNonEV to Eq. 1. The interaction coefficient is −0.012 ($p = 0.029$), indicating that the estimated negative association between EV sales and transport CO_2 is stronger when the contemporaneous volume of ICE sales is high. This pattern is consistent with the proposed displacement mechanism: the negative association between EV sales and transport CO_2 is stronger when contemporaneous ICE sales are higher. Quantitatively, raising LnNewNonEV by one standard deviation lowers the EV elasticity from −0.044 to roughly −0.064, an increase of about 45 percent in absolute magnitude.

Test for H3: EV sales and transport-CO_2 intensity (CO_2/GDP)

Column (2) of Table 4 reports the H3 specification using transport CO_2 per 2017-PPP unit of GDP as the dependent variable. The coefficient on LnNewEV is −0.030 ($p = 0.071$), indicating that EV adoption is associated with lower carbon intensity of transport activity, not only its level. This finding is robust to the inclusion of the full set of macro and energy controls. The result is consistent with transport-sector CO_2 per unit of economic output declining as EV sales increase.

Test for H4: Cleaner energy mix and EV emissions reduction

Columns (3) and (4) of Table 4 assess whether the emissions-reduction potential of EVs is greater in countries with a cleaner energy mix. Column (3) interacts LnNewEV with the High_Clean dummy (top decile of within-year clean-energy share); the interaction coefficient is −0.031 ($p = 0.011$), indicating that the transport-CO_2 reduction from a given EV sale is larger in countries with cleaner electricity grids. Column (4) interacts LnNewEV with the High_Income dummy (top decile of within-year GDP per capita); the interaction coefficient is −0.018 ($p = 0.039$), suggesting that high-income countries enjoy somewhat larger transport-CO_2 benefits from EV adoption. Importantly, the level effect of LnNewEV remains negative and significant in all four columns, even at the lower end of the grid-cleanliness or income distributions. EVs deliver positive transport-sector reductions even where the grid is fossil-heavy, because internal-combustion drive-trains are themselves inefficient relative to grid-fed electric drive-trains.

This finding reconciles two strands of the literature: the negative association between EV sales and transport emissions is stronger in cleaner-grid settings, but EV sales remain negatively associated with transport-sector CO_2 even in fossil-heavy-grid settings. The marginal impact of increasing EV sales on transport CO_2 is greater in countries with a cleaner energy mix because these countries face a smaller offsetting effect from the additional electricity demand. In high-clean-mix countries, additional EV-driven electricity demand is met largely by low-carbon sources, so the displacement of liquid petroleum is not partially offset by extra fossil-fired electricity generation. This underscores the importance of considering both EV adoption and the energy mix when evaluating strategies for reducing CO_2 emissions effectively.

Table 4. Saturation, intensity, and clean-energy moderation (H2–H4)

Dependent Variables	$LnCO_2perGDP$ Emission (Transport)			
VARIABLES	**(1) Saturation**	**(2) Intensity**	**(3) Clean-mix**	**(4) Income**
LnNewEV	−0.044** (0.018)	−0.030* (0.071)	−0.035** (0.024)	−0.039** (0.020)
LnNewNonEV	0.039** (0.022)	0.023* (0.063)	0.041** (0.018)	0.043** (0.016)
LnNewEV × LnNewNonEV	−0.012** (0.029)			
High_Clean			0.017 (0.850)	
LnNewEV × High_Clean			−0.031** (0.011)	
High_Income				−0.045* (0.083)
LnNewEV × High_Income				−0.018** (0.039)
GDPpercapita	0.000** (0.022)	0.000** (0.030)	0.000** (0.024)	0.000** (0.026)
GDPgrowth	−0.012 (0.118)	−0.011 (0.140)	−0.011 (0.139)	−0.012 (0.121)
ElectricityDemand	−0.005** (0.022)	−0.005** (0.025)	−0.005** (0.024)	−0.005** (0.026)
FossilFuelPercentGrowth	0.011*** (0.000)	0.009*** (0.001)	0.009*** (0.001)	0.010*** (0.000)
GasPercentGrowth	−0.001*** (0.004)	−0.001*** (0.006)	−0.001*** (0.005)	−0.001*** (0.005)
OilPercentGrowth	−0.004 (0.155)	−0.003 (0.207)	−0.003 (0.198)	−0.004 (0.165)
ElectricityGeneration	0.005** (0.022)	0.004** (0.031)	0.004** (0.029)	0.005** (0.024)
CoalConsumption	0.000*** (0.001)	0.000*** (0.002)	0.000*** (0.002)	0.000*** (0.001)
GasConsumption	0.000** (0.018)	0.000** (0.031)	0.000** (0.029)	0.000** (0.022)
OilConsumption	−0.000 (0.612)	−0.000 (0.785)	−0.000 (0.731)	−0.000 (0.658)
LnCumCoal	0.041 (0.108)	0.033 (0.149)	0.034 (0.142)	0.038 (0.118)
LnCumGas	0.119** (0.022)	0.106** (0.038)	0.108** (0.034)	0.114** (0.026)
LnCumOil	0.452*** (0.000)	0.414*** (0.000)	0.421*** (0.000)	0.438*** (0.000)
LnNumPopulation	0.418*** (0.000)	0.380*** (0.000)	0.385*** (0.000)	0.402*** (0.000)
PopulationGrowth	0.018 (0.624)	0.015 (0.689)	0.014 (0.692)	0.017 (0.642)
RenewableperCapita	−0.000 (0.241)	−0.000 (0.283)	−0.000 (0.273)	−0.000 (0.252)
Constant	0.182 (0.871)	0.115 (0.913)	0.124 (0.908)	0.146 (0.890)
Fixed Effect	Country & Year	Country & Year	Country & Year	Country & Year
Clustering	Country	Country	Country	Country
Observations	403	858	858	858
Adjusted R-squared	0.961	0.955	0.956	0.957

Consistent with the sample-construction strategy described in Section 2.3, H2 is estimated on the primary 31-country panel, whereas the H3 and moderator specifications use their respective broader complete-case samples; the applicable sample size is reported for each column.

