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FACULTY OF SOCIAL SCIENCES

Center for Economic Research and Graduate Education – Economics Institute

Master's Thesis

2026 **Giovana Maggi Cardoso**

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Financial Incentives and Sustainable Mobility:

Evaluating the Impact of the Ecobonus Program in Italy

Master's Thesis

Author of the Thesis:	Giovana Maggi Cardoso
Study program:	Master in Economic Research
Supervisor:	Sebastian Ottinger, Ph.D.
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Declaration

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2. I hereby declare that my thesis has not been used to gain any other academic title.
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4. During the preparation of this thesis, the author used the AI tools ChatGPT (chatgpt.com) and Claude (claude.com) in order to edit and rephrase parts of this thesis. After using these tools, the author reviewed and edited the content as necessary and takes full responsibility for the content of the publication.
5. This thesis builds on earlier versions of some sections developed as part of the Research Writing course at CERGE-EI. These sections have been revised, expanded, and integrated into the present manuscript.

In Prague on 5 May 2026. Giovana Maggi Cardoso

References

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Length of the Thesis: 101,327 characters

Abstract

This thesis evaluates the impact of the Italian *Ecobonus* program (a purchase subsidy for low- and zero-emission vehicles introduced in 2019) on eco-vehicle adoption, using national, regional, and international evidence. The national difference-in-differences analysis estimates that the program is associated with approximately 209,000 additional eco-vehicle registrations per year relative to petrol vehicles, a result stable across five specifications and supported by an event study that does not reject parallel pre-trends. The implied cumulative effect over 2019–2024 is approximately 1.26 million additional registrations. The regional analysis estimates that eco-vehicle market share increased by approximately 26 percentage points across Italian regions after 2019, with the increase visible in all 20 regions, though pre-existing regional heterogeneity precludes a causal interpretation of this estimate. The international analysis does not detect a significant average treatment effect in static specifications; TWFE event-study estimates suggest gradual positive dynamics, but cohort-specific estimators following Callaway and Sant'Anna (2021) find near-zero average treatment effects throughout the event window. This divergence is a key methodological finding: it indicates that standard TWFE estimates are substantially biased in this staggered adoption setting, and that the post-treatment dynamics visible in the TWFE event study likely reflect cohort heterogeneity rather than a causal average effect of subsidies. Italy's adoption path broadly tracks the European average rather than diverging from it, consistent with the interpretation that the transition to eco vehicles is driven by common technological and regulatory forces, and that national subsidies contributed at the margin but were not the primary driver of the observed shift. Overall, the findings suggest that financial incentives may contribute to eco-vehicle adoption, though their effectiveness depends on broader market conditions and pre-existing adoption trends.

Abstrakt

Tato diplomová práce hodnotí dopad italského programu *Ecobonus* na adopci udržitelných vozidel. Analýza kombinuje národní, regionální a mezinárodní důkazy prostřednictvím metod difference-in-differences a event study. Národní analýza poskytuje nejsilnější důkazy: odhady naznačují, že program je spjat s přibližně 209 000 dalšími registracemi ekologických vozidel ročně ve srovnání s benzinovými vozidly, přičemž kumulativní účinek v období 2019–2024 činí přibližně 1,26 milionu dalších registrací. Výsledky event study ukazují, že efekt se projevuje po roce 2020 a v čase roste, přičemž koeficienty před zavedením politiky nejsou statisticky odlišné od nuly. Regionální analýza odhaduje nárůst podílu ekologických vozidel o přibližně 26 procentních bodů ve všech 20 italských regionech po roce 2019, avšak přeexistující regionální heterogenita omezuje kauzální interpretaci těchto výsledků. Mezinárodní analýza nenachází statisticky významný průměrný účinek léčby ve statických specifikacích; odhadnáče specifické pro kohorty dle Callaway a Sant'Anna (2021) nalezájí ATT blízké nule. Italská trajektorie adopce zhruba sleduje evropský průměr. Celkové výsledky naznačují, že finanční pobídky mohou přispět k adopci udržitelných vozidel, ačkoli jejich účinnost závisí na širších tržních podmínkách a přeexistujících trendech.

Keywords

sustainable mobility; electric vehicles; subsidies; Ecobonus; Italy; difference-in-differences; event study

Klíčová slova

udržitelná mobilita; elektrická vozidla; dotace; Ecobonus; Itálie; difference-in-differences; event study

Title

Financial Incentives and Sustainable Mobility: Evaluating the Impact of the Ecobonus Program in Italy

Název práce

Finanční pobídky a udržitelná mobilita: Hodnocení dopadu programu Ecobonus v Itálii

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Introduction[1]

The transition away from internal combustion vehicles is one of the central challenges of European climate policy. In Italy, the share of eco vehicles (including hybrids, plug-in hybrids, and battery electric vehicles) in total new car registrations rose from under 5% in 2018 to nearly 47% by 2024. This shift coincided with the introduction of the *Ecobonus* in 2019, a national purchase subsidy program targeting low- and zero-emission vehicles. Whether this program contributed to the observed increase, or whether the growth would have occurred independently of the policy, is an open empirical question.

This thesis asks: did the *Ecobonus* program increase eco-vehicle adoption in Italy? To answer this, I combine three levels of analysis. At the national level, I estimate a difference-in-differences model comparing eco and conventional vehicle registrations before and after the policy. At the regional level, I estimate eco-vehicle market share regressions across the 20 Italian regions to document the geographic distribution of the post-2019 increase. At the international level, I construct a panel of 26 European countries with staggered subsidy adoption to situate the Italian experience within the wider European transition.

The results are as follows. At the national level, the preferred fixed-effects specification estimates approximately 209,000 additional eco registrations per year relative to conventional vehicles (SE = 41,420; $p < 0.001$), a result stable across five specifications and supported by an event study that does not reject parallel pre-trends ($F = 1.07$, $p = 0.376$). Post-treatment coefficients increase gradually from 2020 onward, consistent with a market response that built over time. At the regional level, eco-vehicle market share increased by approximately 26 percentage points across Italian regions after 2019 in the preferred specification, with the increase visible in all three macro-areas and all 20 regions. However, the regional event study rejects parallel pre-trends, and I treat those results as descriptive rather than causal. At the international level, static two-way fixed effects specifications do not detect a significant average treatment effect. The TWFE event study suggests gradual positive dynamics, but cohort-specific estimators following Callaway and Sant'Anna (2021) find near-zero average treatment effects throughout the event window. Crucially, this large divergence between the TWFE and cohort-specific estimates is itself a key finding: it reveals that standard TWFE estimates are substantially distorted by cohort heterogeneity in this staggered adoption setting, and should not be taken at face value. Italy's adoption path broadly tracks the European average rather than diverging from it, suggesting that the transition to eco

[1] Some sections of this thesis build on earlier versions developed as part of the Research Writing course at CERGE-EI. Those sections have been substantially revised, expanded, and integrated into the present manuscript. The author takes full responsibility for all content.

vehicles across Europe is driven by common technological and regulatory forces, and that national subsidies contributed at the margin but were not the primary driver of the observed shift.

This thesis contributes to a growing literature on the effectiveness of financial incentives for eco-vehicle adoption. Several studies document a positive cross-sectional association between purchase subsidies and EV market shares across countries (Sierzchula et al., 2014; Bakker et al., 2014; Onat et al., 2017). However, cross-sectional evidence cannot isolate the causal effect of a specific policy from confounding country characteristics. This thesis addresses that gap by applying a difference-in-differences design to Italy, a setting that has received limited causal empirical attention, with no published study having applied a quasi-experimental design to the Italian *Ecobonus* specifically. The thesis further combines national, regional, and international evidence to assess both internal validity and external comparability. In terms of methodology, it is most closely related to Jenn, Azevedo, and Ferreira (2013), who apply a difference-in-differences design to US state-level EV incentives, and to Springel (2021), who exploits quasi-experimental variation in Norwegian EV subsidies. Relative to these papers, the contribution here is to bring this identification approach to the Italian context and to complement it with the modern staggered-adoption estimators of Callaway and Sant'Anna (2021) and Sun and Abraham (2021) applied to a European cross-country panel.

The remainder of the thesis is organised as follows. Section 1 provides institutional background on the *Ecobonus* program and the European policy context. Section 2 reviews the related literature. Section 3 describes the data. Section 4 presents the empirical strategy, including the modern staggered-adoption estimators used in the international analysis. Sections 5, 6, and 7 report the main results at each level of analysis. Section 8 presents robustness checks. The final section concludes.

1. Institutional Background

1.1 The European Policy Context

The *Ecobonus* was introduced against the backdrop of a broader set of European Union policies aimed at decarbonising road transport. The transport sector accounts for approximately 25% of global CO_2 emissions (IPCC, 2022), and road vehicles represent the largest share of transport-related emissions within the EU. Italy's transport emissions have historically exceeded the EU average, making the transition to lower-emission vehicles a policy priority both domestically and at the European level.

The EU Green Deal, adopted in 2019 (European Commission, 2019), set the objective of achieving net-zero greenhouse gas emissions by 2050. Within the transport sector, the *Fit for 55* package, proposed in 2021 (European Commission, 2021), required a 55% reduction in average CO_2 emissions from new passenger cars by 2030 relative to 2021 levels, and committed to ending the sale of new internal combustion engine vehicles in EU member states by 2035. These targets created binding pressure on European car markets and provided the regulatory context within which national policies such as the *Ecobonus* were implemented.

EU-level regulation interacts with national incentive programs in important ways. Stricter fleet-average CO_2 standards raise the cost to manufacturers of selling conventional vehicles, which may independently shift production and marketing toward lower-emission models. National purchase subsidies, by contrast, directly lower the cost to consumers. Both mechanisms operate simultaneously in the post-2019 period, which is a relevant consideration when interpreting the empirical results. The analysis in this thesis focuses on the national subsidy as the primary source of variation but cannot separately identify its contribution from that of EU-level regulation, since both changes (the national subsidy and the tightening of EU fleet CO_2 standards) occurred simultaneously for Italy. The cross-national analysis in Section 7 helps gauge the relative importance of these two forces, by comparing Italy's adoption trajectory to that of European countries which introduced subsidies at different points in time under the same EU regulatory framework.

1.2 The Ecobonus Program

The *Ecobonus* is a national purchase subsidy program introduced in Italy in March 2019. The program provides financial incentives for the purchase of new passenger vehicles with low or zero CO_2 emissions, with subsidy amounts differentiated by emission class and conditioned on whether the buyer simultaneously scraps a vehicle registered before 2010 (i.e., trades in an older vehicle for destruction, a practice known as vehicle scrapping).

The eligibility structure is organised around three emission bands. Vehicles with CO_2 emissions below 20 grams per kilometre (fully battery-electric and hydrogen fuel cell vehicles) receive the largest subsidies: EUR 6,000 with simultaneous scrapping and EUR 4,000 without. Vehicles with CO_2 emissions between 21 and 60 grams per kilometre (corresponding broadly to plug-in hybrid vehicles) receive EUR 2,500 with scrapping and EUR 1,500 without. Mild hybrids and conventional internal combustion engine vehicles are not eligible under the *Ecobonus* framework.[2]

The program is administered by the Italian Ministry of Infrastructure and Transport (*Ministero delle Infrastrutture e dei Trasporti*) and funded through annual budget allocations. Subsidies are disbursed at the point of purchase through dealerships, which submit reimbursement claims to the ministry. Funding availability has been a recurring constraint: in several years, annual appropriations were exhausted before the end of the calendar year, temporarily suspending access to the incentive. This creates some within-year variation in the effective availability of subsidies that the annual registration data used in this study do not capture.

The program also co-exists with regional and municipal incentive schemes in some Italian regions, which may provide additional subsidies or preferential access to restricted traffic zones for eco-vehicle owners. These regional policies are not separately identified in the analysis, and their presence may cause the national estimates to partially reflect the combined effect of multiple policy layers rather than the *Ecobonus* in isolation.

1.3 Vehicle Market Context in Italy

Prior to the introduction of the *Ecobonus*, Italy's vehicle market was large and structurally dominated by petrol and diesel technologies. Annual new car registrations averaged approximately 1.6 million units in the years immediately before the policy, of which petrol and diesel vehicles jointly accounted for nearly all sales. The market had recovered gradually from the contraction of the 2011–2013 financial crisis, reaching approximately 1.9 million units in 2017 and 1.9 million in 2018.

Eco-vehicle registrations were growing in the pre-policy period but from a very low base. In 2014, total eco registrations across all low-emission technologies amounted to approximately 22,600 units, representing less than 2% of the market. By 2018, this had risen to approximately 91,800 units, driven primarily by growth in non-plug-in hybrid vehicles. Full battery-electric vehicles remained marginal, with fewer than 5,000 units registered in 2018, and plug-in hybrids totalled around 4,600 units. The market was thus overwhelmingly conventional at the time the *Ecobonus* was introduced.

[2] The eligibility thresholds and subsidy amounts described here correspond to the original 2019 program structure. The program was subsequently renewed and modified in 2020, 2021, and 2022, with adjustments to emission thresholds and funding envelopes, but the core architecture of differentiated incentives by emission class remained in place throughout the period covered by this study.

After 2019, the composition of new registrations shifted markedly. Eco-vehicle registrations rose from 127,000 in 2019 (6.6% market share) to 282,000 in 2020 (20.4%), and continued increasing to 560,000 in 2021 (38.4%), 564,000 in 2022 (42.9%), 701,000 in 2023 (44.7%), and 741,000 in 2024 (47.5%). Two concurrent developments complicate the attribution of this increase. First, the COVID-19 pandemic caused a sharp contraction in total registrations in 2020 and 2021, affecting both supply chains and consumer demand, so some of the increase in eco-vehicle share reflects a decline in conventional registrations rather than an absolute increase in eco sales. Second, broader technological trends (declining battery costs, expanding charging networks, and EU regulatory pressure) were simultaneously pulling consumers toward lower-emission vehicles across all European markets. Italy's network of public EV charging points also expanded rapidly after 2019 (from approximately 9,000 points in 2019 to over 60,000 by 2024; IEA, 2024), which may itself have stimulated eco-vehicle demand independently of the subsidy, and represents an additional confounding factor that the national analysis cannot separately identify. These factors motivate the use of a comparison group and the careful assessment of pre-policy trends in the empirical analysis.

Figure 1 illustrates the evolution of eco and petrol vehicle registrations in Italy over the full sample period, and Figure 2 shows the concurrent expansion of the public EV charging network.

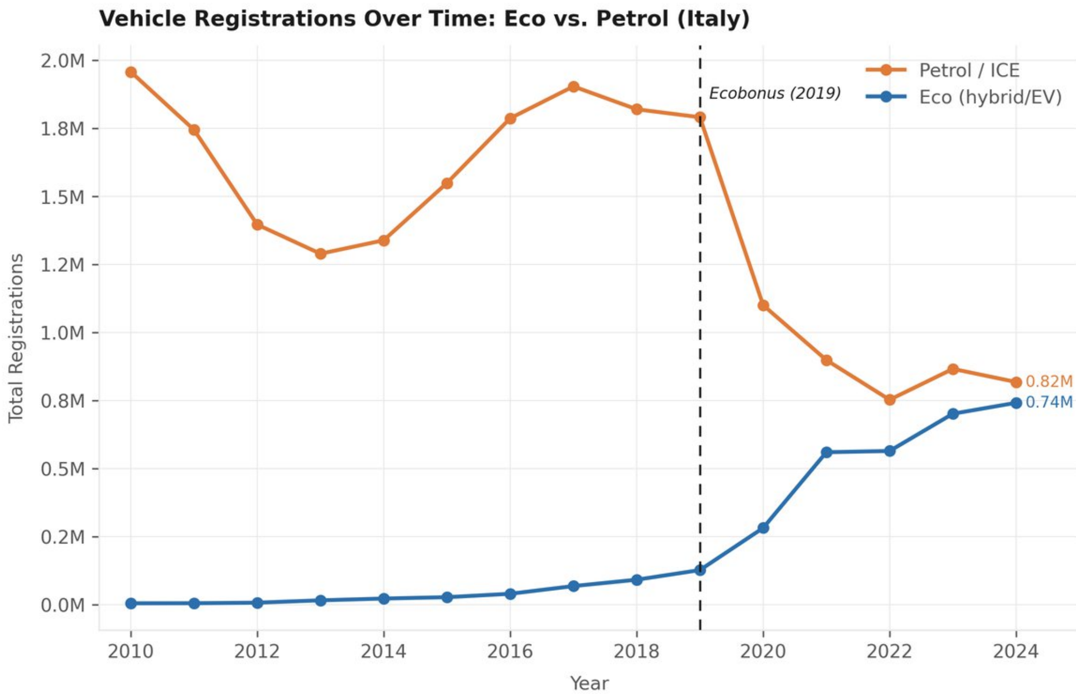

Figure 1: Vehicle Registrations Over Time: Eco vs. Petrol (Italy, 2010–2024). Eco vehicles include hybrids, plug-in hybrids, and battery-electric vehicles. Dashed vertical line marks the introduction of the *Ecobonus* in 2019. The near-flat pre-policy trajectory of eco registrations and the sharp post-2019 acceleration motivate the difference-in-differences design.

