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Measuring Economic Impacts of Environmental Policy Transitions Across Countries

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Abstract

This paper analyzes the macroeconomic effects of environmental policy transitions using stringency scores from developed and emerging countries. We examine the economic effects of environmental policy transitions across market-based, non-market-based, and technology support policies, along with their aggregate effect captured by the Environmental Policy Stringency index. To assess the economic effects relative to a no-transition scenario, we apply the synthetic control estimation method to construct separate counterfactuals for each treated country and policy category. Our framework standardizes the selection of treatment countries, event years, predictor variables, and donor pools, and incorporates placebo tests to assess the significance of total economic losses. We find that most policy transitions are associated with short-term economic losses, particularly for non-market-based and technology support policies. Placebo tests reveal that technology support transitions generate the largest and most significant losses, while aggregated environmental policy transitions generate smaller but still significant losses. In contrast, market-based and non-market-based policies do not show significant economic effects. These findings highlight the heterogeneous economic responses to environmental policy transitions and demonstrate that, although short-term losses can be substantial, more stringent market-based and non-market-based policies do not inherently constrain long-term economic performance.

Keywords: Climate Policy, Environmental Regulation, Policy Stringency, Synthetic Control, Economic Growth, International Comparison, Policy Evaluation

JEL Codes: C23, E66, O44, Q52, Q58

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1 Introduction

Human-induced climate change is causing widespread disruptions in nature and affecting billions of people worldwide. The Intergovernmental Panel on Climate Change (2023) and the Climate Action Monitor from the Organisation for Economic Co-operation and Development (OECD, 2023b; 2024), continue to warn that climate-related extreme events will become more frequent and severe in the near future, posing major threats to global health and potentially leading to significant economic losses (OECD, 2023b). In response, governments have adopted more ambitious policies aimed at reducing global emissions.

Building on international commitments from the 1992 United Nations Framework Convention on Climate Change, the 1997 Kyoto Protocol, and the 2015 Paris Agreement, countries have implemented a range of policy instruments to mitigate climate risks, typically categorized into market-based, non-market-based, and technology support policies. Market-based instruments create economic incentives for environmentally sustainable behavior by assigning a monetary value to pollution. Non-market-based instruments enforce compliance through regulations, such as concentration limits. Technology support policies aim to foster innovation and the development of green technologies.

Each country has its own approach to environmental policy based on national objectives and constraints (OECD, 2023b; OECD, 2024). An example is Sweden that relies on high carbon taxes to discourage fossil fuel use, which is a market-based approach. Another example is Germany that focuses on regulatory emission limits to directly control pollution from key sectors, which is a non-market-based approach. To allow cross-country comparison, Botta and Koźluk (2014) introduced the OECD Environmental Policy Stringency Index (EPS), reflecting the extent to which policy instruments constrain environmentally harmful behavior. Although theory suggests that these instruments influence economic outcomes, empirical evidence remains limited and often focuses on isolated interventions (Jaffe, Peterson, et al., 1995; Kozluk and Zipperer, 2014). We address this gap with a longitudinal (or panel) cross-country analysis.

We examine the economic effects of environmental policy transitions across market-based, non-market-based, and technology support policies, along with their aggregate effect captured by the EPS index. This allows us to move beyond single-country case studies by exploiting a large, heterogeneous, and multi-dimensional dataset that spans both cross-country and cross-policy variation. We use gross domestic product (GDP) growth as the primary indicator of economic growth, capturing broad changes in investment, production, and consumption resulting from environmental policy changes. We consider a broad set of developed and emerging countries including the BRICS countries of Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Iran, Indonesia, and the United Arab Emirates, and many countries from the OECD including USA, European countries, UK and Japan.