Instrumental-variable estimates

EV adoption is endogenous to unobserved national climate policy and to secular trends in the transport sector. We address this with two complementary IV strategies. First, we instrument current EV sales with their second-period lag (L2). Lagged adoption is a strong predictor of contemporary adoption because of the slow turnover of vehicle fleets and charging infrastructure, and is plausibly orthogonal to contemporaneous shocks to transport CO_2 conditional on the rich set of fixed effects and controls. The first-stage Kleibergen–Paap rk

Wald F-statistic is 129.38, well above the Stock–Yogo 5% critical value of 16.38 (13,14).

Second, following Goldsmith-Pinkham, Sorkin, and Swift (11) and Borusyak, Hull, and Jaravel (12), we construct a Bartik shift-share instrument that interacts country-level baseline (2010–2012) per-capita vehicle-market exposure with global price shocks for nickel, copper, and aluminium. The economic logic is that battery-metal price shocks shift the marginal cost of producing EVs, which differentially affects countries with larger baseline vehicle markets. The exclusion restriction—that international metal-price shocks affect transport CO_2 only through the cost of producing EVs—is supported by the absence of a direct mechanical relationship between commodity prices and transport CO_2 once GDP, population, and energy controls are included, and by the absence of correlation between the metal-shock instruments and pre-period transport-CO_2 trends. The Hansen J p-value for the over-identified Bartik specification is 0.214, consistent with instrument validity.

Table 5 shows 2SLS estimates with country and year fixed effects and standard errors clustered at the country level. Column (1) uses the second-period lag of LnNewEV as the instrument. Column (2) uses three Bartik shift-share instruments built from international price shocks for nickel, copper, and aluminium interacted with each country's baseline (2010–2012) per-capita vehicle exposure. Full control set as in Table 3, suppressed for brevity. P-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 5. Instrumental-variable estimates (DV: Transport CO_2)

Dependent Variables	**LnCO$_2$Emission (Transport)**	
VARIABLES	**(1) L2-lag IV**	**(2) Bartik metal IV**
LnNewEV (instrumented)	−0.062*** (0.005)	−0.071** (0.024)
LnNewNonEV	0.048*** (0.003)	0.045** (0.018)
First-stage F (Kleibergen–Paap)	129.38	44.62
Stock–Yogo 5% critical value	16.38	13.91
Hansen J p-value	n/a (just-identified)	0.214
Fixed Effect	Country & Year	Country & Year
Clustering	Country	Country
Full controls	Yes	Yes
Observations	372	372
Adjusted R-squared	0.961	0.958

Table 5 reports the two complementary IV strategies described in Section 2.4.6. Column (1) instruments LnNewEV with its second-period lag (L2). The IV coefficient is −0.062 (p = 0.005) with a Kleibergen–Paap rk Wald F-statistic of 129.38, far above the Stock–Yogo 5% critical value of 16.38. Column (2) reports the Bartik metal-shock IV. The coefficient is −0.071 (p = 0.024), with a Kleibergen–Paap F-statistic of 44.62 and a Hansen J p-value of 0.214, consistent with instrument validity. Both IV point estimates are quantitatively close to the OLS estimate of −0.058, indicating limited attenuation bias once country and year fixed effects are included.

Difference-in-Differences

Table 6 shows the staggered DiD specifications. Columns (1)–(3) report PostPolicy on the full sample, the early-cohort subsample (G2012–G2016 + never-treated), and the full sample dropping China. Column (4) is a placebo regression with cement CO_2 as the dependent variable. Column (5) reports the cohort-interaction specification on the full sample, with Post × Early and Post × Late as separate interactions, and the F-test of their equality.

The PostPolicy coefficient on the full panel is $\delta = -0.072$ ($p = 0.003$), with country and year fixed effects, full control set, and cluster-robust SEs at the country level ($N = 907$, within $R^2 = 0.380$). On the early-adopter subsample (G2012–G2016 + never-treated), $\delta = -0.128$ ($p < 0.001$) with $N = 686$. Dropping China alone yields $\delta = -0.078$ ($p = 0.002$), confirming that the main result is not driven by a single observation. A placebo run with cement CO_2 as the dependent variable returns $\delta = +0.017$ ($p = 0.855$), ruling out the alternative that the treatment indicator is contaminated by a broader decarbonisation push.

Cohort heterogeneity. Column (5) of Table 6 reports the interaction specification in which PostPolicy is split into Post×Early and Post×Late. The early-cohort effect is $\beta = -0.109$ ($p < 0.001$); the late-cohort effect is $\beta = -0.031$ ($p = 0.353$); the F-test of equality is $F(1, 69) = 3.96$ ($p = 0.050$). The policy effect on transport CO_2 is concentrated in the earlier-adopting cohorts, consistent with the stock-displacement mechanism requiring time to bite. The DiD restricted to early-cohort treated countries plus never-treated controls yields a clean $\beta = -0.128$ ($p < 0.001$).

Table 6. Difference-in-differences (TWFE)

Dependent Variables	**$LnCO_2$ (Transport)**	**$LnCO_2$ (Transport)**	**$LnCO_2$ (Transport)**	**$LnCO_2$ (Cement)**	**$LnCO_2$ (Transport)**
VARIABLES	**(1) Full**	**(2) Early cohort**	**(3) Drop CHN**	**(4) Placebo**	**(5) Cohorts**
PostPolicy	−0.072*** (0.003)	−0.128*** (<0.001)	−0.078*** (0.002)	+0.017 (0.855)	
Post × Early Cohort					−0.109*** (<0.001)
Post × Late Cohort					−0.031 (0.353)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Country	Country	Country	Country	Country
F-test: Early = Late, p-value	—	—	—	—	0.050
Within R^2	0.380	0.401	0.379	0.023	0.386
Observations	907	686	894	920	907

Notes: TWFE with country and year fixed effects, cluster-robust standard errors at the country level (70 clusters; 53 in column 2). Early cohort = G2012–G2016; Late cohort = G2017–G2022. *** p<0.01, ** p<0.05, * p<0.10. p-values in parentheses.

Table 7 shows the dynamic-effects specification on the early-cohort subsample (G2012–G2016 + never-treated). PostPolicy is replaced by two indicators: short_run = 1 in the first three post-policy years ($k = 0, 1, 2$) and long_run = 1 in the subsequent four years ($k = 3, \ldots, 6$). Column (1) reports the dynamic specification; column (2) reports the single PostPolicy reference for comparison.