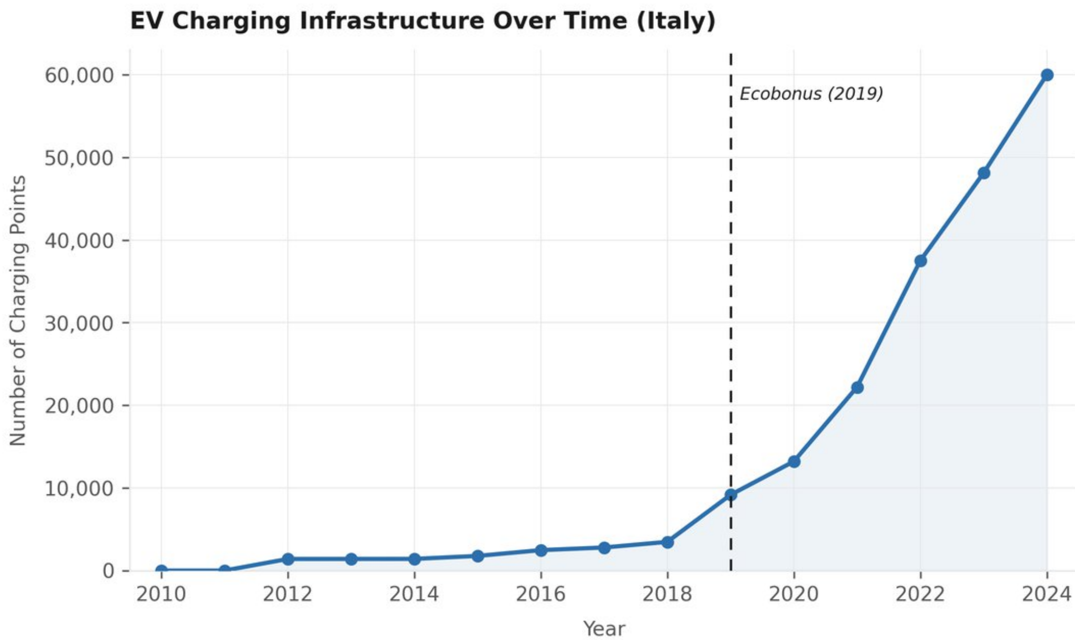

Figure 2: EV Charging Infrastructure Over Time, Italy (2010–2024). Number of publicly available charging points (IEA data). The rapid expansion after 2019 coincides with the introduction of the *Ecobonus* and represents a potential confounding factor discussed in Section 5.

1.4 Implications for Identification

The design of the *Ecobonus* generates two dimensions of variation useful for causal identification. First, the program targets eco vehicles directly and leaves conventional petrol and diesel vehicles unsubsidised, creating cross-sectional variation by vehicle type. Second, the introduction of the program in 2019 creates a temporal break in the treatment indicator, generating before-and-after variation over time. The interaction of these two dimensions (eco vehicles after 2019) forms the basis for the difference-in-differences identification strategy.

The key identifying assumption is that, absent the *Ecobonus*, registrations of eco and petrol vehicles would have followed parallel trends over time. This assumption is plausible to the extent that the two vehicle types were subject to common macroeconomic drivers before 2019, both responding to income, fuel prices, and consumer confidence. It may be violated, however, if eco vehicles were already on a steeper growth trajectory before the policy due to anticipation effects, pre-existing industry investment, or technology diffusion dynamics independent of the subsidy.

The validity of this assumption is assessed empirically using event-study specifications that estimate pre-policy placebo effects. At the national level, pre-treatment coefficients are not statistically different from zero and a joint F-test does not reject parallel pre-trends ($F = 1.07$, $p = 0.376$), supporting the assumption. At the regional level, by contrast, the parallel trends assumption is rejected ($F = 102.99$, $p < 0.001$), suggesting that eco and petrol registrations were already diverging across Italian regions before 2019. This may reflect pre-existing heterogeneity in regional infrastructure, consumer preferences, or local policy environments. The regional results are accordingly treated as descriptive rather than causal, as discussed in detail in Section 5.

A further identification concern is that the post-2019 period coincides with the acceleration of EU fleet CO_2 regulation, which affected all European car markets simultaneously. The national difference-in-differences cannot separately identify the contribution of the *Ecobonus* from that of EU regulation. The international comparison in Section 7 provides partial evidence on this question by examining whether the Italian adoption path differs from that of European countries that introduced subsidies at different points in time, under the assumption that EU regulatory pressure affected all member states equally. Additional descriptive evidence on Italy's vehicle market evolution, fuel prices, and GDP per capita over the sample period is presented in Figures 12 and 13 in Appendix A, which provide further context for the identification setting.

2. Literature Review

This section reviews the literature most closely related to the present thesis, organised into three strands: the economics of technological change and environmental policy; empirical evidence on the effect of financial incentives on eco-vehicle adoption; and methodological contributions on causal identification with staggered policy adoption.

2.1 Directed Technical Change and Environmental Policy

A first body of work examines the relationship between policy and technological innovation in the energy and transport sectors. Newell, Jaffe, and Stavins (1999) test the Hicksian induced innovation hypothesis empirically, using a product-characteristics model applied to household appliances. They find that the post-1973 improvement in the energy efficiency of consumer durables was driven primarily by rising energy prices rather than by autonomous technological change, with regulatory standards playing a secondary role. Their results imply that price instruments and direct subsidies can redirect the composition of innovation toward more efficient technologies, a finding with direct relevance to how purchase subsidies for eco vehicles may stimulate further cost reductions over time.

Acemoglu, Aghion, Bursztyn, and Hemous (2012) build a growth model with endogenous technical change to study how policy instruments shape the allocation of R&D between clean and dirty sectors. They show that a carbon price alone is insufficient for a rapid decarbonisation path because it raises the value of clean innovation but does not directly fund it; conversely, a clean-technology subsidy alone expands R&D but does not penalise dirty inputs. The two instruments are therefore complementary: acting together, a carbon tax redirects market incentives while a subsidy simultaneously stimulates clean research investment. The paper is relevant to the *Ecobonus* context because it provides a theoretical foundation for why purchase subsidies may have dynamic effects beyond the immediate demand stimulus: by increasing the market for eco vehicles, subsidies may induce further investment in the technology and reduce costs over time, consistent with the gradual build-up of the estimated effect documented in this thesis.

2.2 Financial Incentives and Eco-Vehicle Adoption

A more applied literature examines the effect of financial incentives on consumer demand for hybrid and electric vehicles. Beresteanu and Li (2011) estimate a discrete choice model of hybrid vehicle demand in the United States, finding that both fuel costs and federal purchase incentives are significant drivers of consumer choice. Their structural approach decomposes the contributions of price signals and policy instruments to the observed expansion of hybrid sales during the 2000s, providing evidence that demand-side subsidies meaningfully shift market composition even within a short horizon.

Jenn, Azevedo, and Ferreira (2013) provide quasi-experimental evidence on the effect of tax incentives on EV adoption in the United States, exploiting variation in the generosity and availability of state-level tax credits across US states and over time. Using a difference-in-differences design, they find a positive and statistically significant effect of these incentives on hybrid vehicle registrations, with the largest responses observed in the years immediately after each incentive was introduced. This paper is methodologically close to the national DiD analysis in the present thesis, though the identification relies on cross-state variation rather than the vehicle-type comparison used here.

Sierzchula, Bakker, Maat, and van Wee (2014) examine cross-country variation in EV adoption rates using data from 30 countries in 2012. Their regression analysis shows that subsidy generosity and the availability of public charging infrastructure both predict higher national eco-vehicle market shares, whereas socio-demographic characteristics such as household income and education level are less reliably significant across specifications. Although the cross-sectional design cannot establish causality, the results document a robust descriptive correlation between subsidy regimes and adoption outcomes that motivates the causal analysis in the present thesis.

Muehlegger and Rapson (2022) study the incidence and pass-through of EV subsidies in the United States, examining how much of the subsidy benefit is captured by consumers versus producers. They find that pass-through to buyers is indistinguishable from 100%, implying that consumers capture essentially the full value of the subsidy. Their analysis is relevant to the interpretation of the *Ecobonus* results: if Italian dealers absorbed part of the subsidy in higher prices, the estimated demand effect would understate the true consumer benefit of the program relative to a full-pass-through benchmark.

Springel (2021) studies the Norwegian EV market using a two-sided market framework, exploiting variation in both consumer price subsidies and charging station subsidies across municipalities. A key finding is that the relative cost-effectiveness of these two instruments depends on the level of charging infrastructure already in place: in the early phase of adoption, investing in charging stations generated more additional EV purchases per dollar than direct price subsidies, though this advantage diminished as the network matured. Norway's experience differs from Italy's in several important ways, including the size of the subsidies, the pre-existing charging network, and consumer income levels, so the magnitude of the Norwegian estimates cannot be directly applied to the Italian context. Nevertheless, Springel (2021) provides the closest methodological precedent for the national DiD analysis in this thesis.

2.3 Identification with Staggered Policy Adoption

A third strand of the literature addresses methodological challenges in the evaluation of policies adopted at different times by different units, the setting of the international analysis in this thesis. Goodman-Bacon (2021) provides a decomposition theorem showing that, under staggered adoption, the TWFE coefficient is a weighted average of every feasible two-group, two-period DiD estimate in the data. This includes estimates that benchmark later adopters against units that have already received treatment, which is problematic when treatment effects grow over time: such units serve as a "clean" control only if their post-treatment trend matches what would have happened absent treatment, an assumption that fails when effects are heterogeneous. The practical implication is that the aggregate TWFE estimate can be biased in ways that are not apparent from the regression output alone, motivating the diagnostic approach advocated in his paper.

Callaway and Sant'Anna (2021) propose an alternative estimator that computes cohort-specific average treatment effects on the treated (ATTs) and aggregates them in a way that avoids contamination from already-treated controls. Their estimator is more credible than the TWFE when treatment effects are heterogeneous but requires a "never-treated" or "not-yet-treated" comparison group, which limits its application in settings where almost all units eventually adopt treatment.

Sun and Abraham (2021) develop a related approach that addresses the same contamination problem while remaining implementable as a linear regression. By interacting each event-time indicator with cohort membership, their estimator recovers cohort-specific treatment effects that can be aggregated or plotted as an event study, preserving the familiar visual format while avoiding the negative-weighting issue that afflicts the standard TWFE event study.

The present thesis applies both the TWFE event study and an approximation of the Callaway-Sant'Anna estimator to the international panel. As documented in Section 7, the two approaches yield substantially different results: near-zero ATTs from the CS estimator versus large and growing estimates from the TWFE event study, which illustrates the practical relevance of the Goodman-Bacon (2021) critique and motivates the cautious interpretation of the international evidence adopted in this thesis.

2.4 Positioning of the Present Thesis

The present thesis sits at the intersection of the second and third strands reviewed above. Relative to the existing empirical literature, it makes three contributions. First, it provides new quasi-experimental evidence on the effect of a large-scale EV subsidy program in Italy, a setting that has received limited causal empirical attention. Italy represents a particularly interesting case for several reasons: it is one of the largest car markets in the European Union, its pre-policy eco-vehicle adoption rate was among the lowest in Western Europe, and the *Ecobonus* was introduced at a specific and clearly defined date, which allows the construction of a credible control group. Despite these favourable features, no published study has applied a quasi-experimental design specifically to the Italian *Ecobonus*, leaving the causal contribution of the program largely unexamined.

Second, the thesis introduces the regional eco-share analysis as a complement to the national DiD. Documenting the geographic pattern of adoption across all 20 Italian regions provides a directly interpretable headline measure of the policy's association with market composition, and reveals the persistent North–South gradient in eco-vehicle diffusion that aggregate national estimates conceal.

Third, it applies modern staggered-adoption estimators to an international panel of 26 European countries, comparing their results to the standard TWFE and documenting the practical significance of cohort heterogeneity bias in this setting. The divergence between the Callaway-Sant'Anna and TWFE estimates, documented in Section 7, is itself a substantive finding: it suggests that the cross-country literature on EV subsidies may have systematically overstated the causal effect of national policies by relying on TWFE estimators that are contaminated by heterogeneous pre-adoption trajectories.

Relative to the methodological literature, this thesis does not develop new estimators but rather applies and compares existing approaches in an applied policy evaluation context. The value of this exercise lies in illustrating concretely how the choice of estimator shapes the interpretation of the evidence, and in providing a worked example of the Goodman-Bacon (2021) critique in a setting with genuine policy relevance.

3. Data

3.1 Data Sources

The analysis draws on three complementary datasets, each described in turn below.

National dataset. The national dataset contains annual vehicle registration data for Italy disaggregated by fuel type, covering 12 vehicle technology categories over the period 2010–2024. The data are sourced from ANFIA (*Associazione Nazionale Filiera Industria Automobilistica*), from the table *New Car Registrations by Fuel* (spreadsheet: *Alimentazione ed emissioni medie* CO_2 */ Fuel and average* CO_2), available on the ANFIA *Autovetture – Passenger Cars* statistics page. The full sample covers 180 observations (12 vehicle types $\times$ 15 years). The dataset is complemented by three macroeconomic variables: fuel prices (in EUR per 1,000 litres) from the Italian Ministry for the Environment and Energy Security (SISEN); GDP per capita (indicator: *PIL pro capite*, in EUR) from ISTAT (*Istituto Nazionale di Statistica*); and the number of publicly available EV charging points from the IEA (IEA, 2024).

Regional dataset. The regional dataset covers the 20 Italian administrative regions over the period 2014–2024, yielding 440 observations (20 regions $\times$ 2 vehicle types $\times$ 11 years). Vehicle registration counts by fuel type and region are sourced from ACI (*Automobile Club d'Italia*), from the table *Prime iscrizioni autovetture nelle regioni secondo la cilindrata e l'alimentazione* (Chapter 2 of the ACI *Annuario Statistico*). Annual editions were downloaded individually and consolidated into a single panel dataset. Vehicle registrations are disaggregated into two categories (eco vehicles and petrol vehicles), with eco vehicles defined as hybrids, plug-in hybrids, and battery-electric vehicles combined. Population (indicator: *Popolazione al 1° gennaio, regioni*; variable: `popolazione_residente`, in number of residents) and income per capita (indicator: *Reddito medio annuale delle famiglie*; variable: `reddito_disponibile_procapite`, in EUR) at the regional level are sourced from ISTAT (2024). No disaggregated data on public EV charging points at the regional level and year are available for the sample period; charging infrastructure is therefore not included as a control variable in the regional specifications.

International dataset. The international dataset is a panel of 26 European countries over the period 2014–2024, yielding 286 country-year observations. It covers the share of eco vehicles in total new registrations, GDP per capita, fuel prices, and the availability of public charging infrastructure, as well as information on the year in which each country introduced a national EV purchase subsidy program.

New passenger car registrations disaggregated by fuel type are sourced from Eurostat, dataset `road_eqr_carpda` (*New passenger cars by type of motor energy*). From these data, the eco-vehicle share (the share of battery-electric, plug-in hybrid, and hybrid vehicles in total registrations) is constructed for each country-year. GDP per capita is sourced from Eurostat dataset `nama_10_pc` (*GDP and main components per capita*), expressed in EUR. Fuel prices (Euro-Super 95 petrol, EUR per 1,000 litres) are sourced from the European Commission's Weekly Oil Bulletin (Directorate-General for Energy). The year of national subsidy adoption for each country was determined from European Commission policy documents and national ministry sources. Charging infrastructure data (number of publicly available charging points per country-year) are from the IEA *Global EV Outlook* (IEA, 2024), and are available for a subset of 14 countries.

3.2 Sample Construction

National sample. The national analysis uses the full sample of 180 observations. For the difference-in-differences specifications, vehicle types are collapsed into two groups: eco vehicles, comprising fully electric, plug-in hybrid, and all hybrid technologies, and conventional vehicles, comprising petrol, diesel, and other non-electric types. This binary classification mirrors the eligibility structure of the *Ecobonus*. For the triple-difference specification, the eco group is further restricted to fully electric and plug-in hybrid vehicles, which attract the highest subsidies.

Regional sample. The regional analysis covers all 20 Italian regions. In the log-registration specifications, the sample contains registrations for both eco and petrol vehicle categories per region-year (440 observations). In the eco-share specifications, the sample is collapsed to one observation per region-year, with eco share as the outcome variable (220 observations).

International sample. The baseline international analysis uses 257 country-year observations with non-missing eco share, GDP per capita, and fuel price, covering 25 European countries over 2014–2024. The 26th country (Luxembourg) is excluded from some specifications due to missing fuel price data in early years. Three robustness samples are also used. First, the preferred specification excludes early adopters (the United Kingdom, Estonia, and Croatia, which adopted subsidies before 2014 and therefore spend most of the sample period in the treated state, providing limited pre-treatment variation), yielding 231 observations across 22 countries. Second, a charging-infrastructure specification is restricted to the 14 countries for which IEA charging data are available, yielding 132 observations. Third, for the modern staggered-adoption estimators applied in Section 4, the sample excludes early adopters and restricts observations to within a $\pm$5-year event window around each country's adoption date, yielding 196 country-year observations. The subsidy adoption year for each country was verified against European Commission documents and national ministry sources; Table A.12 in Appendix A displays the full distribution of adoption years across the panel.

3.3 Key Variables

Outcome variables. The primary outcome variable in the national analysis is the level of vehicle registrations Y_{it} (in units per year), or its natural logarithm $\ln Y_{it}$ in log specifications. In the regional analysis, the two main outcomes are log registrations $\ln \text{Reg}_{irt}$ and the eco-vehicle share, defined as eco registrations divided by total registrations in each region-year cell:

$$\text{EcoShare}_{rt} = \frac{\text{EcoReg}_{rt}}{\text{TotalReg}_{rt}} \in [0, 1].$$

The eco share is the preferred outcome for headline results, as it abstracts from total market fluctuations and is directly interpretable as a percentage point change in market composition. In the international analysis, the sole outcome variable is EcoShare_{ct}, constructed analogously at the country-year level from Eurostat registration data.

Treatment variables. In the national and regional analyses, the treatment variable is a post-policy binary indicator ($\text{Post}_t = 1$ for years $t \geq 2019$, 0 otherwise) interacted with an eco vehicle indicator ($\text{Eco}_i = 1$ for eco vehicle types, 0 for petrol/conventional types). Their product, $\text{Eco}_i \times \text{Post}_t$, is the DiD interaction term whose coefficient is the main parameter of interest. In the international analysis, treatment is defined relative to each country's subsidy adoption year as $\text{Treated}_{ct} = 1$ for $t \geq \text{PolicyYear}_c$, 0 otherwise. The event-time variable $k = t - \text{PolicyYear}_c$ measures years elapsed since adoption, with $k = -1$ (one year before adoption) as the omitted reference period in all event-study specifications.