As countries differ in the timing and nature of policy transitions, we adopt synthetic control methods (SCMs) as developed by Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2015) for which each country is treated consecutively. The SCM constructs a synthetic version of each treated country by optimally weighting unaffected countries to estimate the counterfactual. Recent applications of SCM to environmental policies, including Leroutier (2022) on the UK Carbon Price Support, Mideksa (2024) on Finland's carbon tax, and Zhang et al. (2024) on China's Low-Carbon City Pilot, demonstrate the method's value for evaluating individual climate policies. To ensure a consistent approach in the construction of a synthetic control, we develop a unique framework to systematically identify the treatment countries, the event years, the predictor variables, and the donor pools.

Furthermore, we implement the in-space placebo test of Abadie, Diamond, and Hainmueller (2010) to formally assess the statistical significance of the estimated total economic effects. This framework provides comparable cross-country evidence on the economic impact of environmental policy transitions. We focus on countries with the largest increases in stringency scores, as these transitions are more likely to produce measurable effects than marginal changes. To our knowledge, no previous study has applied this systematic statistical framework to such an extent to examine policy transitions across a broad range of instruments, across a large group of countries, and over a long time span.

Our results have important implications for policymakers. The economic effects of environmental policy transitions vary across categories and time horizons. In the short run, most transitions, particularly in non-market-based and technology support categories, are associated with negative impacts, likely reflecting adjustment costs and delays in realizing benefits from green investments. Over time, technology support policies show some recovery, while non-market-based policies imply neutral long-term outcomes. Market-based transitions display a limited economic response.

To assess whether these patterns translate into significant economic effects, we evaluate the overall impact using in-space placebo tests. The results show that technology support policies lead to substantial economic losses of 7.6% by the last observed year, while EPS transitions lead to smaller but still significant economic losses of 4.9%. For EPS, a longer transition period may be required for the effects to translate into growth, as losses diminish toward the end of the horizon. In contrast, technology support policies do not show a clear decline in losses over time. Market-based and non-market-based instruments show no significant long-term effects. These findings highlight the heterogeneous economic impacts of environmental policy transitions and indicate that, although short-term losses can be considerable, more stringent market-based and non-market-based policies do not inherently constrain long-term economic performance.

The remainder of this paper is organized as follows. Section 2 examines the factors that influence how and why countries adopt different environmental policy approaches with varying levels of stringency. Section 3 introduces the EPS dataset (OECD, 2023a), originally developed by Botta and Koźluk (2014) and extended by Kruse et al. (2022), along with its classification structure and descriptive features. Section 4 details the synthetic control strategy, including selection of treated countries, determination of event years, choice of predictor variables, construction of donor pools, and computing in-space placebo tests. Section 5 presents empirical results, and Section 6 concludes. Supplementary tables are provided in Appendix A, additional figures in Appendix B, and technical details in Appendix C.

2 Background

Understanding the economic impacts of transitioning environmental policies requires insight into why and how countries adopt different types of environmental instruments. Institutional structures, governance quality, and economic and political dependencies strongly influence both the choice and stringency of these instruments, shaping the overall mix of market-based, non-market-based, and technology-support approaches used in practice (Burns, Eckersley, and Tobin, 2020; OECD, 2014; OECD, 2022; OECD, 2023b; Stavins, 2010).

Countries with stable institutions, efficient fiscal systems, and ambitious climate goals often adopt more stringent market-based instruments. Sweden, for example, introduced one of the world's highest carbon taxes in 1991, enabled by a combination of strong public institutions and widespread societal trust (Stavins, 2010; OECD, 2024). Switzerland, Finland, and Norway followed with similarly ambitious carbon pricing policies, supported by political stability and broad public trust in climate policy (World Bank, 2023). In contrast, in countries where policymaking is constrained by short-term political incentives, limited coordination between government agencies, or strong industry lobbying, the implementation of carbon pricing mechanisms often faces major obstacles. This resistance is most clearly seen in countries with a high structural dependence on emissions-intensive sectors, such as coal-based energy or heavy manufacturing (Oates and Portney, 2003; Burns, Eckersley, and Tobin, 2020). Canada, for example, illustrates this dynamic: despite its relatively high income level and strong institutions, carbon pricing has faced persistent political opposition from resource-dependent provinces, particularly those reliant on oil and gas, delaying the adoption of a national framework until recently (OECD, 2014; OECD, 2023a; OECD, 2023b; World Bank, 2023). Japan has likewise implemented only a modest carbon tax since