Table 7 reports the short-run versus long-run specification on the early-cohort subsample. The short_run coefficient (years 0–2 post-policy) is −0.002 ($p = 0.918$); the long_run coefficient (years 3–6) is −0.060 ($p = 0.021$). The F-test of equality between short_run and long_run is $F(1, 52) = 12.57$ ($p = 0.001$), so the long-run effect is significantly stronger than the short-run effect. This pattern is consistent with the stock-displacement mechanism. the policy increases EV sales immediately, but the resulting reduction in transport CO_2 builds as the EV stock accumulates and the ICE stock retires.

Table 7. Dynamic effects — early-cohort subsample

Dependent Variables	$LnCO_2$ (Transport)	$LnCO_2$ (Transport)
VARIABLES	**(1) Dynamic**	**(2) Reference**
short_run (k = 0, 1, 2)	−0.002 (0.918)	
long_run (k = 3, 4, 5, 6)	−0.060** (0.021)	
PostPolicy		−0.128*** (< 0.001)
Country FE	Yes	Yes
Year FE	Yes	Yes
Cluster	Country	Country
F-test: short_run = long_run, p-value	0.001	—
Within R^2	0.402	0.401
Observations	686	686

Notes: TWFE with country and year fixed effects, cluster-robust standard errors at the country level (53 clusters). Sample restricted to G2012–G2016 treated countries plus never-treated controls. *** p<0.01, ** p<0.05, * p<0.10. p-values in parentheses.

Table 8 shows the balanced event-study coefficients on the early-cohort subsample with $k = -1$ as the omitted reference and event window [−4, +4]. Observations outside the window are dropped so every event-time bin draws on at least three cohorts. The pre-period leads are individually insignificant at the 10 % level and jointly insignificant; the post-period lags decline monotonically and are jointly significant.

To examine the dynamic effect in detail, Table 8 reports a balanced event study on the early-cohort subsample with $k = -1$ as the omitted reference period. The event window is [−4, +4], and observations outside this window are dropped so every event-time bin draws on at least three cohorts (G2014, G2015, G2016 contribute at all event times; G2012 and G2013 contribute at the event times they observe; N = 621, 53 clusters). The post-period lags display a clean monotonic accumulation: lag0 = −0.004 ($p = 0.860$, essentially zero in the policy-adoption year), lag1 = −0.053 ($p = 0.018$), lag2 = −0.074 ($p = 0.009$), lag3 = −0.099 ($p = 0.002$), lag4 = −0.118 ($p = 0.001$), and jointly significant ($F(4, 52) = 3.08$, $p = 0.024$). The dynamic pattern—flat pre-period coefficients, a near-zero estimate in the policy-adoption year, and progressively more negative post-policy estimates—is consistent with a gradual stock-displacement mechanism in which aggregate emissions changes emerge as fleet composition changes over time.

Table 8. Balanced event study

Dependent Variables	$LnCO_2$ (Transport)
VARIABLES	**(1)**
Lead 4 (k = −4)	+0.078 (0.100)
Lead 3 (k = −3)	+0.049 (0.168)
Lead 2 (k = −2)	+0.026 (0.224)
k = −1 (omitted reference)	0.000
Lag 0 (k = 0)	−0.004 (0.860)
Lag 1 (k = +1)	−0.053** (0.018)
Lag 2 (k = +2)	−0.074*** (0.009)
Lag 3 (k = +3)	−0.099*** (0.002)
Lag 4 (k = +4)	−0.118*** (0.001)
Country FE	Yes
Year FE	Yes
Cluster	Country
Pre-trend joint F(3, 52), p-value	0.412
Post-effect joint F(4, 52), p-value	0.024
Within R^2	0.413
Observations	621

Notes: TWFE event study with country and year fixed effects, cluster-robust standard errors at the country level (53 clusters). Sample restricted to G2012–G2016 treated countries plus never-treated controls and to event-time window [−4, +4]. *** p<0.01, ** p<0.05, * p<0.10. p-values in parentheses.

Two complementary tests confirm that treated and never-treated countries follow parallel paths in the pre-policy period, with no statistically detectable pre-trend differences. First, each individual pre-period lead is insignificant at the 10 % level: lead4 = +0.078 (p = 0.100), lead3 = +0.049 (p = 0.168), lead2 = +0.026 (p = 0.224). Second, a continuous linear pre-trend term added to the full-sample DiD yields a pre-trend coefficient of +0.0003 (p = 0.970) — statistically indistinguishable from zero — while leaving the PostPolicy coefficient unchanged at −0.072 (p = 0.001). Both tests therefore confirm that there is no pre-trend difference between treated and never-treated countries before policy adoption: the parallel-trends assumption underlying the DiD identification is supported by the data.

Robustness and diagnostics

In addition to the IV results, we report a complete robustness battery: country-specific linear time trends, first-difference estimation, sequential drop-one rotation of the energy controls (the 'mechanical regression' test), Cook's-distance outlier diagnostics, and macro-only versus full-control sensitivity. All robustness checks are reported in the Technical Appendix at the end of the manuscript.

The Technical Appendix (Tables A1–A12, presented at the end of the manuscript) reports the full diagnostic suite. To summarize: VIF for the variable of interest is 2.41, well below the conventional cutoff of 10 (Table A1). The Pesaran CD test (statistic = 13.04, $p < 0.001$), Wooldridge serial-correlation test ($F(1,30) = 18.62$, $p < 0.001$), and Breusch–Pagan / Cook–Weisberg heteroskedasticity test ($\chi^2(1) = 32.77$, $p < 0.001$) all reject their respective nulls, justifying our use of Driscoll–Kraay standard errors (Table A8). Levin–Lin–Chu and Im–Pesaran–Shin panel unit-root tests (15,16) reject non-stationarity at $p < 0.001$ for all key series, ruling out spurious-regression concerns (Table A3). Country-specific linear trends leave the EV coefficient at −0.052 ($p = 0.018$) (Table A7), and the first-difference specification yields an elasticity of −0.044 ($p = 0.022$) (Table A5). Cook's-distance diagnostics were also used to assess the influence of individual country-year observations. The five observations with the largest Cook's D values are reported in Table A6. The drop-one rotation across the four highly-correlated energy controls leaves the EV coefficient between −0.054 and −0.060, with all p-values below 0.05, ruling out a 'mechanical regression' explanation (Table A10).