Control variables. All specifications with macroeconomic controls use the natural logarithm of GDP per capita ($\ln \text{GDP\_pc}_t$, in EUR, source: ISTAT, indicator *PIL pro capite*, for Italy; Eurostat dataset `nama_10_pc` for the international panel) and the natural logarithm of fuel prices ($\ln \text{FuelPrice}_t$, in EUR per 1,000 litres, source: SISEN for Italy; European Commission Weekly Oil Bulletin for the international panel). Both controls are included in logarithmic form to reduce the influence of outliers and to yield elasticity-style coefficients. The regional specifications additionally include log regional population ($\ln \text{Pop}_{rt}$, in number of residents, source: ISTAT, indicator *Popolazione al 1° gennaio, regioni*) and log regional income per capita ($\ln \text{Inc\_pc}_{rt}$, in EUR, source: ISTAT, indicator *Reddito medio annuale delle famiglie*). Where available, the log of the number of publicly available EV charging points ($\ln \text{Charging}_{ct}$, source: IEA) is included as a control in international specifications to capture supply-side infrastructure variation. Table 1 reports summary statistics for all key variables across the three datasets.

3.4 Descriptive Statistics

Table 1 reports summary statistics for the main variables used in each analysis. Several patterns are worth noting.

In the national sample, eco registrations are on average substantially lower than petrol registrations (mean 27,171 versus 350,087 units), reflecting the dominance of conventional vehicles in the pre-policy years. The standard deviation of eco registrations is large relative to the mean (84,064), reflecting the sharp increase over the sample period: in the pre-policy years (2010–2018), mean eco registrations were approximately 12,000 units per fuel type per year, while in the post-policy years (2019–2024) the mean exceeded 70,000 units. This within-sample variation, driven by the post-2019 acceleration, is the primary source of identification in the national DiD. GDP per capita averages EUR 30,208, with moderate variation over the 15-year period, while fuel prices range from EUR 1,364 to EUR 1,865 per 1,000 litres, with the upper end reflecting the energy price shock of 2022. EV charging infrastructure grew from zero in 2010 to approximately 60,000 publicly available points by 2024, with the large standard deviation (18,863) reflecting the acceleration of infrastructure rollout after 2019.

In the regional sample, the mean eco vehicle share across all region-years is 0.176, but this figure masks substantial heterogeneity over time: the pre-2019 mean eco share is only 0.018, while the post-2019 mean is 0.307, a difference of approximately 29 percentage points. This before-after contrast motivates the regional eco-share specification and is visible in Figure 5. Income per capita ranges from EUR 25,828 in the lowest-income region to EUR 49,814 in the highest, reflecting well-documented North–South disparities in Italy. Population ranges from 122,877 (Valle d'Aosta) to over 10 million (Lombardia), spanning two orders of magnitude. These regional differences in income and population motivate the inclusion of regional controls in the robustness specifications.

In the international sample, the mean eco share is 0.209 across all country-years. Pre-treatment, the mean eco share is 0.077; post-treatment, it rises to 0.316, a difference of 24 percentage points that mirrors the Italian national pattern. GDP per capita shows substantial variation across countries, ranging from EUR 7,269 (Bulgaria) to EUR 137,782 (Luxembourg), underscoring the heterogeneity of the European panel and the importance of country fixed effects in absorbing permanent cross-country differences. Fuel prices range from EUR 921 to EUR 2,296 per 1,000 litres, with Nordic countries consistently at the upper end. The availability of charging infrastructure data is uneven: only 14 of the 26 countries have non-missing observations, which is why the charging specification is treated as a robustness check rather than a baseline.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	*N*
Panel A: National Dataset (2010–2024)					
Eco registrations (units)	27,171	84,064	0	539,815	120
Petrol registrations (units)	350,087	322,389	1,247	1,112,998	60
Fuel price (EUR/1,000 L)	1,627.8	152.9	1,364.3	1,865.3	180
GDP per capita (EUR)	30,208	4,142	26,881	40,226	180
EV charging points	13,659	18,863	0	60,000	180
Panel B: Regional Dataset (2014–2024, region-year level)					
Eco registrations (units)	14,303	25,363	0	129,285	220
Petrol registrations (units)	68,336	72,017	1,989	317,890	220
Eco share	0.176	0.185	0.000	0.589	220
Population	2,998,000	2,461,000	122,877	10,060,574	220
Income per capita (EUR)	37,065	6,007	25,828	49,814	220
Panel C: International Dataset (2014–2024, country-year level)					
Eco share	0.209	0.212	0.000	0.800	266
GDP per capita (EUR)	38,255	24,705	7,269	137,782	286
Fuel price (EUR/1,000 L)	1,343.0	259.0	921.5	2,295.5	282

Notes: Panel A covers 12 vehicle technology categories $\times$ 15 years. Eco registrations and petrol registrations are reported separately; the sample sizes differ because vehicle types are unbalanced in the national data. Panel B is at the region-year level (20 regions $\times$ 11 years). Panel C is at the country-year level (26 countries $\times$ 11 years); *N* varies across variables due to missing values.

4. Empirical Strategy

This section describes the empirical approach used at each of the three levels of analysis: national, regional, and international. Each level exploits a different source of identifying variation and is subject to different identification concerns, which are discussed in turn.

4.1 National Difference-in-Differences

Baseline specification. The national analysis exploits the fact that the *Ecobonus* targets eco vehicles directly while leaving conventional petrol and diesel vehicles unsubsidised. This creates variation across vehicle types that, combined with the temporal break at the policy introduction, forms the basis for a difference-in-differences (DiD) design. The baseline specification is:

$$Y_{it} = \alpha + \beta_1 \text{Post}_t + \beta_2 \text{Eco}_i + \beta_3 (\text{Eco}_i \times \text{Post}_t) + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes vehicle registrations of technology i in year t, Eco_i is an indicator equal to one for eco vehicle types, and Post_t is equal to one for years from 2019 onward. The coefficient of interest, β_3, captures the change in eco vehicle registrations relative to petrol registrations after the policy introduction, relative to the pre-policy difference. Under parallel trends, this is an unbiased estimate of the average treatment effect of the *Ecobonus* on eco registrations.

Extended specifications. I estimate five specifications to assess the robustness of the baseline result. Column (1) reports the simple DiD with heteroskedasticity-robust (HC1) standard errors, providing the baseline estimate without fixed effects. Column (2) adds year fixed effects and vehicle-fuel-type fixed effects, absorbing any common year-level shocks and permanent technology-level differences in registration levels; standard errors are clustered at the year level. The preferred specification, column (3), retains the same fixed effects structure but uses Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with one lag to account for serial correlation in the residuals, which is a natural concern in time-series panels of this kind.

Column (4) uses the natural logarithm of registrations as the outcome variable. This addresses potential scale sensitivity and yields a proportional interpretation of the treatment effect: the coefficient measures the percentage change in eco registrations relative to petrol registrations after 2019. Column (5) reports a triple-difference (DDD) specification. Rather than comparing all eco vehicle types against all petrol vehicle types, it compares the two vehicle categories that attract the highest subsidies (fully battery-electric and plug-in hybrid vehicles) against all other fuel types. This specification exploits an additional dimension of variation: within the eco category, subsidy amounts differ across technologies. Under the assumption that non-subsidy determinants of registrations are common across fuel types, the DDD coefficient provides a sharper estimate of the subsidy effect.

Inference. Serial correlation in annual time-series data can cause standard errors to be severely understated under conventional heteroskedasticity-robust approaches. Column (2) reports cluster-robust standard errors clustered at the year level as an intermediate step, but this approach relies on only $G = 15$ year-clusters, well below the threshold of approximately 50 clusters typically required for cluster standard errors to be reliable (Cameron and Miller, 2015). With so few clusters, the cluster-based variance estimator can be imprecise and is not the preferred inferential approach here. All preferred specifications therefore use Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with one lag, which are consistent in the presence of both heteroskedasticity and autocorrelation of unknown form without requiring a large number of clusters. This is the standard recommendation for DiD designs with a single treated unit or a single treatment date (Bertrand, Duflo, and Mullainathan, 2004).

4.2 National Event Study

To examine the dynamics of the policy effect and to test the parallel trends assumption more formally, I estimate an event-study specification:

$$Y_{it} = \alpha + \sum_{k \neq -1} \beta_k \big(\mathrm{Eco}_i \times \mathbf{1}[t - 2019 = k]\big) + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

where k indexes years relative to the policy introduction, γ_i are vehicle-fuel-type fixed effects, δ_t are year fixed effects, and HAC standard errors are used throughout. The omitted reference period is $k = -1$ (year 2018), so all coefficients are measured relative to the pre-policy baseline year. The window covers five years before and five years after the policy ($k \in [-5, 5]$), spanning 2014 to 2024.

The event-study serves two purposes. First, the pre-policy coefficients ($k \in \{-5, -4, -3, -2\}$) provide a direct test of the parallel trends assumption: if eco and petrol registrations were evolving similarly before 2019, these coefficients should be close to zero. I assess this formally using a joint F-test of the restriction $\beta_{-5} = \beta_{-4} = \beta_{-3} = \beta_{-2} = 0$. Second, the post-policy coefficients trace the dynamic path of the treatment effect, allowing me to examine whether the effect is immediate or builds over time.

4.3 Regional Analysis

Identification context. The *Ecobonus* is a national policy: all Italian regions face the same treatment timing and the same subsidy amounts. This means that the regional analysis cannot exploit cross-regional variation in treatment assignment, and the difference-in-differences strategy at the regional level continues to rely on the comparison between eco and petrol vehicle types within and across regions over time. The regional panel adds two elements that are absent from the national analysis: cross-regional heterogeneity in the level and growth of eco-vehicle adoption, and region-by-year fixed effects that absorb any region-specific time trend common to both vehicle types.

Log-registration specification. The main regional specification uses the log of vehicle registrations as the outcome:

$$\log(\text{Reg}_{irt}) = \alpha + \beta(\text{Eco}_i \times \text{Post}_t) + \gamma_{rt} + \delta_i + \varepsilon_{irt} \tag{3}$$

where Reg_{irt} denotes registrations for vehicle type i in region r at time t, γ_{rt} are region-by-year fixed effects, δ_i are vehicle-type fixed effects, and standard errors are clustered at the region level. The coefficient β captures the proportional change in eco registrations relative to petrol registrations after 2019, net of any region-specific common trends.

Eco-share specification. Following feedback from the thesis supervisor, I also estimate a specification using the regional eco-vehicle share as the outcome variable. This provides a directly interpretable headline number: the average change in eco vehicles as a share of all new registrations across Italian regions after 2019, expressed in percentage points. The share specification collapses the data to one observation per region-year and estimates:

$$\text{EcoShare}_{rt} = \alpha + \beta\,\text{Post}_t + \gamma_r + \delta_t + X_{rt}'\theta + \varepsilon_{rt} \tag{4}$$

where EcoShare_{rt} is the share of eco registrations in total registrations for region r in year t, γ_r are region fixed effects, δ_t are year fixed effects, and X_{rt} optionally includes log regional income per capita and log population. Standard errors are clustered at the region level. I estimate four variants: a specification with region fixed effects only (S1), one adding year fixed effects (S2), one adding controls (S3), and one excluding 2020 to address COVID-related disruptions (S4).

Regional event study. I complement both specifications with a regional event-study design that replaces Post_t with a full set of year dummies:

$$\log(\text{Reg}_{irt}) = \alpha + \sum_{k \neq -1} \beta_k \big(\text{Eco}_i \times \mathbf{1}[t - 2019 = k]\big) + \gamma_{rt} + \delta_i + \varepsilon_{irt} \tag{5}$$

with the same fixed effects and clustering as in equation (3). The pre-policy coefficients and a joint F-test assess the parallel trends assumption in the regional setting.

4.4 International Analysis

Two-way fixed effects specification. The international analysis exploits cross-country variation in subsidy adoption timing. Countries introduced EV purchase subsidies at different points between 2011 and 2023, providing staggered variation in treatment that can be used for identification. The main outcome variable is the share of eco vehicles in total new registrations. The baseline two-way fixed effects (TWFE) DiD specification is:

$$\text{EcoShare}_{ct} = \alpha + \beta\,\text{Treated}_{ct} + \gamma_c + \delta_t + X_{ct}'\theta + \varepsilon_{ct} \tag{6}$$

where c indexes countries, γ_c are country fixed effects, δ_t are year fixed effects, and X_{ct} includes log GDP per capita and log fuel prices. Standard errors are clustered at the country level. Three versions are estimated: a baseline using all 25 countries (257 observations), a robustness specification excluding early adopters (the United Kingdom, Estonia, and Croatia, which adopted subsidies before 2014 and complicate identification by spending most of the sample in the treated state), and a specification adding log charging infrastructure for the 14 countries with available data.

TWFE event study. To examine dynamic effects and test pre-trends, I estimate:

$$\text{EcoShare}_{ct} = \alpha + \sum_{k\neq -1} \beta_k \mathbf{1}[\text{EventTime}_{ct} = k] + \gamma_c + \delta_t + X_{ct}'\theta + \varepsilon_{ct} \tag{7}$$

where $\text{EventTime}_{ct} = t - \text{PolicyYear}_c$ measures years since country c adopted a subsidy, with $k = -1$ as the omitted reference period. The window spans $k \in [-5, 5]$. Three specifications are estimated: ES1 using all countries, ES2 excluding early adopters, and ES3 adding charging infrastructure, with the preferred specification being ES2.

Limitations of the TWFE estimator with staggered adoption. A well-known limitation of the TWFE estimator in settings with heterogeneous treatment timing is that it uses already-treated units as implicit controls for later-treated units. When treatment effects are heterogeneous across cohorts or grow over time (as is plausible for EV subsidies, whose effects may take several years to materialise), the TWFE estimate can be biased or even have the wrong sign. This concern is particularly relevant in the international panel, where adoption dates span more than a decade and the number of countries per cohort is small.

Callaway-Sant'Anna and Sun-Abraham estimators. To address this concern, I implement two modern staggered-adoption estimators as robustness checks. First, following Callaway and Sant'Anna (2021), I compute cohort-specific average treatment effects on the treated (ATTs) for each event-time relative to adoption, using not-yet-treated units as the control group. The aggregate dynamic ATT is then obtained as a weighted average across cohorts. Second, I implement the interaction-weighted estimator of Sun and Abraham (2021), which avoids contamination by restricting each cohort's comparison to its own "clean" control units. Both estimators are applied to the sample excluding early adopters. The results from these estimators are compared directly to the TWFE event study to assess whether heterogeneous treatment effects distort the baseline estimates.

5. Results: National Analysis

This section presents the main empirical findings from the national difference-in-differences analysis. Before turning to the regression estimates, I briefly document the descriptive patterns in the data that motivate the empirical strategy.

5.1 Descriptive Evidence

Figure 1 in Section 1 plots annual vehicle registrations for eco and petrol vehicles over 2010–2024 and provides the visual motivation for the DiD design: eco registrations are nearly flat before 2019 and accelerate sharply thereafter, while petrol registrations are stable or declining. Figure 3 below disaggregates the post-2019 acceleration by technology, showing which vehicle categories drove the shift.

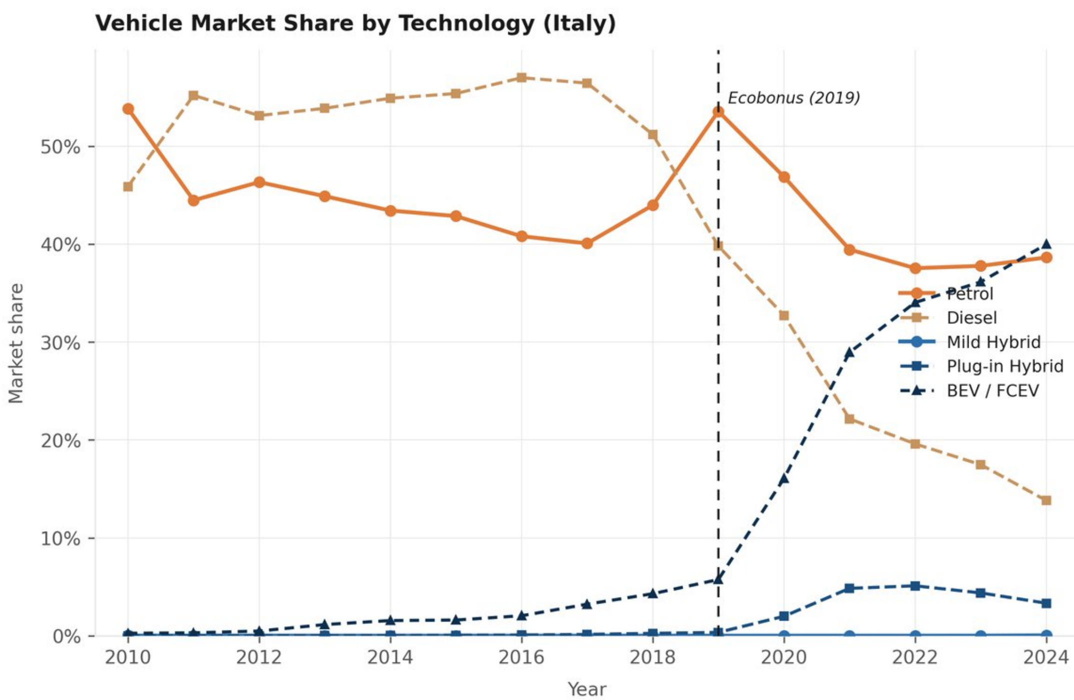

Figure 3: Vehicle Market Share by Technology, Italy (2010–2024). Each line shows the share of total new registrations attributable to one fuel/technology category. The acceleration in Mild Hybrid, Plug-in Hybrid, and BEV/FCEV shares after 2019 is consistent with the subsidy structure of the *Ecobonus*, which provides the largest incentives to zero-emission and plug-in technologies.

Figure 3 shows that the acceleration in eco adoption after 2019 is driven initially by non-plug-in hybrids (the largest technology category in the eco group) and increasingly by fully electric and plug-in hybrid vehicles in later years. This compositional shift is consistent with the subsidy structure of the *Ecobonus*, which offers the highest incentives to zero-emission and plug-in technologies.