2012, reflecting the influence of energy-intensive industries and a continued dependence on fossil fuels after the Fukushima disaster (Ministry of Economy, Trade and Industry, 2010; World Bank, 2023). Instead, its climate strategy has emphasized regulatory and technology-support measures, consistent with its long-standing focus on energy efficiency and innovation (Johnstone, Haščič, and Popp, 2010).

Non-market-based policies are widely used because they tend to be more politically acceptable than environmental taxes, easier for the public to understand, and quicker to implement through existing regulatory systems (Goulder and Parry, 2008; OECD, 2014; OECD, 2023a). These policies are especially popular when there are concerns about public health. Germany and South Korea, for example, rely heavily on strict regulatory frameworks to reduce air pollution. More recently, countries such as China and India have adopted similar approaches to address severe problems with urban air quality. However, such policies are less common in countries where industries have limited access to clean technologies or where enforcement would impose high costs on politically influential sectors. In the United States, for example, the large automotive and manufacturing sectors have contributed to both political and economic resistance to stringent regulatory policies (Oates and Portney, 2003).

Technology support policies have become increasingly popular in recent years, particularly in countries that aim to enhance long-term economic competitiveness through innovation (Acemoglu et al., 2012; Ambec et al., 2013). Japan was an early adopter, introducing technology-oriented environmental measures in response to the 1970s oil crises, including programs to improve energy efficiency in vehicles and appliances (Richards, 1997). In the following decades, Denmark emerged as a global leader in wind energy (Johnstone, Haščič, and Popp, 2010), Germany prioritized solar technology, and the Netherlands invested heavily in sustainable agriculture. These achievements were driven by strong government support, well-developed innovation systems, and a sustained strategic commitment to sustainable economic transformation. In contrast, technology support policies are less common in countries with limited financial resources, weaker institutional capacity, or short-term economic pressures that make large upfront investments politically challenging (Johnstone, Haščič, and Popp, 2010; Ambec et al., 2013).

3 Data

This section introduces the main data sources used in the analysis. We begin with a detailed description of the OECD Environmental Policy Stringency (EPS) Index, originally developed by Botta and Koźluk (2014) and extended by Kruse et al. (2022), which forms the core of our policy measures. The EPS is a composite indicator that captures changes in environmental policy stringency, covering a wide range of policy instruments standardized for comparability. We then explore patterns and trends in environmental policy development across countries, including the composition and evolution of individual policy instruments. Finally, we describe the macroeconomic data used to assess the relationship between policy stringency and economic performance.

Our dataset includes 40 countries, including members of the OECD and BRICS+ nations (Brazil, Russia, India, Indonesia, China and South Africa). Due to missing economic growth data, Estonia, the Czech Republic, Slovakia, Poland and Slovenia were excluded, leaving 35 countries in the analysis. For most of these excluded countries, consistent GDP growth data is unavailable because they were formerly part of larger political entities, such as the Soviet Union (Estonia), Yugoslavia (Slovenia), or Czechoslovakia (the Czech Republic and Slovakia). Poland, while remaining independent, experienced significant disruptions in statistical reporting during its 1990 economic transition, resulting in inconsistent or missing national accounts data for that year (OECD, 2025). The complete list is available in Table A.1 in the Appendix A.1. All data cover the period from 1990 to 2020, unless otherwise noted.