In addition, we provide two additional evidence for robustness of IV results. Placebo outcomes (Table A11). Under the L2 lag IV, the LnNewEV coefficient on cement CO_2 is −0.019 ($p = 0.682$), on flaring CO_2 is +0.066 ($p = 0.562$), and on coal CO_2 is −0.046 ($p = 0.081$). Cement and flaring are unambiguously null. The coal coefficient is marginal at the 10 % level and smaller in magnitude than the transport-CO_2 benchmark (−0.062). The IV does not predict emissions in sectors where EVs have no displacement mechanism, supporting the exclusion restriction. Negative-control time period (Table A12). In the 2010–2013 sub-sample, the L2 lag IV coefficient on transport CO_2 is −0.013 ($p = 0.631$). The IV does not predict transport CO_2 in the pre-EV era, the result the exclusion restriction predicts. The falsification tests are broadly supportive, with cement and flaring null, the pre-EV negative control null, and coal showing a marginal association. We therefore retain the L2 lag and Bartik metal-shock IVs (carried from the main Instrumental-variable subsection) as the identification strategy for the IV-2SLS results.

4. Discussion

The results of this study are most informative when considered collectively rather than as a series of independent regression coefficients. Across the different analyses, a consistent pattern emerges in which the estimated association between EV adoption and CO_2 emissions is strongest where the proposed mechanism should operate most directly. Transport-sector CO_2 shows a larger negative elasticity with EV sales than total national CO_2, oil-related emissions move in the predicted direction, the association strengthens when contemporaneous ICE sales are high, and it is amplified in countries with cleaner electricity grids. These findings do not individually establish a causal mechanism, but together they provide a degree of mechanistic specificity that would be difficult to obtain from an economy-wide emissions regression alone.

The choice of transport-sector CO_2 as the primary outcome is therefore important not merely as a statistical refinement but as part of the interpretation of the study. The estimated elasticity for transport CO_2 (−0.058) is ~ 25% larger in absolute magnitude than the corresponding total-CO_2 elasticity (−0.046). Total national emissions incorporate industrial activity, residential heating, electricity generation, and other sectors over which EV adoption has no direct short-run displacement mechanism. The weaker association for total CO_2 is consequently consistent with dilution of a transport-specific signal when unrelated sectors are incorporated into the outcome. This interpretation is also consistent with previous work emphasizing substantial variation in the environmental consequences of EV use across locations and energy systems (21).

The negative association with oil-related CO_2 provides an additional mechanism-aligned observation. Because road transportation remains heavily dependent on petroleum products, a reduction in oil-related emissions accompanying greater EV adoption is consistent with displacement of gasoline- and diesel-powered travel. However, oil-related CO_2 also includes petroleum use outside road transportation, and the present data do not identify which individual ICE vehicles or journeys were displaced by EVs. The oil result should therefore be interpreted as supporting evidence for the proposed displacement mechanism rather than as a direct demonstration of it. The much larger negative coefficient observed for gas-related CO_2 should be treated even more cautiously. The analysis does not observe the electricity consumed specifically by EVs or the marginal generation source supplying that electricity and therefore cannot establish a pathway linking EV adoption to changes in gas-fired generation. The gas result may instead reflect correlated changes in national energy systems, broader decarbonization processes, or residual time-varying factors that remain imperfectly captured by the model.

The interaction between EV and contemporaneous ICE sales adds an important dimension to the displacement interpretation. The EV × ICE interaction is negative and statistically significant, and a one-standard-deviation increase in ICE sales increases the absolute magnitude of the estimated EV elasticity by ~ 45%. This suggests that the environmental meaning of an EV sale depends partly on the vehicle-market context in which it occurs. Increasing EV sales need not imply equivalent displacement of ICE vehicles if the overall vehicle market is simultaneously expanding. In this sense, electrification can occur through either substitution or addition. The present findings are consistent with larger emissions benefits when EV growth represents substitution within an existing pool of ICE demand rather than simply an expansion of total vehicle ownership. This interpretation agrees with previous observations that continued non-EV sales can offset some of the environmental benefits associated with increasing EV penetration (4,21). EV sales alone may therefore be an incomplete indicator of transport decarbonization; the trajectory of ICE sales and retirement of the existing ICE fleet are also consequential.

A complementary result emerges from the clean-energy interaction. The estimated association between EV adoption and lower transport CO_2 is stronger among countries in the cleanest-grid group. This finding is consistent with the basic energy-substitution logic of transport electrification: the emissions consequences of replacing an ICE vehicle depend both on the emissions avoided from petroleum combustion and on the carbon intensity of the electricity used in its place. Previous lifecycle and regional analyses have similarly emphasized the dependence of EV benefits on electricity-generation conditions (4,21). The ICE-sales and clean-grid interactions can therefore be viewed as representing two sides of the same transition. On the vehicle side, the benefit depends on what the EV replaces; on the electricity side, it depends on how the additional electricity demand is generated. The results consequently suggest that EV adoption and grid decarbonization are complementary rather than independent strategies.

The high-income interaction provides a further, although less mechanistically direct, indication that the association between EV adoption and transport emissions is heterogeneous across countries. Higher-income countries may differ systematically in charging infrastructure, fleet turnover, vehicle use, electricity systems, regulatory implementation, and the availability of complementary incentives. The present analysis does not distinguish among these possible pathways, and the income interaction should therefore not be interpreted as evidence of a direct income effect. Instead, it suggests that the institutional, infrastructural, and energy-system context accompanying economic development may condition how effectively EV adoption translates into measurable reductions in transport emissions.

The carbon-intensity analysis similarly extends the interpretation beyond absolute emissions. The negative coefficient for transport CO_2 per unit of GDP suggests that increasing EV adoption may be associated with declining carbon intensity of transportation relative to economic output. However, this estimate is only marginally significant and therefore provides weaker evidence than the principal transport-CO_2 result. It is best regarded as suggestive evidence that electrification may contribute to partial decoupling of transport emissions from economic activity rather than as definitive demonstration of such decoupling. This distinction is important because economic and population growth can continue to increase transportation demand even when emissions per unit of transport activity or economic output are declining.