These descriptive patterns are consistent with a policy effect, but they do not rule out confounding factors, including EU fleet regulation, falling battery costs, and COVID-related demand shifts, that affected vehicle markets across Europe simultaneously. The COVID-19 pandemic in particular affected both eco and petrol markets in 2020, though the within-type comparison in the DiD absorbs any common shock; the international analysis in Section 7 provides further evidence on whether the observed Italian trajectory is distinguishable from peer countries subject to the same pandemic disruption. The regression analysis exploits the within-year comparison between eco and petrol registrations to control for these common shocks.

5.2 Baseline Estimates

Table 2 reports the main national regression results. Across all five specifications, the coefficient on $\text{Eco}_i \times \text{Post}_t$ is positive and statistically significant at the 1% level, indicating that eco vehicle registrations increased substantially relative to petrol registrations after the introduction of the *Ecobonus*.

In the baseline specification (Column 1), the estimated effect is 209,268 additional eco vehicle registrations per year relative to petrol vehicles (SE = 78,641, $p = 0.008$).

Column (2) adds year and vehicle-fuel-type fixed effects, absorbing common time shocks and permanent technology-level heterogeneity. The point estimate remains at 209,268, while the standard error falls to 56,165 under year-clustered standard errors. The preferred specification, Column (3), retains this fixed-effects structure and uses HAC standard errors with one lag to account for serial correlation in the residuals. This yields a standard error of 41,420, the smallest across all specifications, and the coefficient remains 209,268 ($p < 0.001$). The striking stability of the point estimate across columns (1) through (3) is expected: because the DiD comparison is between eco and petrol vehicle types within the same year, common macroeconomic variation, captured by time fixed effects, is differenced out. The coefficient is therefore mechanically invariant to macroeconomic controls conditional on the fixed effects structure.

The log specification (Column 4) estimates a coefficient of 2.663 ($p < 0.001$), implying that eco registrations grew by a factor of approximately $e^{2.663} \approx 14.3$ relative to petrol registrations after 2019. This large proportional effect is consistent with the low base level of eco registrations before the policy: a large absolute change in a small base produces a large log-change. The triple-difference specification (Column 5) compares fully battery-electric and plug-in hybrid vehicles (the categories receiving the highest subsidies) against all other fuel types. The estimated coefficient is 179,309

(SE = 32,052, $p < 0.001$), somewhat smaller than the baseline, reflecting the fact that the most heavily subsidised technologies represent a subset of all eco vehicles. The consistency of the DDD result with the main DiD provides additional support for a subsidy mechanism.

Table 2: Effect of the Ecobonus on Vehicle Registrations: National Analysis

	(1) Baseline	(2) +FE	(3) Preferred	(4) Log	(5) Triple-Diff
Eco × Post	209,268***	209,268***	209,268***	2.663***	
	(78,641)	(56,165)	(41,420)	(0.460)	
$\text{Eco}_{\text{BEV/PHEV}}$ × Post					179,309***
					(32,052)
Year FE	No	Yes	Yes	Yes	Yes
Vehicle-type FE	No	Yes	Yes	Yes	Yes
SE type	HC1	Cluster-yr	HAC	HAC	HAC
Dep. variable	Regs	Regs	Regs	log(Regs)	Regs
Observations	180	180	180	180	180
R^2	0.413	0.847	0.847	0.890	0.839

Notes: Eco vehicles are the treatment group; petrol vehicles are the control group. $\text{Post}_t = 1$ for years ≥ 2019. Column (5) compares BEV and PHEV technologies against all other types. HAC = Newey–West, one lag. The point estimate is identical across columns (1)–(3) because the macroeconomic controls (fuel price, GDP per capita) vary only at the year level and are therefore identical for eco and petrol vehicle types within each year; by the Frisch-Waugh-Lovell theorem they cannot shift the DiD coefficient once time variation is absorbed. The columns differ in their fixed-effects structure and standard error approach. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 Dynamic Effects and Pre-Trends

The event-study specification in equation (2) allows me to examine the timing of the treatment effect and to test the parallel trends assumption formally. Figure 4 plots the estimated coefficients; Table 3 reports their values.

Pre-policy period. The four pre-policy coefficients ($t-5$ through $t-2$) are economically small and statistically insignificant. Their values range from $-23{,}916$ at $t-2$ to 111,623 at $t-5$, with large standard errors relative to the point estimates in all cases. A joint F-test of the restriction $\beta_{-5} = \beta_{-4} = \beta_{-3} = \beta_{-2} = 0$ does not reject the null ($F = 1.07$, $p = 0.376$). This constitutes direct evidence that eco and petrol registrations were not on diverging pre-policy trends, which supports the key identifying assumption of the difference-in-differences design.

Post-policy dynamics. The coefficient at $t+0$ (year 2019, the year the policy was introduced) is small and insignificant (11,736, SE = 97,735). This absence of an immediate effect is consistent with the implementation timeline of the *Ecobonus*: the program was launched in March 2019, mid-year, and take-up in the first year may have been limited by consumer awareness of the new incentive, supply constraints on eco-vehicle models, and the administrative time required for dealerships to integrate the subsidy disbursement process. From $t+1$ onward, coefficients become large and statistically significant, rising from 203,579 at $t+1$ to 288,760 at $t+2$, 325,791 at $t+3$, and plateauing around 314,000–332,000 at $t+4$ and $t+5$. This gradual build-up is consistent with a dynamic adoption process in which the initial market response is muted but grows as awareness spreads, model variety expands (automakers invested substantially in electrification over 2020–2023 in anticipation of the 2035 ICE ban), and the stock of charging infrastructure increases, reducing range anxiety for prospective buyers. The levelling-off at $t+4$ and $t+5$ may reflect market saturation in the segment of early adopters or the effects of funding exhaustion in some annual budget cycles, both of which are consistent with the program's documented history of mid-year fund depletion.

The pattern of pre-policy flat coefficients followed by a post-policy step increase is the hallmark of a clean difference-in-differences design. It rules out the alternative explanation that eco registrations were already on a faster growth trajectory before 2019 and would have diverged from petrol registrations regardless of the policy.

Table 3: National Event Study: Dynamic Effects of the Ecobonus

Event time	Coefficient	Std. Error
$t-5$	111,623	(77,172)
$t-4$	59,703	(77,776)
$t-3$	1,841	(97,487)
$t-2$	−23,916	(107,476)
$t+0$	11,736	(97,735)
$t+1$	203,579***	(73,528)
$t+2$	288,760***	(89,401)
$t+3$	325,791***	(99,753)
$t+4$	314,521***	(95,276)
$t+5$	331,591***	(102,915)
Pre-trends F-test	$F = 1.07,\ p = 0.376$	
Observations	132	
R^2	0.846	

Notes: Omitted reference period is $t-1$ (2018). Year and vehicle-fuel-type fixed effects included. HAC standard errors (Newey–West, one lag). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

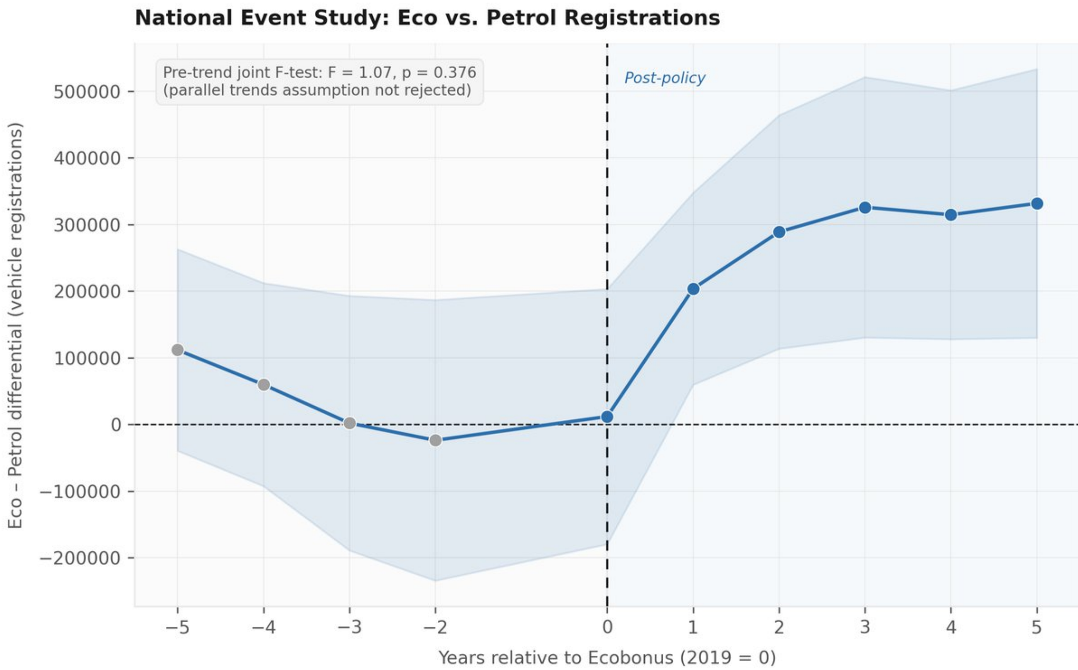

Figure 4: National Event Study: Dynamic Effects of the *Ecobonus*. Coefficients from equation (2). Grey dots indicate pre-policy periods; blue dots indicate post-policy periods. Shaded band is the 95% confidence interval (HAC standard errors, Newey–West one lag). Baseline period is $t-1$ (2018). The annotation box reports the joint pre-trend F-test ($F = 1.07$, $p = 0.376$).

5.4 Back-of-the-Envelope Calculation

To contextualise the magnitude of the estimated effect, I compute a simple back-of-the-envelope measure of the policy's aggregate scale. Using the preferred fixed-effects estimate of 209,268 additional eco registrations per year and applying it uniformly across the six post-policy years (2019–2024), the implied cumulative effect is approximately 1,255,609 additional eco vehicle registrations over the period. Based on the 95% confidence interval of the preferred estimate (which spans 127,985 to 290,551 additional registrations per year), the implied cumulative range is approximately 595,113 to 1,916,105 additional registrations.

These figures should be interpreted with caution for several reasons. First, the DiD estimate is identified off the comparison with petrol vehicles, so it captures the effect relative to what would have happened in the counterfactual. Second, applying a constant annual effect across all six years ignores the event-study evidence of a gradual increase, which suggests the actual effect was smaller in 2019 and larger from 2021 onward. Third, the calculation abstracts from general equilibrium effects, such as whether subsidised eco purchases substituted for petrol purchases that would have occurred anyway or instead expanded the total size of the market. Nevertheless, the implied order of magnitude (roughly one to two million additional eco registrations over six years) suggests the *Ecobonus* was associated with a large shift in market composition during this period.

6. Results: Regional Analysis

The regional analysis examines how the post-2019 acceleration in eco-vehicle adoption was distributed across Italian regions. The section proceeds in four steps: a descriptive overview of regional heterogeneity, the log-registration DiD and event study (which provide the parallel trends test), the eco-share DiD (which provides the headline interpretable result), and an interpretation of the combined evidence.

6.1 Descriptive Evidence: Regional Heterogeneity

Figure 5 shows the evolution of eco-vehicle market share by Italian macro-area over 2014–2024. Several patterns are worth noting. First, eco shares were extremely low and broadly similar across all three macro-areas before 2019: the national mean eco share in the pre-policy years was below 2%. Second, all three macro-areas experienced a sharp increase in eco share after 2019, consistent with the national evidence. Third, the North and Centre reached higher eco shares by 2024 (mean 48.3% and 45.8%, respectively) than the South and Islands (mean 38.9%), a gap of approximately 9 percentage points. The increase from pre- to post-2019 was also larger in the North (+31.3 pp) than in the South (+25.8 pp).

By 2024, eco vehicles accounted for more than 40% of new registrations in 18 of the 20 Italian regions. The highest eco shares were recorded in Lazio (55.1%), Valle d'Aosta (52.8%), and Toscana (50.9%); the lowest in Molise (31.7%) and Campania (35.3%), both in the South. The presence of Lazio (which includes Rome) among the leaders likely reflects the combination of urban mobility incentives and a large urban consumer base. The relatively lower shares in Southern regions are consistent with the income and infrastructure disparities documented in the descriptive statistics.

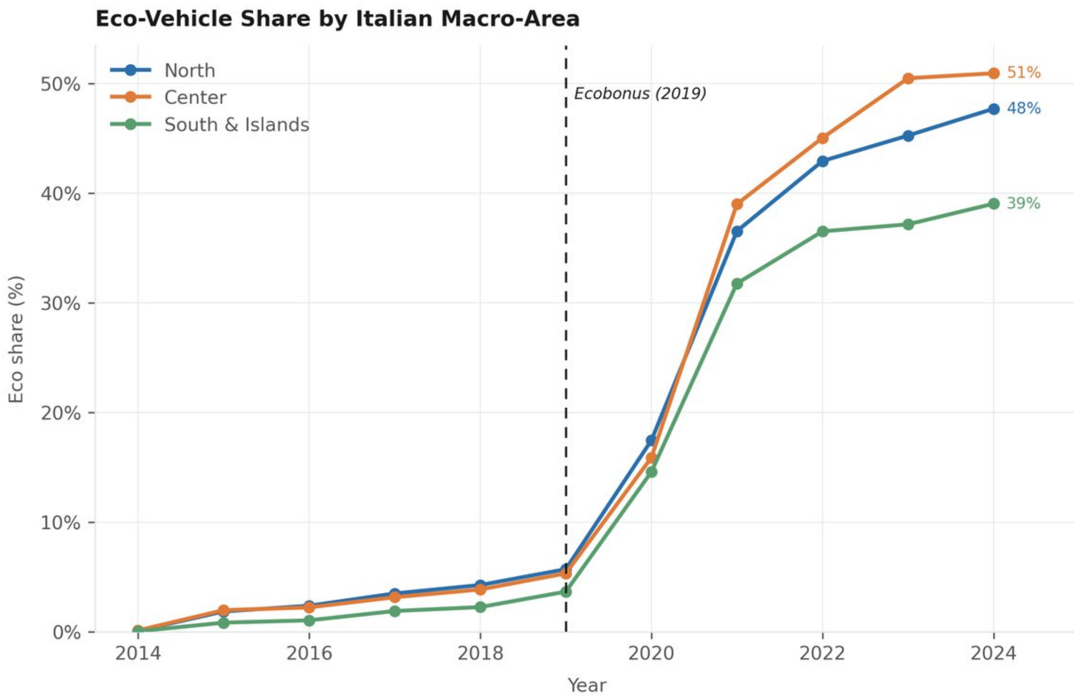

Figure 5: Eco-Vehicle Share by Italian Macro-Area (2014–2024). Each series shows the weighted average eco-vehicle share across regions within the macro-area. Dashed vertical line marks 2019. Endpoint labels show the 2024 eco share for each macro-area (North: 48%; Centre: 46%; South and Islands: 39%).

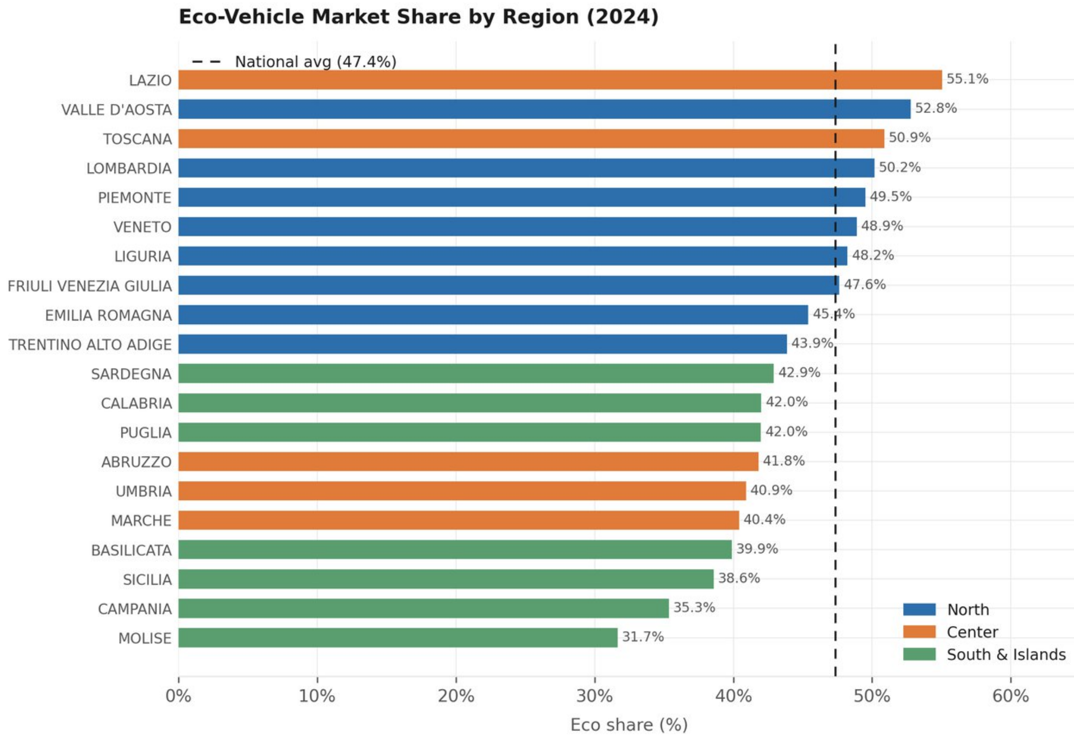

Figure 6: Eco-Vehicle Market Share by Region (2024). Horizontal bars sorted by eco share within each macro-area (blue = North; orange = Centre; green = South and Islands). Dashed vertical line marks the national average (47.5%). All regions in the North and Centre exceed 40%; the two lowest values are Molise (31.7%) and Campania (35.3%) in the South.

This regional heterogeneity is economically informative but raises an important identification concern. The event-study results below show that eco and petrol registrations were already on diverging paths across regions before 2019, which limits the causal interpretation of the regional DiD estimates.