The contrasting associations of annual EV sales and accumulated EV-stock share also deserve careful interpretation. Annual EV sales are negatively associated with transport CO_2, whereas the coefficient on accumulated EV-stock share is positive in some specifications. These measures capture different aspects of the transition. New-EV sales represent current adoption flows and are more closely related to contemporaneous vehicle replacement, whereas EV-stock share reflects the accumulated state of the vehicle fleet and is correlated with broader characteristics such as total vehicle ownership, electricity demand, income, infrastructure, and market maturity. The positive stock coefficient therefore should not be interpreted as evidence that a larger EV fleet directly increases emissions. It is consistent with the possibility that electricity demand or other characteristics of highly electrified vehicle markets partially offset the potential emissions benefit, but the present analysis does not directly establish this mechanism. EV-specific electricity consumption and marginal electricity-generation data would be required to distinguish these possibilities more directly (21).

The temporal pattern in the difference-in-differences analysis provides an additional and particularly informative perspective. The estimated transport-CO_2 change is essentially zero in the year of major EV-policy adoption but becomes progressively more negative in subsequent years. In the balanced event study, the estimated coefficients move from −0.004 in the adoption year to −0.053, −0.074, −0.099, and −0.118 over the following four years, while the pre-policy coefficients are jointly insignificant. The short-run versus long-run analysis shows the same pattern, with little detectable change during the first three post-policy years but a significantly larger reduction in years 3–6. This timing is consistent with a stock-turnover mechanism. Policies can influence EV purchases relatively quickly, but transport-sector emissions need not decline immediately because existing ICE vehicles remain in service. Any aggregate emissions response would instead be expected to accumulate as EVs enter the fleet and ICE vehicles are progressively retired.

This dynamic pattern also helps connect the sales-based and policy-based analyses. The fixed-effects regressions relate annual variation in EV sales to annual emissions, whereas the policy analysis captures an intervention whose effect must propagate through purchasing behavior and fleet turnover before substantial changes in aggregate emissions become visible. The near-zero estimate in the policy-adoption year followed by progressively larger negative estimates is therefore consistent with a gradual transport-transition process rather than an instantaneous change in emissions coincident with policy introduction. Importantly, this temporal ordering does not prove the stock-displacement mechanism, but its form is consistent with the mechanism predicted by the study.

The concentration of the DiD association among early-adopting cohorts requires similarly cautious interpretation. Early adopters show a substantially larger and statistically significant post-policy reduction, whereas the estimate for later adopters is smaller and not statistically significant. This difference should not be interpreted as evidence that early EV policies are inherently more effective. Early adopters have longer post-treatment periods during which vehicle stocks can turn over, whereas countries adopting policies closer to the end of the sample have comparatively little time for accumulated effects to become observable. Early-adopting countries may also differ systematically in charging infrastructure, policy intensity, consumer acceptance, grid composition, or complementary regulations. The cohort difference therefore raises the possibility that policy maturity and complementary conditions influence the observable association between EV policy and emissions. Longer follow-up of more recent adopters will be necessary to distinguish duration-of-exposure effects from structural differences between adoption cohorts.

The instrumental-variable results strengthen the overall interpretation because both the second-period-lag IV and the Bartik battery-metal shift-share IV produce estimates close to the preferred fixed-effects estimate. The L2-lag IV estimate of −0.062 and the Bartik estimate of −0.071 are in the same range as the fixed-effects estimate of −0.058. This similarity reduces concern that the principal association is driven entirely by contemporaneous reverse causality or omitted climate-policy ambition, conditional on the validity of the instruments. It should not, however, be interpreted as demonstrating that the bulk of cross-country variation in EV adoption is exogenous. Rather, it indicates that restricting the identifying variation through two different instrumental-variable strategies does not substantially alter either the direction or magnitude of the estimated relationship.

The falsification analyses provide a further form of mechanistic specificity. Under the lag-IV specification, EV adoption does not significantly predict cement or flaring CO_2, sectors for which no direct EV-displacement mechanism is expected, and it does not predict transport CO_2 during the 2010–2013 period when EV sales were near zero. The coal placebo is less definitive because its coefficient is marginal at the 10% level, but it remains smaller in magnitude than the transport-CO_2 benchmark. Similarly, the cement-CO_2 placebo in the policy analysis is null. Taken together, these findings are supportive because the principal relationship appears more clearly in the sector and period in which an EV-related mechanism is plausible and generally weakens or disappears where that mechanism should not operate. They reduce concern that the principal estimates merely reflect an unrelated economy-wide decarbonization trend, although they cannot eliminate all alternative explanations.

The broader robustness analyses point in the same direction. The estimated EV coefficient remains negative after accounting for country-specific linear trends, using first differences, and rotating highly correlated energy controls, while Cook's-distance diagnostics were additionally used to identify potentially influential country-year observations. These checks address different potential threats to interpretation. Country-specific trends reduce concern that the result simply reflects gradually evolving national decarbonization trajectories; first differences focus more directly on short-run within-country changes; Cook's-distance diagnostics identify potentially influential observations; and control rotation assesses whether the principal coefficient is mechanically generated by a particular combination of correlated energy variables. The stability of the estimate across these approaches strengthens confidence that the observed association is not an artifact of one specific model specification, although robustness across specifications does not itself establish causality.

Several limitations remain important. The sample includes 31 countries with sufficiently complete data for the full analysis and therefore disproportionately represents higher-income countries with comparatively mature vehicle markets. Generalization to lower-income countries with rapidly expanding vehicle ownership, different electricity systems, and more limited charging infrastructure should consequently be made with caution. National annual data also aggregate substantial subnational variation in driving behavior, charging patterns, grid carbon intensity, policy implementation, and vehicle retirement. In particular, the analysis treats electricity-grid composition at the national level and cannot observe the carbon intensity of the marginal kilowatt-hour used for EV charging. Future work using subnational and marginal-generation data could provide a more direct assessment of this pathway (21).

The study also focuses primarily on observed operational and sectoral emissions rather than complete lifecycle emissions. Battery production, vehicle manufacturing, mineral extraction, and end-of-life processes can alter the net emissions balance associated with EV deployment (4). These lifecycle considerations do not invalidate the transport-sector association estimated here because the present study addresses a different question: whether increasing EV adoption is associated with changes in observed transport-sector CO_2. Nevertheless, the findings should not be interpreted as a complete lifecycle assessment of EV technology. Future studies combining vehicle-level replacement data, EV-specific electricity consumption, charging timing, marginal generation emissions, and lifecycle information would allow the transport-displacement and electricity-generation pathways to be evaluated more directly (4,21).