6.2 Log-Registration DiD and Pre-Trends Test

Table 4 reports the main regional DiD result using log registrations as the outcome variable. The coefficient on $\text{Eco}_i \times \text{Post}_t$ is 3.620 (SE = 0.093, $p < 0.001$). This large log-coefficient reflects the near-zero base of eco registrations before the policy: eco vehicles went from essentially absent to a large share of regional markets over this period, so even a modest absolute increase produces a very large proportional change relative to the petrol baseline.

Table 4: Effect of the Ecobonus on Vehicle Registrations: Regional Analysis

	(1) log(Registrations)
Eco × Post	3.6197***
	(0.0929)
Region × Year FE	Yes
Vehicle-type FE	Yes
SE clustering	Region
Observations	440
R^2	0.920
Adj. R^2	0.838

Notes: Standard errors clustered at the region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The regional event-study results in Table 5 and Figure 14 in Appendix A reveal the limitation of this approach. While the post-policy coefficients are large and significant from $t+0$ onward (rising from 0.418 at $t+0$ to 3.230 at $t+5$), the pre-policy coefficients are also statistically significant and economically meaningful. The coefficient at $t-5$ is -4.103 (SE = 0.230), and those at $t-4$, $t-3$, and $t-2$ are also negative and significant, indicating that eco and petrol registrations were already on diverging log-trajectories before the *Ecobonus* was introduced. A joint F-test strongly rejects the null of parallel pre-trends ($F = 102.99$, $p < 0.001$).

The pre-trends pattern in the regional event study is the mirror image of the national event study: nationally, where the analysis compares eco against petrol in aggregate, the parallel trends assumption holds; regionally, where we additionally allow the comparison to vary across regions, it does not. This suggests that the pre-existing divergence is driven by cross-regional heterogeneity rather than by a common national trend. Regions with higher baseline incomes, better infrastructure, or stronger environmental preferences may have been on steeper eco adoption trajectories already before 2019, producing the negative pre-trend coefficients observed.

Table 5: Regional Event Study: Dynamic Effects and Pre-Trends Test

Event time	Coefficient	Std. Error
$t-5$	-4.1028***	(0.2295)
$t-4$	-0.9536***	(0.1160)
$t-3$	-0.7316***	(0.1111)
$t-2$	-0.2042***	(0.0429)
$t+0$	0.4183***	(0.0404)
$t+1$	1.8239***	(0.0883)
$t+2$	2.8495***	(0.1220)
$t+3$	3.0973***	(0.1420)
$t+4$	3.1087***	(0.1541)
$t+5$	3.2299***	(0.1273)
Pre-trends F-test	$F = 102.99$, $p < 0.001$	
Observations	440	
R^2	0.992	

Notes: Omitted reference period is $t-1$ (2018). Region-by-year and vehicle-type fixed effects included. Standard errors clustered at the region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.3 Eco-Share DiD: Headline Results

To provide a directly interpretable measure of the policy's association with market composition, I estimate the eco-share specification in equation (4). The outcome variable is the share of eco vehicles in total registrations at the region-year level, expressed as a decimal (ranging from 0 to 1). The coefficient on Post_t is interpreted as the average change in eco-vehicle market share across Italian regions after 2019, in percentage points.

Table 6 reports the four share specifications. Across all columns, the coefficient is positive, large, and statistically significant at the 1% level. In the simplest specification with region fixed effects only (Column S1), the estimated effect is 0.289 (SE = 0.009), implying that the eco-vehicle share increased by approximately 28.9 percentage points across Italian regions after 2019, relative to the pre-policy average. Adding year fixed effects (Column S2), which absorb common time trends, reduces the estimate slightly to 0.263 (26.3 pp), reflecting that a portion of the increase in eco share was part of a broader European-wide trend rather than specific to Italy's 2019 policy. Adding controls for regional income and population (Column S3) raises the estimate to 0.296 (29.6 pp), and excluding 2020 to address COVID-related disruptions (Column S4) yields 0.313 (31.3 pp). The consistency across specifications suggests the headline result is not sensitive to the choice of controls or sample composition.

Table 6: Effect of the Ecobonus on Eco-Vehicle Market Share: Regional Analysis

	(S1) Region FE	(S2) +Year FE	(S3) +Controls	(S4) Excl. 2020
Post-policy	0.2888***	0.2628***	0.2960***	0.3133***
	(0.0090)	(0.0090)	(0.0280)	(0.0309)
Region FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Income & pop. controls	No	No	Yes	Yes
Excl. 2020	No	No	No	Yes
SE clustering	Region	Region	Region	Region
Observations	220	220	220	200
R^2	0.624	0.971	0.974	0.978

Notes: Dependent variable is the share of eco vehicles in total new registrations (region-year level). Post-policy = 1 for years $\geq$ 2019. Standard errors clustered at the region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.4 Interpretation

The regional results paint a consistent but cautious picture. On one hand, they are consistent with the national finding of a large increase in eco-vehicle adoption after 2019: the preferred share specification (Column S2) implies that eco vehicles gained approximately 26 percentage points of market share across Italian regions after the *Ecobonus* was introduced. This is a large effect and is robust across specifications. The descriptive evidence further shows that this increase occurred in all three macro-areas and in all 20 Italian regions, with eco shares exceeding 40% in 18 of the 20 regions by 2024.

The persistent North–South gradient documented in Figure 5 is economically interpretable. Northern regions benefit from higher average household incomes, which make the upfront purchase cost of eco vehicles more manageable even after the subsidy, as well as a denser network of urban infrastructure and higher environmental awareness among consumers. Central regions (notably Lazio, which includes Rome) show eco shares comparable to the North, likely reflecting the combination of urban mobility incentives, restricted traffic zones that favour zero-emission vehicles, and a large concentration of public-sector employees whose commuting patterns differ from those in Southern regions. The Southern regions and Islands face compounding disadvantages: lower average incomes, sparser charging infrastructure, and a higher reliance on vehicles for long-distance rural travel, where range anxiety remains a more binding constraint. The result is that the *Ecobonus* subsidy appears to have been effectively taken up across the country, but the magnitude of market share gains correlates with structural conditions that the policy itself does not directly address.

On the other hand, the failure of parallel trends in the log-registration event study ($F = 102.99$, $p < 0.001$) means that the regional DiD coefficients (both in levels and in shares) cannot be interpreted as clean causal estimates of the *Ecobonus* effect. Pre-existing differences in eco adoption trajectories across regions, driven by income disparities, infrastructure availability, and consumer preferences, were already producing divergence before 2019. Because the *Ecobonus* is a national policy that does not vary across regions, the regional DiD cannot isolate the policy effect from these pre-existing trends.

I therefore treat the regional analysis as descriptive evidence on the geographic pattern of eco-vehicle diffusion in Italy rather than as a causal estimate of the subsidy program. The national DiD, which compares eco against petrol vehicle types in the aggregate and passes the parallel trends test, remains the primary source of causal identification in this thesis.

7. Results: International Analysis

The international analysis asks whether EV purchase subsidies are associated with higher eco-vehicle shares in a cross-country panel of 26 European countries over 2014–2024. The section presents three sets of results in sequence: the static TWFE DiD, the TWFE event study, and the modern staggered-adoption estimators (Callaway-Sant'Anna and Sun-Abraham). Together, they provide a careful, qualified picture of the international evidence.

7.1 Descriptive Evidence

Figure 7 shows the distribution of subsidy adoption years across European countries. Adoption is genuinely staggered: the United Kingdom and Estonia adopted subsidies as early as 2011, while Denmark and Cyprus did not introduce them until 2023. Italy adopted in 2019, along with Belgium, Hungary, Luxembourg, Netherlands, and Slovakia, a large cohort that reduces the number of clean "not yet treated" controls available for that event time.

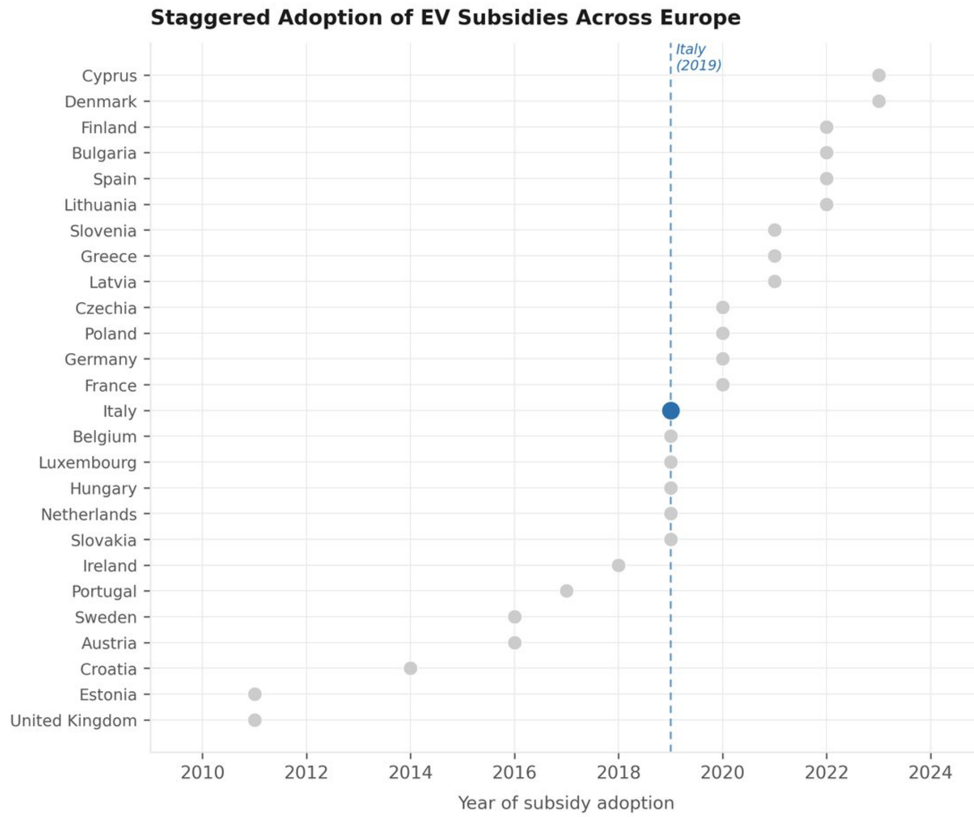

Figure 7: Staggered Adoption of EV Subsidies Across Europe (2011–2023). Each dot marks the year in which a country introduced a national EV purchase subsidy program. Italy (2019) is highlighted in blue. Countries are listed in order of adoption year. Early adopters (United Kingdom, Estonia, Croatia) are excluded from the preferred event-study specification (ES2) and from the modern staggered-adoption estimators.

Figure 8 plots the path of eco-vehicle share around the time of subsidy adoption for both TWFE and Callaway-Sant'Anna estimates, compared to the average path of other European countries. In the first year after adoption ($t+0$), Italy gained 1.9 percentage points relative to its pre-adoption share, while the EU average gained 5.6 pp. By $t+2$, Italy had gained 31.9 pp versus an EU average of 22.6 pp; by $t+5$, Italy reached 42.8 pp while the EU average reached 47.3 pp. Italy's trajectory therefore broadly tracks the European average, without evidence of unusual acceleration or deceleration relative to peer countries.

7.2 Static Difference-in-Differences

Table 7 reports the static TWFE DiD results. Across all three specifications (baseline, excluding early adopters, and including charging infrastructure), the estimated average treatment effect on eco-vehicle share is small and not statistically significant. The baseline coefficient is 0.0002 (SE = 0.029, $p = 0.994$), the specification excluding early adopters yields -0.016 (SE = 0.019, $p = 0.391$), and the specification with charging infrastructure gives -0.020 (SE = 0.028, $p = 0.477$). In all cases, the confidence interval is wide and includes both positive and negative values of economically meaningful magnitude, so the null result should not be interpreted as evidence of no effect; rather, the static TWFE is simply uninformative about whether an average treatment effect exists.

The absence of a significant static effect is consistent with the gradual adoption dynamics expected for EV subsidies: the effect of a purchase incentive on market share is unlikely to be fully realised in the year of adoption, but rather accumulates over several years as models proliferate, infrastructure expands, and consumer habits adjust. The event-study results below examine whether this dynamic pattern is visible in the data.

Table 7: International DiD: Effect of Subsidy Adoption on Eco-Vehicle Share

	(1) Baseline	(2) Excl. early adopters	(3) +Charging
Treated	0.0002	-0.0161	-0.0200
	(0.0286)	(0.0188)	(0.0281)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Log GDP per capita	Yes	Yes	Yes
Log fuel price	Yes	Yes	Yes
Log charging points	No	No	Yes
SE clustering	Country	Country	Country
Observations	257	231	132
Countries	25	22	14
R^2	0.883	0.889	0.948

Notes: Dependent variable is eco-vehicle share. Early adopters excluded in column (2) are United Kingdom, Estonia, and Croatia. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

7.3 TWFE Event Study

Table 8 reports the TWFE event-study estimates. The preferred specification (ES2, excluding early adopters) shows a clear pattern of growing positive effects after adoption. Post-policy coefficients are statistically significant from $t+1$ onward, rising from 0.085 at $t+1$ (SE = 0.026, $p = 0.001$) to 0.121 at $t+2$, 0.162 at $t+3$, 0.208 at $t+4$, and 0.270 at $t+5$ (SE = 0.084, $p = 0.001$).

This pattern suggests that the association between subsidy adoption and eco-vehicle share is not contemporaneous but develops over time, with effects reaching more than 20 percentage points after four years.

The joint pre-trends test does not reject the null of zero pre-treatment effects in ES2 ($p = 0.120$). However, individual pre-treatment coefficients at $t-5$ through $t-2$ are negative and statistically significant, which is a warning sign. Negative pre-treatment coefficients in an event study suggest that the treated units had relatively lower eco shares before adopting subsidies than the control units, which is plausible if countries adopted subsidies precisely because they were lagging in eco-vehicle adoption, creating reverse causality in the treatment indicator. This pattern is sometimes called "Ashenfelter's dip" in the context of training programs, and it means that the post-treatment recovery may partly reflect mean-reversion rather than a causal policy effect.

The full-sample specification (ES1) and the specification with charging infrastructure (ES3) produce qualitatively similar post-treatment dynamics, though with somewhat smaller and less precisely estimated effects in ES3, consistent with the smaller and less representative sample available for the charging specification.

Table 8: International Event Study: Dynamic Effects of Subsidy Adoption on Eco-Vehicle Share

Event time	ES1: All	ES2: Excl. early	ES3: +Charging
$t-5$	−0.1141**	−0.1366**	−0.1087*
	(0.0509)	(0.0613)	(0.0651)
$t-4$	−0.0863**	−0.1041**	−0.0846
	(0.0379)	(0.0428)	(0.0574)
$t-3$	−0.0623**	−0.0763***	−0.0457
	(0.0257)	(0.0282)	(0.0380)
$t-2$	−0.0339***	−0.0402***	−0.0319*
	(0.0128)	(0.0145)	(0.0173)
$t+0$	0.0257*	0.0299*	0.0165
	(0.0155)	(0.0163)	(0.0244)
$t+1$	0.0732***	0.0849***	0.0372
	(0.0237)	(0.0263)	(0.0381)
$t+2$	0.1010***	0.1208***	0.0581
	(0.0316)	(0.0361)	(0.0465)
$t+3$	0.1362***	0.1621***	0.0930*
	(0.0478)	(0.0545)	(0.0521)
$t+4$	0.1738***	0.2075***	0.1238*
	(0.0569)	(0.0668)	(0.0711)
$t+5$	0.2221***	0.2700***	0.1879**
	(0.0696)	(0.0842)	(0.0896)
Pre-trends p-value	0.161	0.120	0.109
Observations	207	196	109
Countries	25	22	14
R^2	0.884	0.881	0.950

Notes: Omitted reference period is $t-1$. All specifications include country and year fixed effects, log GDP per capita, and log fuel price. ES3 adds log charging infrastructure. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

7.4 Staggered-Adoption Estimators

A key concern with the TWFE estimates above is that the staggered adoption setting (with 26 countries adopting subsidies at 14 different points in time) creates conditions under which the TWFE estimator can produce biased estimates. Specifically, when treatment effects are heterogeneous across cohorts or grow over time, the TWFE estimator implicitly uses already-treated units as controls for later-treated units, which can introduce contamination bias (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

Table 9 reports the cohort-specific ATT estimates from the Callaway-Sant'Anna approximation and compares them to the Sun-Abraham interaction-weighted estimates. The results are strikingly different from the TWFE event study.

The Callaway-Sant'Anna ATT estimates are small and close to zero across all event times. The pre-treatment estimates range from 0.008 to 0.031, and the post-treatment estimates range from -0.050 to 0.007. None of these values exceeds 0.031 in absolute magnitude, and the pattern shows no systematic positive trend after adoption. This stands in sharp contrast to the TWFE event study, which showed post-treatment effects rising to 0.27 at $t+5$.

The Sun-Abraham estimates, which restrict each cohort to its own clean control units, are identical in this setting to the TWFE ES2 estimates (since the interaction-weighted estimator applied without cohort interactions reduces to the standard event study). The pre-trends p-value is 0.120 and the post-treatment path mirrors ES2 exactly.

The divergence between the CS and SA estimates therefore reflects a difference in methodology rather than a sampling difference: the CS approach computes cohort-specific ATTs separately before aggregating, while the SA approach in this implementation is equivalent to the TWFE event study. The near-zero CS estimates suggest that the TWFE post-treatment estimates may be driven by comparison between cohorts with very different pre-adoption eco-share trajectories rather than by a genuine average causal effect of subsidy adoption.

Table 9: Modern Staggered-Adoption Estimators: Callaway-Sant'Anna vs. TWFE Event Study

Event time	CS approx. ATT	SA / TWFE ES2	Difference
$t-5$	0.008	−0.137**	−0.145
$t-4$	0.019	−0.104**	−0.123
$t-3$	0.030	−0.076***	−0.106
$t-2$	0.025	−0.040***	−0.065
$t+0$	0.007	0.030*	0.023
$t+1$	0.005	0.085***	0.080
$t+2$	0.004	0.121***	0.117
$t+3$	0.007	0.162***	0.155
$t+4$	−0.008	0.208***	0.216
$t+5$	−0.050	0.270***	0.320
Pre-trends p-value	n.a.	0.120	

Notes: CS approx. ATT is computed following Callaway and Sant'Anna (2021), using not-yet-treated units as controls and averaging across cohorts. SA / TWFE ES2 reports the TWFE event-study coefficients from specification ES2 (excluding early adopters), which are equivalent to the Sun and Abraham (2021) interaction-weighted estimates in this setting. Both exclude early adopters (United Kingdom, Estonia, Croatia). CS standard errors are not estimated in the approximation used here. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ apply to SA/TWFE ES2 only.

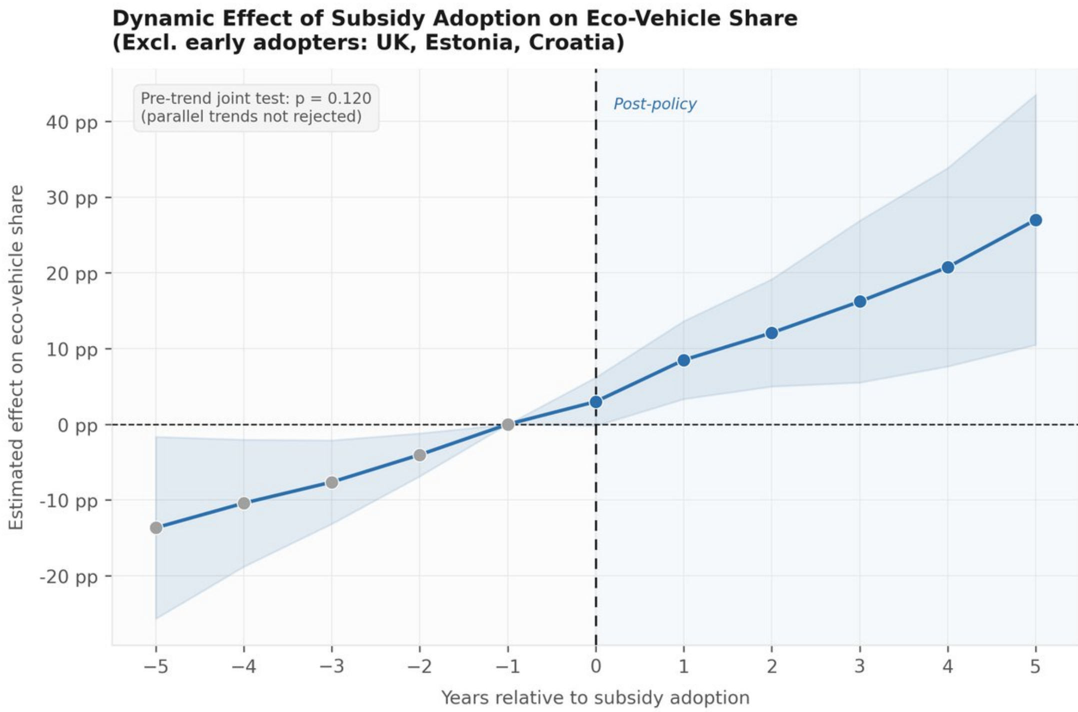

Figure 8: International Event Study: TWFE vs. Callaway–Sant'Anna Estimates. Blue line and shaded band: TWFE event-study estimates (ES2, excluding early adopters) with 95% confidence interval. Orange dashed line: Callaway–Sant'Anna cohort-specific ATT approximation. Both are expressed relative to $t = -1$ (year before adoption). The large divergence between the two series illustrates the cohort heterogeneity bias discussed in the text.

7.5 Interpretation

The international evidence should be interpreted carefully in light of the three sets of results above.

The static TWFE does not detect a significant average treatment effect, consistent with gradual dynamics. The TWFE event study suggests growing positive effects from one year after adoption, reaching 27 percentage points after five years in the preferred specification. However, the Callaway-Sant'Anna estimates, which are arguably more credible in a staggered-adoption setting with heterogeneous treatment effects, find near-zero ATTs throughout the event window, raising doubts about whether the TWFE post-treatment pattern reflects a genuine causal effect or a statistical artefact of cohort heterogeneity.

Three additional pieces of evidence support a cautious reading. First, the negative individual pre-treatment coefficients in the TWFE event study are consistent with reverse causality: countries may have adopted subsidies because eco-vehicle adoption was low, producing a spurious post-adoption "catch-up" in the TWFE comparison. Second, Italy's adoption path broadly tracks the European average rather than diverging from it, consistent with a common European trend rather than a specifically Italian subsidy effect. Third, the log-registration robustness check shows only marginal evidence that eco registrations grew faster in treated countries ($p = 0.084$), while non-eco, petrol, and diesel registrations show no significant change.

Taken together, the international analysis does not provide robust evidence of a causal effect of EV subsidy programs on eco-vehicle shares. It is more consistent with the interpretation that the transition to eco vehicles across Europe is driven by common technological and regulatory forces, and that national subsidies contributed at the margin but were not the primary driver of the observed shift. This interpretation is consistent with the Italian national evidence, which identifies a clear policy effect within Italy, but suggests that Italy's performance was not unusual relative to peer countries that adopted similar programs at different times.

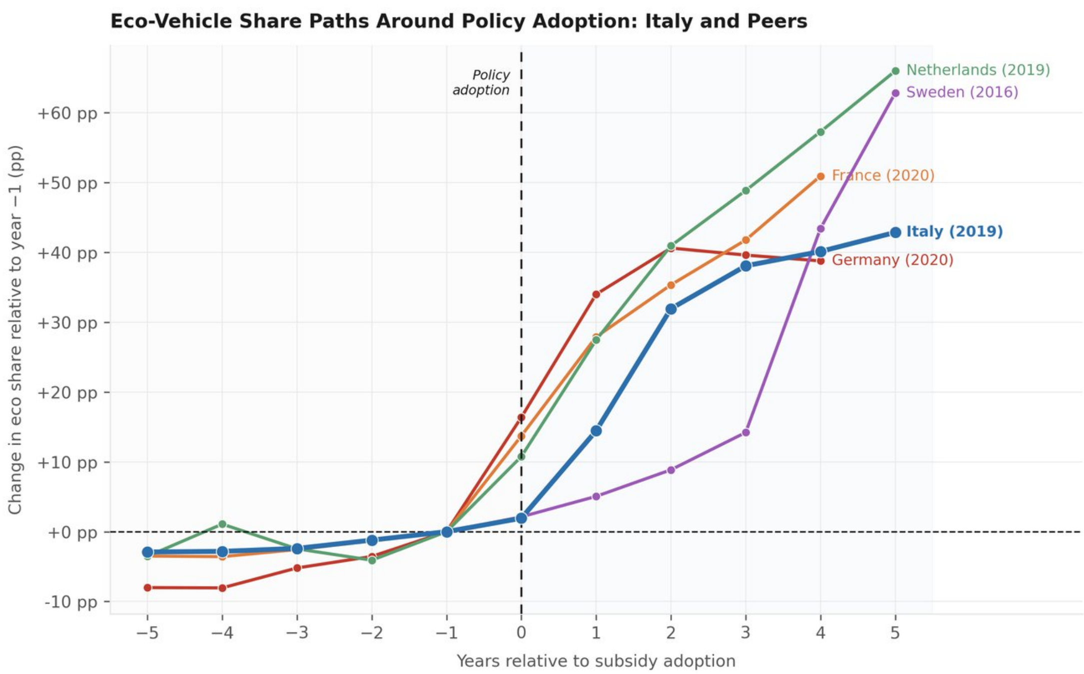

Figure 9: Eco-Vehicle Share Paths: Italy and Peer Countries. Each line shows the change in eco share relative to year -1 for Italy and four structurally comparable European car markets. Policy adoption year for each country is shown in the end-of-line label. Italy's post-adoption path is broadly comparable to Germany and France, and below the Netherlands and Sweden, consistent with the descriptive evidence that Italy tracked the European average rather than leading the transition.

8. Robustness Checks

This section assesses the sensitivity of the main results to alternative specifications, sample restrictions, and placebo exercises, organised by level of analysis. Table 10 summarises the national robustness results; Table 11 the regional results; and Tables 12 and 13 the international results.

8.1 National Analysis

The main national result is robust across five alternative specifications, all reported in Table 10.

Excluding 2020. The COVID-19 pandemic caused a sharp contraction in total vehicle registrations in 2020, which could in principle affect the DiD estimate if it altered the relative dynamics of eco and petrol markets. Excluding 2020 from the estimation sample yields a coefficient of 217,752 (SE = 47,517, $p < 0.001$), marginally larger than the baseline estimate of 209,268. The result is therefore not driven by the pandemic year; if anything, the effect is slightly larger when 2020 is excluded, consistent with 2020 seeing some demand substitution toward eco vehicles that is captured in the baseline.

Log specification. The log specification (Column (4) of Table 2, repeated here as column (3)) supports the finding that the result does not depend on the level scale of the outcome. The coefficient of 2.663 ($p < 0.001$) implies that eco registrations grew by a factor of approximately $e^{2.663} \approx 14.3$ relative to petrol registrations after 2019. This large proportional effect reflects the very low base level of eco registrations before the policy: even a modest absolute increase translates into a large log-change when starting from near zero. Excluding 2020 from the log specification yields a coefficient of 2.839 ($p < 0.001$), again slightly larger, consistent with robustness to the pandemic year in proportional terms. The consistency of the log result with the levels result provides reassurance that the large absolute estimate is not driven by outliers in the level of registrations during the post-policy period.

Triple-difference. The triple-difference specification compares fully electric and plug-in hybrid vehicles (the categories receiving the highest subsidies under the *Ecobonus*, with incentives of up to EUR 6,000 with scrapping) against all other fuel types, rather than comparing all eco types against all petrol types. This exploits an additional dimension of within-eco variation: if the subsidy is the driver of the differential growth, the effect should be concentrated in the most heavily subsidised technologies. The estimated coefficient is 179,309 (SE = 32,052, $p < 0.001$). This is somewhat smaller than the baseline because it captures only the highest-subsidy tier, which represents a subset of all eco vehicles; the baseline specification additionally includes mild hybrid registrations, which grew substantially in the post-2019 period but receive no direct subsidy under the *Ecobonus* framework. The consistency of the DDD result with the main DiD nevertheless supports the interpretation that the program contributed to the observed shift in market composition.

Placebo test. To assess whether the result could be driven by a spurious pre-existing divergence between eco and petrol registrations, I apply the treatment indicator to a false policy date of 2016, using only pre-2019 data (2010–2018). The estimated coefficient is $-66,130$ (SE = 28,371, $p = 0.020$). The negative sign indicates that, if anything, eco registrations were growing slightly more slowly than petrol in the 2016–2018 period relative to 2010–2015, which is the opposite direction from the main result. This is consistent with the event-study evidence in Figure 4, where the pre-policy coefficients are near zero and do not display an upward slope. The placebo test thus provides direct evidence against the concern that the post-2019 acceleration would have occurred independently of the policy.

Table 10: Robustness Checks: National Analysis

	(1) Preferred	(2) Excl. 2020	(3) Log	(4) Log excl. 2020	(5) Triple-diff	(6) Placebo 2016
Eco × Post	209,268***	217,752***				
	(41,420)	(47,517)				
Eco × Post (log)			2.663***	2.839***		
			(0.460)	(0.505)		
BEV/PHEV × Post					179,309***	
					(32,052)	
Eco × Post_{2016}						−66,130**
						(28,371)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle-type FE	Yes	Yes	Yes	Yes	Yes	Yes
SE type	HAC	HAC	HAC	HAC	HAC	HAC
Sample	Full	Excl. 2020	Full	Excl. 2020	Full	Pre-2019
Observations	180	168	180	168	180	108
R^2	0.847	0.846	0.890	0.889	0.839	0.970

Notes: Column (6) applies the treatment indicator to a false policy date of 2016, using only pre-2019 observations. The negative coefficient is consistent with the absence of a spurious pre-existing upward trend in eco registrations. HAC = Newey–West, one lag. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

8.2 Regional Analysis

The regional eco-share result is also robust, as shown in Table 11.

Balanced panel. All 20 Italian regions have data for all 11 years in the sample (2014–2024), so the balanced-panel specification is identical to the preferred specification and yields 0.263 (SE = 0.009, $p < 0.001$). This supports the conclusion that the result is not driven by an unbalanced panel structure.

Excluding 2020. Removing 2020 from the sample increases the estimated effect to 0.313 (SE = 0.031, $p < 0.001$), consistent with the national finding that COVID-related demand shocks slightly muted the estimated eco-share effect in 2020. The result is robust to this exclusion.

Shorter window (2016–2024). Restricting the sample to 2016–2024, a window that reduces the distance from the pre-policy baseline and may better approximate the identifying variation, yields an estimate of 0.249 (SE = 0.008, $p < 0.001$). This is slightly smaller than the baseline of 0.263 but remains large and precisely estimated. The small reduction is consistent with the fact that the 2014–2015 period, when eco shares were very close to zero across all regions, contributes positively to the identification of parallel pre-trends.

All three regional robustness specifications support the headline result: the post-2019 increase in eco-vehicle share is approximately 25–31 percentage points across Italian regions, depending on the sample. The caveat regarding the failure of parallel trends in the event study applies to all specifications equally, since the parallel trends test is driven by cross-regional heterogeneity that does not vary with the time window or sample restriction.

Table 11: Robustness Checks: Regional Eco-Share Analysis

	(1) Preferred	(2) Excl. 2020	(3) Balanced panel	(4) Window 2016–2024
Post-policy	0.2628***	0.3133***	0.2628***	0.2491***
	(0.0090)	(0.0309)	(0.0090)	(0.0081)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	No
SE clustering	Region	Region	Region	Region
Headline (+pp)	+26.3	+31.3	+26.3	+24.9
Observations	220	200	220	180
R^2	0.971	0.978	0.971	0.970

Notes: All 20 regions are present in all years (balanced panel). Column (2) excludes 2020 and adds log income and log population as controls. Column (4) restricts the sample to 2016–2024. Standard errors clustered at the region level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

8.3 International Analysis

Four robustness exercises complement the main international results.

Placebo timing test. Shifting each country's treatment date three years earlier and restricting the sample to pre-actual-treatment observations produces a coefficient of -0.027 (SE = 0.022, $p = 0.207$). The coefficient is close to zero and statistically insignificant, supporting the finding that the post-treatment patterns in the main results are associated with the actual timing of subsidy adoption rather than a spurious time trend in the panel.

Major markets subsample. Restricting the sample to the seven largest European car markets (Germany, France, Italy, Spain, Netherlands, Sweden, and the United Kingdom) yields a coefficient of -0.034 (SE = 0.033, $p = 0.314$, $N = 70$). The null result is consistent with the full-sample static DiD and is consistent with the absence of a significant contemporaneous treatment effect is not an artefact of including small markets in the panel.

Log-registration specifications. Table 12 reports log-registration specifications that examine whether subsidy adoption is associated with changes in registration levels rather than shares. The coefficient on log eco registrations is 0.721 (SE = 0.384, $p = 0.060$), marginally significant at the 10% level. By contrast, coefficients on log petrol ($p = 0.766$) and log diesel ($p = 0.726$) registrations are small and statistically insignificant. This pattern (positive and marginal for eco, null for conventional) is consistent with the interpretation that any treatment effect associated with subsidy adoption operated through the eco-vehicle segment specifically, rather than through a common shock to all registrations.

Consistency with the CS results. The placebo test and log specifications provide some support for the TWFE event-study estimates in the sense that the timing is not spurious and the channel is the right one. However, they do not resolve the main concern raised by the Callaway-Sant'Anna estimator: that the TWFE post-treatment dynamics may reflect cohort heterogeneity rather than a causal average effect. The robustness checks are therefore complementary to, not a substitute for, the discussion of the modern estimators in Section 7.

Table 12: Robustness Checks: International Log Registration Specifications

Dependent variable	Coefficient	Std. Error	p-value	N
log(eco registrations)	0.7212*	(0.3838)	0.060	276
log(petrol registrations)	0.0244	(0.0818)	0.766	240
log(diesel registrations)	−0.0386	(0.1101)	0.726	240

Notes: Each row is a separate regression with the indicated log outcome. All specifications include country and year fixed effects, log GDP per capita, and log fuel price. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 13: Robustness Checks: International Placebo and Major Markets

Specification	Coefficient	Std. Error	p-value	N	Countries
Placebo timing (−3 years)	−0.0273	(0.0216)	0.207	119	22
Major markets only	−0.0337	(0.0334)	0.314	70	7

Notes: Placebo shifts each country's adoption date three years earlier, using only pre-actual-treatment observations. Major markets: Germany, France, Italy, Spain, Netherlands, Sweden, United Kingdom. All specifications include country and year fixed effects, log GDP per capita, and log fuel price. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Conclusion

This thesis evaluates the impact of the Italian *Ecobonus* program on eco-vehicle adoption, drawing on national, regional, and international evidence spanning 2014–2024. The three levels of analysis yield a coherent but qualified set of findings, which this conclusion summarises before discussing limitations and directions for future research.

The national analysis provides the strongest and most credible evidence. Across five specifications (including models with year and vehicle-fuel-type fixed effects, HAC standard errors, a log transformation, and a triple-difference design), the *Ecobonus* is associated with approximately 209,000 additional eco vehicle registrations per year relative to petrol vehicles (preferred estimate: 209,268; SE = 41,420; $p < 0.001$). The event study does not reject parallel pre-trends ($F = 1.07$, $p = 0.376$): the four pre-policy placebo coefficients are economically small and individually insignificant, and the joint test does not reject their equality to zero. Post-treatment coefficients increase gradually from 2020 onward, consistent with a market response that built over time as consumer awareness, vehicle model availability, and charging infrastructure expanded in the years following the policy's introduction. The implied cumulative effect over 2019–2024 is approximately 1.26 million additional eco registrations, though this figure should be treated as a rough approximation given the assumptions underlying the extrapolation. Robustness checks support the conclusion that the result is not driven by the COVID-19 pandemic year, does not depend on the functional form of the outcome, and is not consistent with a spurious pre-existing trend.