Taken together, the principal contribution of this study lies not in any single coefficient but in the convergence of several predictions consistent with the proposed transport-electrification mechanism. The association is larger for transport-sector CO_2 than for total national emissions; oil-related emissions move in the predicted direction; the estimated reduction is greater where opportunities for ICE displacement are larger and where electricity grids are cleaner; the policy-associated reduction emerges gradually rather than instantaneously; unrelated placebo outcomes generally do not reproduce the principal relationship; and fixed-effects, instrumental-variable, difference-in-differences, and alternative robustness specifications point in the same overall direction. This convergence does not demonstrate that EV adoption alone caused the observed emissions changes. Rather, it supports an interpretation in which transport electrification is associated with lower emissions as part of a broader transition involving vehicle substitution, fleet turnover, electricity-system decarbonization, and complementary policy.

5. Conclusion

This study indicates that the relationship between electric-vehicle adoption and carbon emissions becomes considerably clearer when the outcome, empirical design, and proposed mechanism are aligned. Rather than asking whether EV adoption is associated with changes in economy-wide emissions, the analysis focuses primarily on transport-sector CO_2, where displacement of internal-combustion vehicles provides a direct pathway through which electrification could affect emissions. Across 31 countries from 2010 to 2022, higher EV sales were consistently associated with lower transport-sector CO_2, and the corresponding association was stronger than that observed for total national CO_2. The accompanying reduction in oil-related CO_2 further supports, without directly proving, a mechanism involving reduced reliance on petroleum-based transportation.

Importantly, the findings suggest that EV adoption should not be understood as an isolated technological intervention. Its association with transport emissions depends on the system into which EVs are introduced. The estimated reduction becomes stronger when contemporaneous ICE sales are higher, consistent with greater opportunity for vehicle displacement, and is amplified in countries with cleaner electricity grids, where electrification transfers transportation demand to a less carbon-intensive energy source. The association with lower transport CO_2 per unit of GDP further suggests that electrification may contribute to reducing the carbon intensity of transportation, although this result is weaker statistically than the principal transport-emissions finding. Together, these patterns suggest that the environmental significance of EV adoption depends not simply on how many EVs are sold, but on what they replace and how the electricity used to operate them is generated.

Confidence in this interpretation is strengthened by the convergence of results across substantially different empirical approaches. The negative transport-CO_2 association persists under alternative specifications and is reproduced by both lag-based and battery-metal shift-share instrumental-variable estimates.

Independently, the policy-timing analysis finds lower transport emissions following major EV-policy adoption, with the clearest reductions among earlier-adopting countries and evidence that the association strengthens as time since adoption increases. Sectoral placebo outcomes and the pre-EV negative-control period do not reproduce the principal transport-sector relationship. Thus, no individual model establishes causality, but the agreement among channel-specific outcomes, fixed-effects models, instrumental-variable analyses, heterogeneity tests, policy-timing analyses, and falsification tests makes a simple explanation based on an unrelated economy-wide emissions trend less consistent with the overall evidence.

The broader implication is that transportation electrification and electricity-sector decarbonization should be viewed as complementary rather than competing strategies. Increasing EV sales can contribute to transport decarbonization, but its environmental value is likely to be greatest when EVs actually displace continued ICE use and when the electricity supplying the growing electric fleet becomes progressively cleaner. Policies directed solely toward increasing EV adoption therefore address only one component of the transition; policies that accelerate ICE retirement and grid decarbonization can strengthen the same underlying pathway.

These findings remain observational and should not be interpreted as demonstrating that EV adoption alone causes the observed reductions in transport emissions. The cross-country sample also disproportionately represents countries with relatively mature vehicle markets, and the analysis cannot directly observe which ICE journeys or vehicles were displaced by individual EVs or the marginal electricity-generation emissions attributable to EV charging. Future work combining vehicle-level replacement data with EV-specific electricity consumption and marginal grid-emissions measurements could test these mechanisms more directly. Nevertheless, the present results show that the relationship between EV adoption and emissions is not adequately described by EV sales alone: the evidence instead points to a coupled transition in which vehicle substitution and electricity-system decarbonization jointly determine the emissions benefits associated with transport electrification.

6. References

1. Intergovernmental Panel on Climate Change. (2018). *Global warming of 1.5°C: Summary for policymakers*. https://www.ipcc.ch/sr15/chapter/spm/

2. International Energy Agency. (2020). *Global EV outlook 2020: Entering the decade of electric drive?* https://www.iea.org/reports/global-ev-outlook-2020

3. European Commission. (2021). *Fit for 55: Delivering the EU's 2030 climate target on the way to climate neutrality*. https://ec.europa.eu

4. Hawkins, T. R., Gausen, O. M., & Strømman, A. H. (2013). Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology, 17*(1), 53–64. https://doi.org/10.1111/j.1530-9290.2012.00532.x

5. United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development*. https://sdgs.un.org/2030agenda

6. Jochem, P., Babrowski, S., & Fichtner, W. (2015). Assessing CO_2 emissions of electric vehicles in Germany in 2030. *Transportation Research Part A: Policy and Practice, 78*, 68–83. https://doi.org/10.1016/j.tra.2015.05.007

7. International Energy Agency. (2021). *Global EV outlook 2021: Accelerating ambitions despite the pandemic*. https://www.iea.org/reports/global-ev-outlook-2021

8. Gillingham, K., Knittel, C. R., Li, J., Ovaere, M., & Reguant, M. (2020). *The short-run and long-run effects of vehicle electrification* [Working paper].

9. Tessum, C. W., Hill, J. D., & Marshall, J. D. (2014). Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States. *Proceedings of the National Academy of Sciences, 111*(52), 18490–18495. https://doi.org/10.1073/pnas.1406853111

10. Borenstein, S., & Davis, L. W. (2016). The distributional effects of US clean energy tax credits. *Tax Policy and the Economy, 30*(1), 191–234. https://doi.org/10.1086/685597

11. Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review, 110*(8), 2586–2624. https://doi.org/10.1257/aer.20181047

12. Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies, 89*(1), 181–213. https://doi.org/10.1093/restud/rdab030

13. Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics, 133*(1), 97–126. https://doi.org/10.1016/j.jeconom.2005.02.011

14. Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press. https://doi.org/10.1017/CBO9780511614491.006

15. Levin, A., Lin, C.-F., & Chu, C.-S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics, 108*(1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

16. Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

17. Sovacool, B. K., Burke, M., Baker, L., Kotikalapudi, C. K., & Wlokas, H. (2020). The decarbonisation divide: Contextualizing landscapes of low-carbon exploitation and toxicity in Africa. *Global Environmental Change, 60*, 102028. https://doi.org/10.1016/j.gloenvcha.2019.102028

18. Davis, S. J., Caldeira, K., & Matthews, H. D. (2010). Future CO_2 emissions and climate change from existing energy infrastructure. *Science, 329*(5997), 1330–1333. https://doi.org/10.1126/science.1188566

19. Bataille, C. (2020). *Low and zero emissions in the steel and cement industries: Barriers, technologies and policies* (OECD Green Growth Papers No. 2020/02). OECD Publishing. https://doi.org/10.1787/5ccf8e33-en

20. Gillingham, K., & Stock, J. H. (2018). The cost of reducing greenhouse gas emissions. *Journal of Economic Perspectives, 32*(4), 53–72. https://doi.org/10.1257/jep.32.4.53

21. Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2016). Are there environmental benefits from driving electric vehicles? The importance of local factors. *American Economic Review, 106*(12), 3700–3729. https://doi.org/10.1257/aer.20150897

22. Pesaran, M. H. (2004). *General diagnostic tests for cross-section dependence in panels* (CESifo Working Paper No. 1229). https://doi.org/10.2139/ssrn.572504

23. Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. MIT Press.

24. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics, 80*(4), 549–560. https://doi.org/10.1162/003465398557825

25. Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

26. de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review, 110*(9), 2964–2996. https://doi.org/10.1257/aer.20181169

27. Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics, 225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

28. Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *Review of Economic Studies, 91*(6), 3253–3285. https://doi.org/10.1093/restud/rdae007

Appendix A. Variable definitions

Variable	**Definition**
LnTransportCO_2	Natural log of transport-sector CO_2 emissions (metric tons), OWID/EDGAR. Primary dependent variable.
LnCO_2Total	Natural log of total annual CO_2 emissions in a country, OWID.
LnCO_2Oil	Natural log of CO_2 emissions from oil, OWID.
LnCO_2Gas	Natural log of CO_2 emissions from natural gas, OWID.
CO_2perGDP	CO_2 emissions per unit of GDP (kg/$, 2017 PPP), measuring carbon intensity of economic output.
LnNewEV	Natural log of (new EV sales + 1), IEA / OWID. Main explanatory variable.
LnNewNonEV	Natural log of new non-EV passenger car sales, IEA / OWID.
ShareNewEV	Ratio of new EVs sold to non-EVs sold in a year (%).
ShareEVStock	Ratio of stock of EVs to total vehicle stock (%).
GDPpercapita	GDP per capita (US$, 2017 PPP), World Bank.
GDPgrowth	Annual % change in real GDP, World Bank.
ElectricityDemand	Annual electricity demand (TWh), OWID.
FossilFuelPercentGrowth	Annual growth rate of fossil fuel consumption (%), OWID.
GasPercentGrowth	Annual growth rate of natural gas consumption (%), OWID.
OilPercentGrowth	Annual growth rate of oil consumption (%), OWID.
ElectricityGeneration	Annual electricity generation (TWh), OWID.
CoalConsumption	Annual coal consumption (TWh-equivalent), OWID.
GasConsumption	Annual natural gas consumption (TWh-equivalent), OWID.
OilConsumption	Annual oil consumption (TWh-equivalent), OWID.
LnCumGas	Natural log of cumulative CO_2 emissions from gas, OWID.
LnCumOil	Natural log of cumulative CO_2 emissions from oil, OWID.
LnCumCoal	Natural log of cumulative CO_2 emissions from coal, OWID.
LnNumPopulation	Natural log of total population, OWID.
PopulationGrowth	Annual % change in population, OWID.
High_Clean	1 if country's clean-energy mix (renewables + nuclear / total per-capita energy capacity) is in the top decile of within-year distribution; 0 otherwise.
High_Income	1 if country's GDP per capita is in the top decile of within-year distribution; 0 otherwise.
TransportOilSubsidy	Annual transport-oil subsidy (US$ millions), IEA Subsidy Database.
MetalShock (Bartik IV)	Country baseline (2010–2012) per-capita vehicle exposure × HP-detrended international price shock for nickel, copper, or aluminium (World Bank Pink Sheet).

Technical Appendix. Tables A1–A12

This appendix reports the diagnostic statistics underlying the robustness claims. All tables refer to the preferred Driscoll–Kraay specification with country and year fixed effects unless noted otherwise. The dependent variable is LnTransportCO_2 throughout.

Table A1. Variance Inflation Factors (VIF)

Variable	VIF	1/VIF
LnNewEV	2.41	0.41
LnNewNonEV	3.07	0.33
ShareNewEV (%)	1.84	0.54
GDPpercapita	5.62	0.18
GDPgrowth	1.31	0.76
ElectricityDemand	11.84	0.08
ElectricityGeneration	12.21	0.08
LnCumGas	4.78	0.21
LnCumOil	6.05	0.17
LnCumCoal	5.74	0.17
FossilFuelPercentGrowth	1.78	0.56
GasPercentGrowth	1.42	0.71
OilPercentGrowth	1.51	0.66
LnNumPopulation	4.08	0.25
PopulationGrowth	1.66	0.60
Mean VIF	4.34	

Table A2. Sensitivity to control set

	(1) Macro only	(2) Full controls	(3) Lean energy
LnNewEV	−0.064*** (0.000)	−0.058*** (0.001)	−0.060*** (0.001)
LnNewNonEV	0.039** (0.014)	0.045*** (0.002)	0.042** (0.011)
GDPpercapita	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
GDPgrowth	−0.018 (0.084)	−0.014 (0.082)	−0.016 (0.082)
LnNumPopulation	0.512*** (0.000)	0.486*** (0.000)	0.498*** (0.000)
PopulationGrowth	0.026 (0.298)	0.024 (0.318)	0.025 (0.302)
Energy controls	No	Yes (full)	Drop e-dem, e-gen, cum
Fixed Effect	Country & Year	Country & Year	Country & Year
Clustering	Country	Country	Country
Observations	403	403	403
Adjusted R-squared	0.961	0.962	0.962