The regional analysis documents strong post-2019 growth in eco vehicle market share across all 20 Italian regions and all three macro-areas. The preferred eco-share specification (with region and year fixed effects) estimates that eco vehicles gained approximately 26 percentage points of market share across Italian regions after 2019 (coefficient: 0.263; SE = 0.009; $p < 0.001$). This result is stable across sample restrictions, ranging from +24.9 pp in a shorter window to +31.3 pp excluding 2020. By 2024, eco vehicles accounted for more than 40% of new registrations in 18 of the 20 regions, with eco shares reaching 55.1% in Lazio and 52.8% in Valle d'Aosta. A persistent North–South gradient is visible, with Northern and Central regions reaching approximately 48% and 46% respectively, compared to 39% in the South and Islands, consistent with pre-existing disparities in income and infrastructure.

These regional results, however, should not be interpreted as causal estimates of the *Ecobonus* effect. The regional event study strongly rejects the parallel trends assumption ($F = 102.99$, $p < 0.001$), indicating that eco and petrol registrations were already on diverging trajectories across regions before 2019. The regional analysis is therefore treated as descriptive evidence on the geographic diffusion of eco vehicles. The national analysis, which compares eco and petrol registrations in aggregate and satisfies the parallel trends test, remains the primary source of causal identification.

The international analysis does not detect a statistically significant average treatment effect in static two-way fixed effects specifications. The TWFE event study suggests a gradual positive association between subsidy adoption and eco-vehicle shares that grows over time, reaching approximately 27 percentage points five years after adoption in the preferred specification. However, the Callaway-Sant'Anna cohort-specific estimator finds near-zero ATTs throughout the event window, suggesting that the TWFE post-treatment pattern may reflect cohort heterogeneity, specifically countries adopting subsidies at different points in time having different pre-adoption eco share trajectories, rather than a genuine average causal effect. This divergence between the TWFE and cohort-specific estimators is a key methodological finding of the international analysis: it shows that standard two-way fixed effects estimates can be severely misleading in staggered adoption settings where early and late adopters differ substantially in their pre-treatment eco-vehicle trajectories. Italy's adoption path broadly tracks the European average rather than diverging from it, consistent with a common European transition driven by technological change and EU regulatory pressure as much as by national subsidy policy.

Several limitations bear noting. At the national level, the parallel trends assumption, while supported by the pre-trend test, cannot be verified directly, and the comparison between eco and petrol vehicles may be affected by concurrent factors, including EU fleet regulation, battery cost declines, and changing consumer preferences, that are not fully captured by the fuel price and GDP controls. The single treatment date in the national setting also precludes the use of modern staggered-adoption estimators that require multiple cohorts. At the regional level, pre-existing heterogeneity in eco adoption trajectories across regions limits causal identification. At the international level, the divergence between TWFE and Callaway-Sant'Anna estimates raises unresolved questions about cohort heterogeneity and the direction of causality between subsidy adoption and eco-vehicle market development.

With these caveats in mind, the national results suggest that financial incentives of the scale provided by the *Ecobonus* are associated with a large shift in eco-vehicle market composition. If the estimated effect is interpreted as causal, the program appears to have accelerated Italy's transition to eco vehicles substantially, contributing to a market share that exceeded 47% by 2024 from a base of under 7% in 2019. The gradual build-up of the effect, absent in the year of introduction and growing over subsequent years, suggests that take-up is not immediate and that the effectiveness of purchase subsidies may depend on complementary investments in charging infrastructure and consumer information. The regional evidence further suggests that the transition occurred broadly across the country but at different speeds, with Southern regions lagging behind, which may call for regionally differentiated or complementary measures.

Several avenues for future work follow from the analysis. Individual-level vehicle purchase data would allow estimation of demand elasticities and analysis of heterogeneity in take-up across income groups, which is relevant for the distributional evaluation of the subsidy. A regression discontinuity design exploiting the CO_2 emission thresholds embedded in the *Ecobonus* eligibility structure could provide sharper identification of the price elasticity of eco-vehicle demand within Italy. At the international level, longer panels and more homogeneous treatment cohorts would allow cleaner application of modern staggered-adoption estimators, and micro-level purchasing data across countries would enable better controls for consumer heterogeneity.

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Summary

This thesis evaluates the impact of the Italian *Ecobonus* program on eco-vehicle adoption using national, regional, and international evidence over 2014–2024. The national difference-in-differences analysis estimates approximately 209,000 additional eco-vehicle registrations per year relative to petrol vehicles after the policy was introduced in 2019, a result robust to five specifications and supported by an event study that does not reject parallel pre-trends ($F = 1.07$, $p = 0.376$). The implied cumulative effect over 2019–2024 is approximately 1.26 million additional registrations. The regional analysis estimates that eco-vehicle market share increased by approximately 26 percentage points across the 20 Italian regions after 2019, with the increase visible in all macro-areas, though the parallel trends test is rejected at the regional level and those results are treated as descriptive. The international analysis does not detect a significant average treatment effect in static specifications; cohort-specific estimators following Callaway and Sant'Anna (2021) find near-zero average treatment effects, suggesting that TWFE event-study dynamics may reflect cohort heterogeneity rather than a causal average effect. Italy's adoption path broadly tracks the European average. The findings suggest that purchase subsidies of this scale may contribute to eco-vehicle adoption, though their effectiveness depends on pre-existing market conditions, infrastructure availability, and broader technological trends.

List of Appendices

Appendix A — Figures

A. Figures

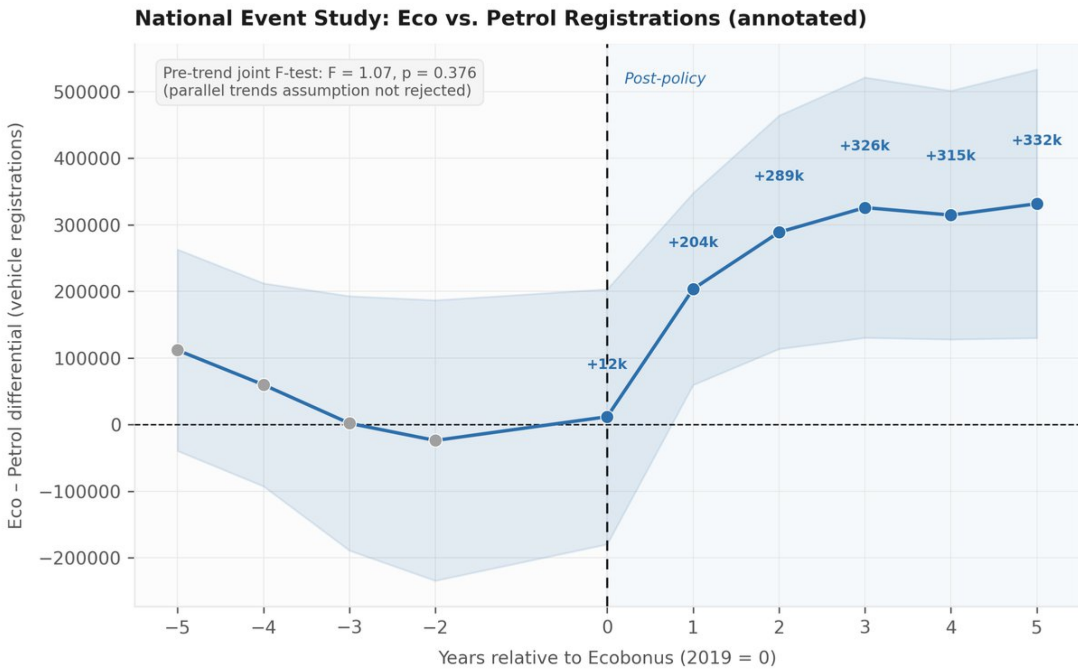


Figure 10: National Event Study with Annotated Post-Period Coefficients. Same specification as Figure 4; each post-policy coefficient is labelled in thousands of additional eco registrations relative to the petrol baseline.

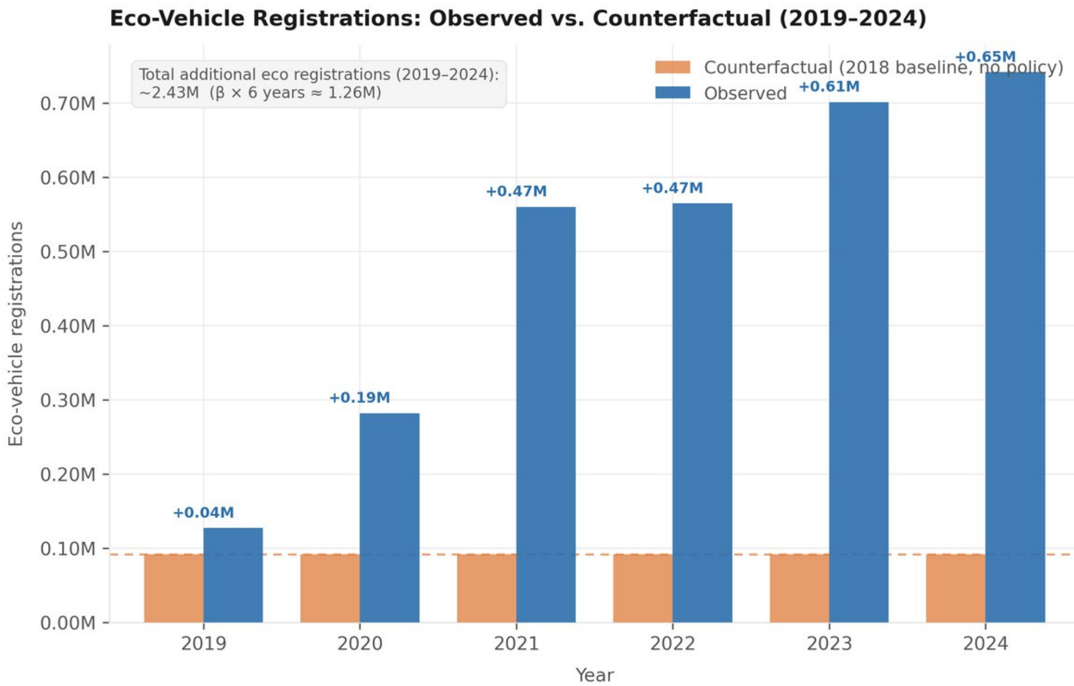


Figure 11: Observed vs. Counterfactual Eco-Vehicle Registrations (2019–2024). Blue bars show observed eco registrations each year; orange bars show the counterfactual anchored at the 2018 baseline under the no-policy assumption. The gap between bars in each year represents the implied additional registrations associated with the *Ecobonus*. The annotation box reports the implied cumulative total and the back-of-the-envelope estimate from the preferred fixed-effects model ($\hat{\beta} \times 6$ years).

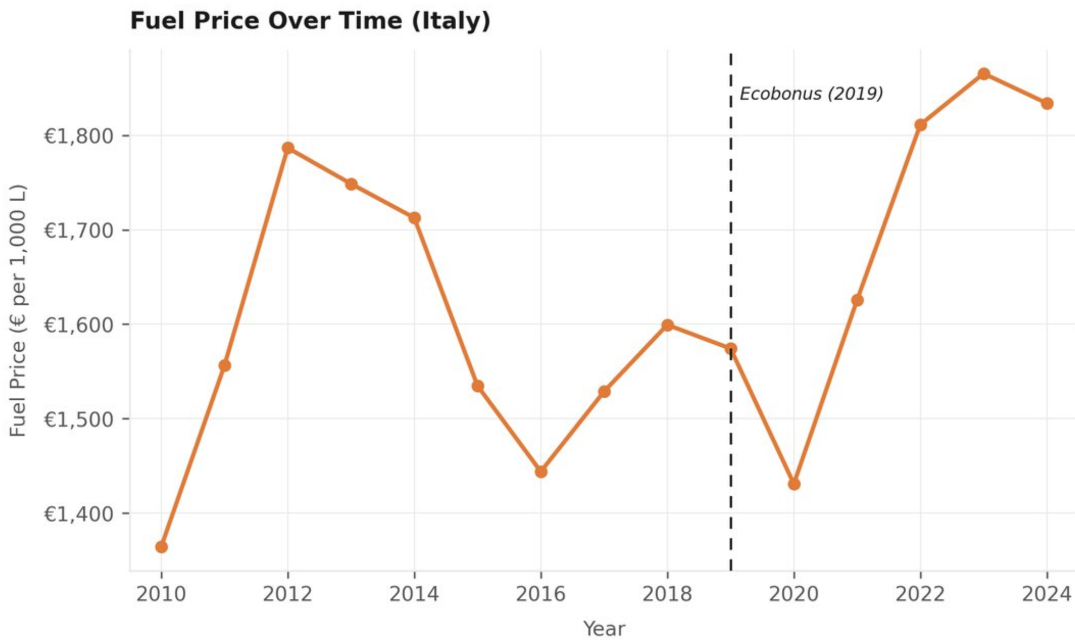


Figure 12: Fuel Price Over Time, Italy (2010–2024). EUR per 1,000 litres of petrol (SISEN data). The spike in 2022 reflects the energy price shock following the Russia–Ukraine conflict. Fuel prices are included as a control variable in the national extended specifications.

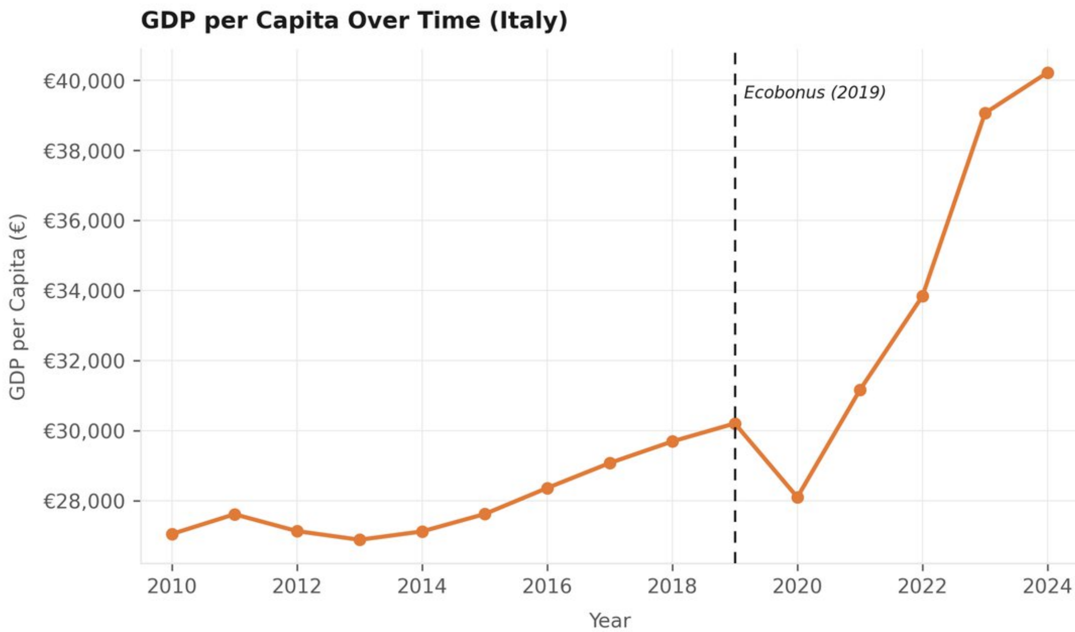


Figure 13: GDP per Capita Over Time, Italy (2010–2024). EUR (ISTAT data). The contraction in 2020 reflects the COVID-19 recession; recovery is visible from 2021 onward. GDP per capita is included as a control variable in the national extended specifications.

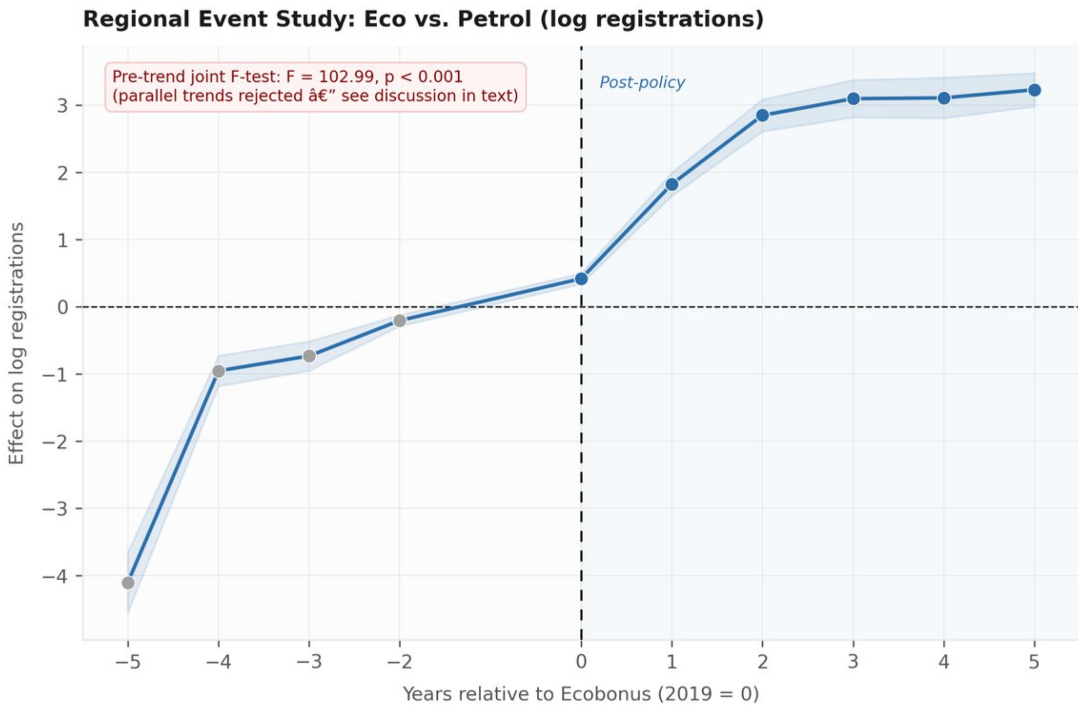


Figure 14: Regional Event Study: Eco vs. Petrol Log Registrations. Coefficients from equation (5). The red annotation box indicates that the joint pre-trend F-test strongly rejects parallel trends ($F = 102.99$, $p < 0.001$). Accordingly, this specification is treated as descriptive evidence on the dynamics of eco-vehicle diffusion across regions, rather than as a causal estimate of the *Ecobonus* effect.