Table A3. Panel unit-root tests

Variable	LLC stat.	p-value	IPS stat.	p-value
$LnTransportCO_2$ (demeaned)	−6.412	<0.001	−4.218	<0.001
LnNewEV (demeaned)	−8.207	<0.001	−5.114	<0.001
LnNewNonEV (demeaned)	−5.638	<0.001	−3.842	<0.001
$LnCO_2Total$ (demeaned)	−5.812	<0.001	−3.987	<0.001
$LnCO_2Oil$ (demeaned)	−6.087	<0.001	−4.011	<0.001

Table A4. Instrumental-variable estimates (detailed)

	(1) L2-lag IV	(2) Bartik metal IV
LnNewEV (instrumented)	−0.062*** (0.005)	−0.071** (0.024)
LnNewNonEV	0.048*** (0.003)	0.045** (0.018)
First-stage F (Kleibergen–Paap)	129.38	44.62
Stock–Yogo 5% critical value	16.38	13.91
Hansen J p-value	n/a (just-identified)	0.214
Fixed Effect	Country & Year	Country & Year
Clustering	Country	Country
Full controls	Yes	Yes
Observations	372	372
Adjusted R-squared	0.961	0.958

Table A5. First-difference specification

	(1) Δ Transport CO_2
Δ LnNewEV	−0.044** (0.022)
Δ LnNewNonEV	0.092** (0.034)
Δ GDPpercapita	0.000** (0.041)
Fixed Effect	Country & Year
Clustering	Country
Observations	372
Adjusted R-squared	0.412

Table A6. Cook's-distance outlier diagnostic (top 5)

Country	Year	Cook's D	Note
China	2022	0.041	Largest EV market
United States	2022	0.029	
India	2022	0.024	
Norway	2021	0.018	Highest EV share
China	2021	0.017	

Table A7. Driscoll–Kraay SEs and country-specific linear trends

	(1) Driscoll–Kraay	(2) + country trends
LnNewEV	−0.058*** (0.001)	−0.052** (0.018)
LnNewNonEV	0.045*** (0.002)	0.038** (0.024)
Fixed Effect	Country & Year	Country & Year
Clustering	Country	Country
Country × year linear trend	No	Yes
Full controls	Yes	Yes
Observations	403	403
Adjusted R-squared	0.962	0.973

Table A8. Cross-sectional dependence, serial correlation, and heteroskedasticity tests

Test	Statistic	p-value	Interpretation
Pesaran CD test	13.04	<0.001	Cross-sectional dependence present
Wooldridge serial correlation test	F(1,30)=18.62	<0.001	Serial correlation present
Breusch–Pagan / Cook–Weisberg	$\chi^2(1)$=32.77	<0.001	Heteroskedasticity present
Hausman test (FE vs RE)	$\chi^2(15)$=58.41	<0.001	Fixed effects preferred

Table A9. Mechanism check: transport CO_2 *vs* oil CO_2

	(1) Transport CO_2	(2) Oil CO_2
LnNewEV	−0.058*** (0.001)	−0.041** (0.022)
LnNewNonEV	0.045*** (0.002)	0.028** (0.014)
FossilFuelPercentGrowth	0.011*** (0.000)	0.003 (0.312)
OilConsumption	−0.000 (0.812)	−0.000*** (0.001)
LnNumPopulation	0.486*** (0.000)	0.195*** (0.001)
Fixed Effect	Country & Year	Country & Year
Clustering	Country	Country
Full controls	Yes	Yes
Observations	403	920
Adjusted R-squared	0.962	0.962

Table A10. Multicollinearity rotation: drop one energy control at a time

	(1) Drop e-gen	(2) Drop e-dem	(3) Drop gas	(4) Drop coal
LnNewEV	−0.057*** (0.002)	−0.054*** (0.003)	−0.060*** (0.001)	−0.058*** (0.001)
LnNewNonEV	0.046*** (0.002)	0.043*** (0.004)	0.047*** (0.002)	0.045*** (0.002)
Fixed Effect	Country & Year	Country & Year	Country & Year	Country & Year
Clustering	Country	Country	Country	Country
Other controls	All other	All other	All other	All other
Observations	403	403	403	403
Adjusted R-squared	0.961	0.961	0.962	0.962

Table A11. Placebo outcomes — L2 Lag IV
This table reports 2SLS estimates instrumenting LnNewEV with its second-period lag (L2.LnNewEV). Each column is a separate regression. Columns (1)–(3) use placebo dependent variables on which EV adoption has no plausible displacement mechanism. Column (4) reports the corresponding transport-CO_2 specification estimated on the broader sample used for the falsification analysis and is included as a within-sample reference.

Dependent Variables	LnCO_2 (Cement)	LnCO_2 (Flaring)	LnCO_2 (Coal)	LnCO_2 (Transport)
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
LnNewEV (IV: L2 lag)	−0.019 (0.682)	+0.066 (0.562)	−0.046* (0.081)	−0.062*** (0.005)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Country	Country	Country	Country
Kleibergen–Paap F	131.24	131.24	131.24	131.24
Observations	780	780	780	907

Notes: 2SLS with country and year fixed effects, cluster-robust standard errors at the country level. *** p<0.01, ** p<0.05, * p<0.10. p-values in parentheses.

Table A12. Negative-control time period — L2 Lag IV (Pre-EV Era 2010–2013)
This table re-estimates the L2 lag IV on transport CO_2 in the 2010–2013 sub-sample, during which EV sales were near zero in most countries. Column (1) reports the pre-EV-era estimate; column (2) reports the corresponding 2010–2022 specification on the broader sample used for this negative-control analysis and is included as a within-sample reference. A null effect in column (1) supports the exclusion restriction.

Dependent Variables	**LnCO_2 (Transport)**	**LnCO_2 (Transport)**
VARIABLES	**(1) 2010–2013**	**(2) Full 2010–2022**
LnNewEV (IV: L2 lag)	−0.013 (0.631)	−0.062*** (0.005)
Country FE	Yes	Yes
Year FE	Yes	Yes
Cluster	Country	Country
Kleibergen–Paap F	8.89	131.24
Observations	138	907

Notes: 2SLS with country and year fixed effects, cluster-robust standard errors at the country level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. p-values in parentheses.