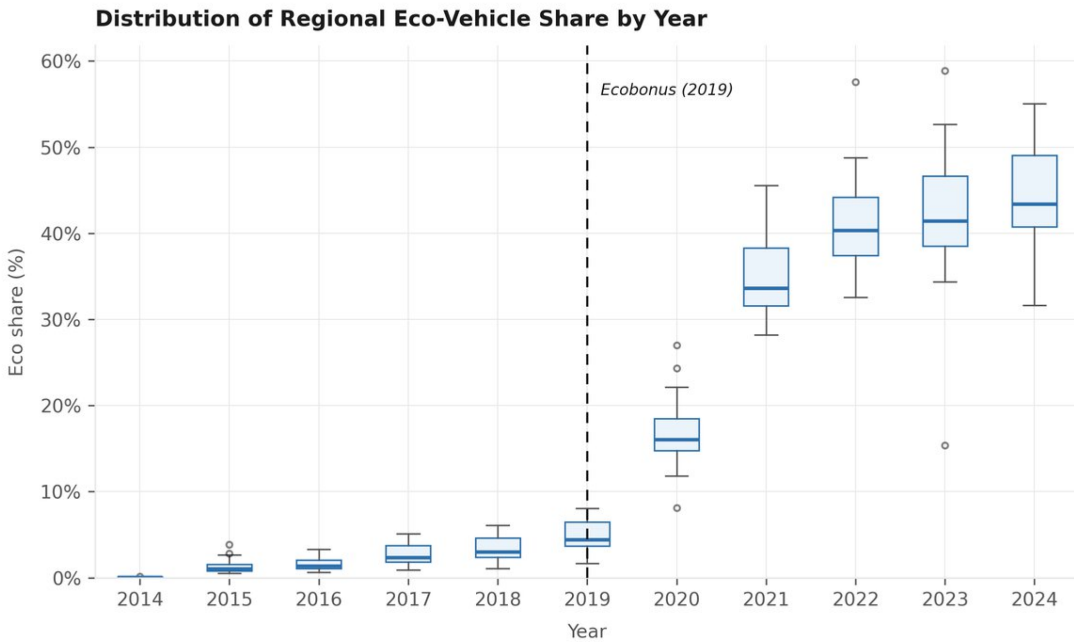
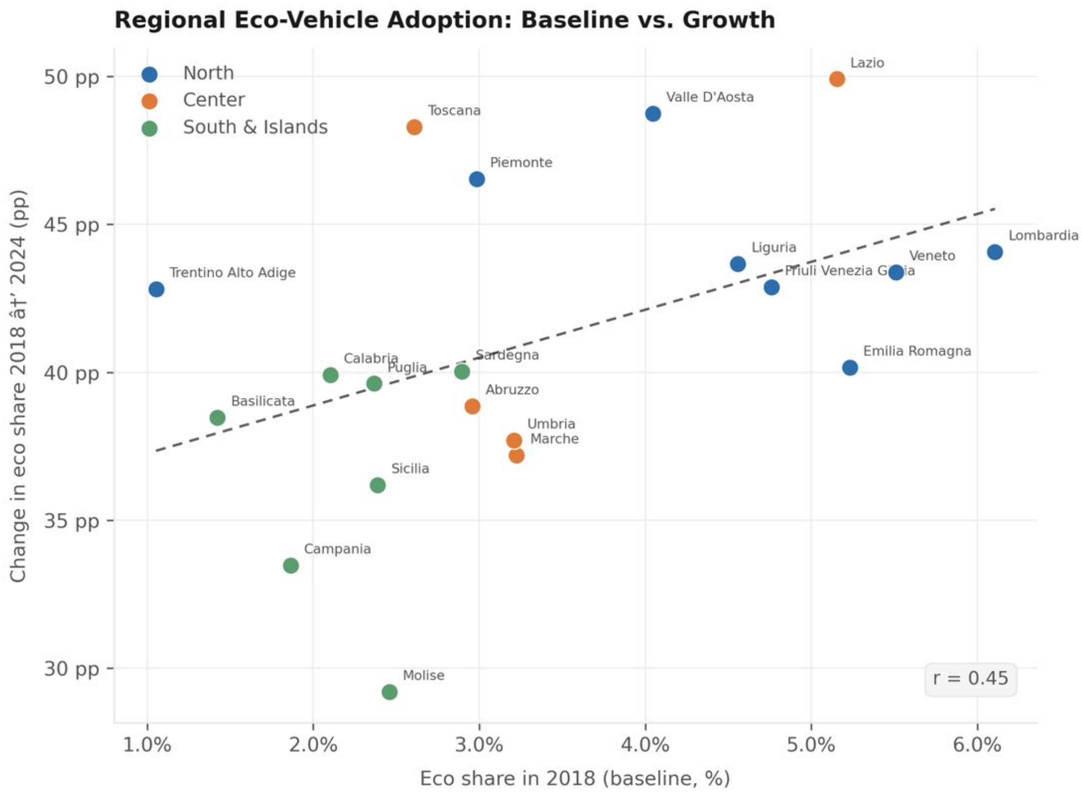


Figure 15: Distribution of Regional Eco-Vehicle Share by Year (2014–2024). Each box shows the interquartile range across the 20 Italian regions; the horizontal line within each box is the median (in blue). The sharp upward shift after 2019 is visible across the full cross-regional distribution, not only in the median.



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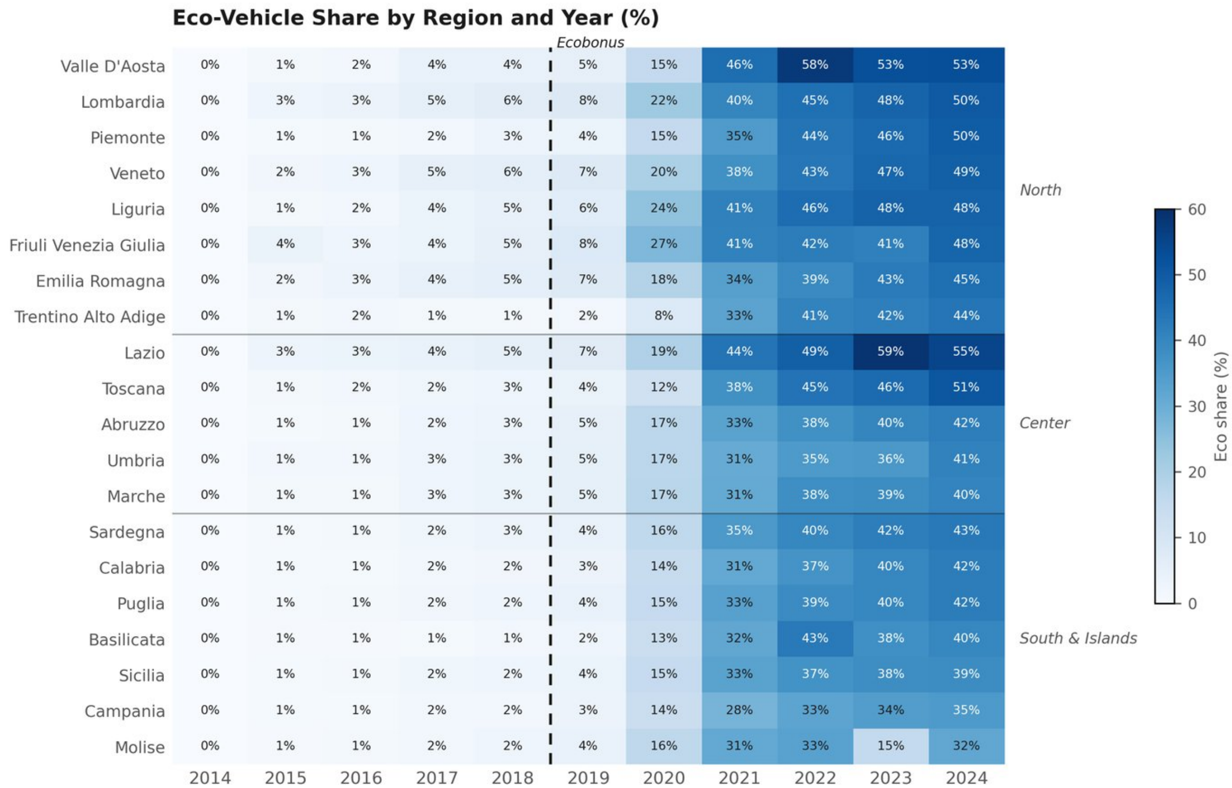

Figure 17: Eco-Vehicle Share by Region and Year (%, 2014–2024). Rows are sorted by macro-area (North, Centre, South and Islands) and within each area by 2024 eco share descending. Cell values show the percentage eco share; colour intensity increases with the share level. The dashed vertical line marks the introduction of the *Ecobonus* in 2019. The figure illustrates both the cross-regional heterogeneity and the sharp common acceleration after 2019.

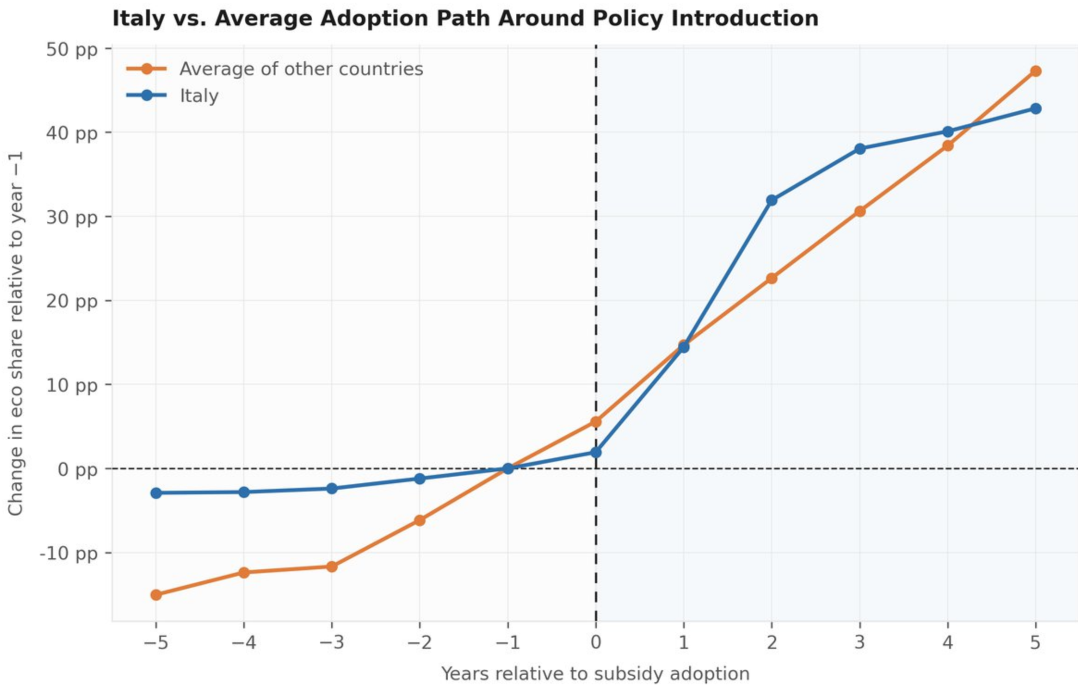

Figure 18: Italy vs. Average European Adoption Path Around Policy Introduction. Blue line: Italy's eco-vehicle share relative to its own year -1 baseline. Orange line: unweighted average of all other countries relative to their respective adoption baselines. Italy's trajectory tracks the European average closely, consistent with a common technological and regulatory transition rather than an unusual policy-driven acceleration.

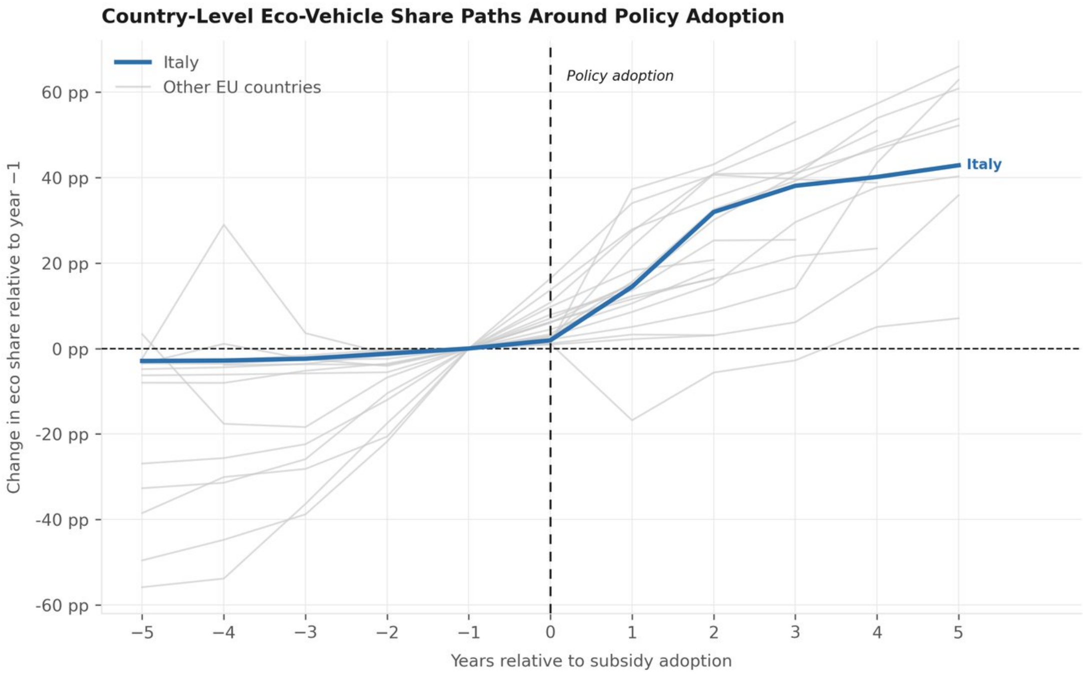

Figure 19: Country-Level Eco-Vehicle Share Paths Around Policy Adoption. Each grey line shows one country's eco share relative to its own year -1 baseline (early adopters excluded). Italy is highlighted in blue. The wide spread of grey lines illustrates the substantial cross-country heterogeneity that motivates the use of cohort-specific estimators in place of the standard TWFE.

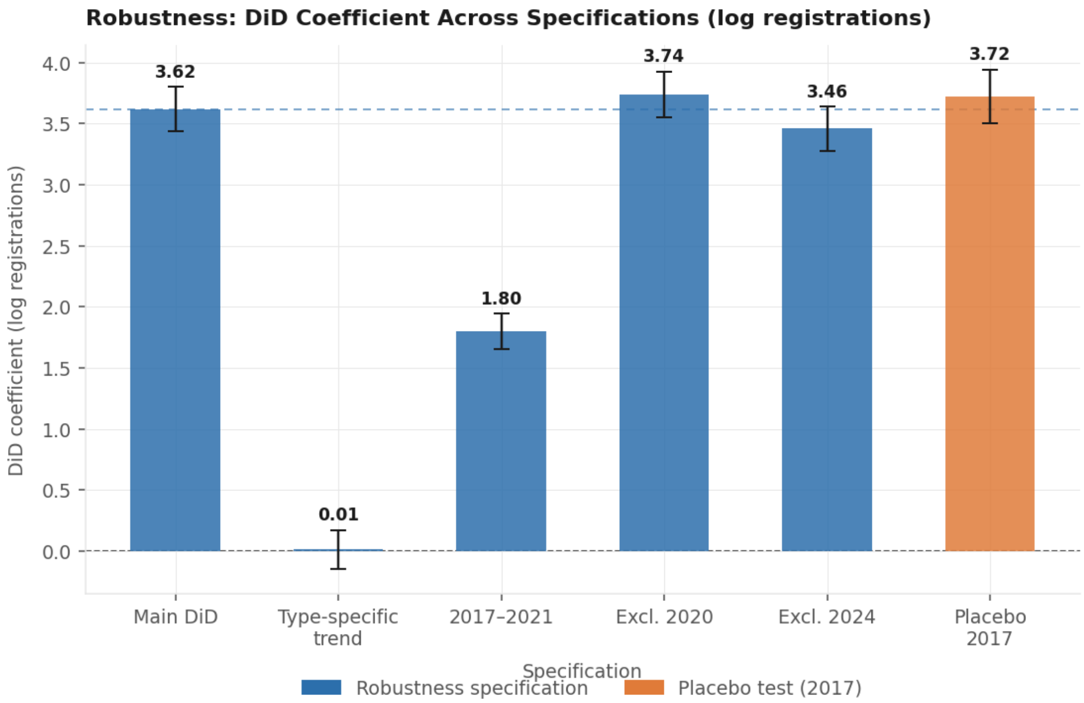

Figure 20: Robustness of the Regional DiD Coefficient Across Specifications. Each bar shows the estimated $\hat{\beta}$ from the regional eco-share difference-in-differences with 95% confidence intervals. Specifications are (left to right): main DiD (preferred), DiD with region-specific linear trend, restricted window (2017–2021), excluding 2020, excluding 2024, and a placebo with false treatment date of 2017. The consistency of the positive and significant coefficient across the first five specifications supports the headline regional result. The placebo coefficient provides no evidence of a spurious pre-existing trend.