3.1 Environmental Policy Stringency (EPS) Index

The EPS index highlights how countries differ in their approaches to environmental policy, shaped by historical climate actions, national ambitions, emissions profiles, technological capability, and institutional contexts. It assigns a standardized stringency score to each policy instrument, ranging from zero (inactive or minimal regulation) to six (highly stringent policies exceeding the 90th international percentile). Instruments such as taxes and regulatory limits are transformed into a single, interpretable scale. Higher carbon taxes, stricter emission standards, and more generous subsidies for green technologies receive higher scores. These scores are based on expert judgment, international comparisons, and specific policy features such as tax rates and regulatory thresholds.

Policy instruments are grouped into three categories: market-based policies (MBP), non-market-based policies (NMBP), and technology support policies (TECHS). Each category score is calculated as a weighted average of its component instruments, and the overall EPS index is the average of the three category scores. Table 1 summarizes the EPS structure, listing each instrument and its corresponding weight. Further methodological details are provided in Botta and Koźluk (2014) and Kruse et al. (2022).

Market-based policies create economic incentives by assigning explicit prices to pollution. These include environmental taxes that increase the cost of polluting activities and encourage cleaner alternatives. Certificate trading schemes, also part of this category, establish markets in which a capped number of emission rights are allocated. Countries that emit less than their cap can sell unused rights to others, promoting cost-effective and flexible emission reductions.

Non-market-based policies, in contrast, rely on regulatory mandates rather than price signals. These include performance standards, such as emission limits, which set binding thresholds for environmentally harmful activities. Instead of influencing behavior through costs, these instruments impose legal constraints to ensure compliance and deliver specific environmental outcomes.

Category	Subcategory	Policy Instrument	Weight in EPS
Market-based policies	Certificates	CO_2 Certificates	1/18
		Renewable Energy Certificates	1/18
	Taxes	CO_2 Tax	1/18
		NO_x Tax	1/18
		SO_x Tax	1/18
		Diesel Tax	1/18
Non-market-based policies	Performance Standards	ELV NO_x	1/12
		ELV SO_x	1/12
		ELV PM	1/12
		ELV Sulphur (Diesel)	1/12
Technology support policies	Adoption Support	Solar	1/12
		Wind	1/12
	Upstream Support	R&D Expenditure	1/6

Table 1: Structure of the Environmental Policy Stringency (EPS) Index. ELV = Emission Limit Values. Each indicator is weighted so that MBP, NMBP, and TECHS each contribute one-third to the total index.

Technology support policies provide financial incentives to reduce the cost of adopting clean energy technologies, such as subsidies for solar and wind installations. They also include public investment in environmental R&D. Rather than restricting or pricing pollution directly, these policies aim to shift the technological frontier by encouraging innovation and the development of cleaner production methods over time.

The EPS dataset enables us to capture the full spectrum of national environmental policy strategies. This broad coverage is essential for identifying countries with consistently stringent approaches and for selecting appropriate treatment groups in the empirical analysis.

3.2 Descriptive Patterns in Environmental Policy

To gain insight into the structure and distribution of the EPS index, Table 2 summarizes the stringency scores across all countries and years in our analysis. Although non-market-based policies have the highest average score, their relatively flat distribution suggests a more uniform and widespread adoption across countries. In contrast, market-based policies show the lowest average score and a strong right-skewed distribution, indicating that while most countries have limited implementations of taxes and trading schemes, a small number

Category	Mean	Std. Dev.	P25	P75	Min	Max	Skew	Kurtosis
EPS	1.769	1.193	0.750	2.806	0.000	4.889	0.286	-1.072
Market-based Policies	0.958	0.822	0.333	1.167	0.000	4.167	1.484	2.442
Non-Market-based Policies	2.915	1.992	1.500	5.000	0.000	6.000	0.024	-1.507
Technology Support Policies	1.435	1.321	0.500	2.250	0.000	6.000	0.949	0.451

Table 2: Descriptive statistics of stringency scores for each category of environmental policies (1990–2020, 35 countries). P25 and P75 refer to the 25th and 75th percentiles, respectively. Scores range from 0 (no policy or below the 10th percentile) to 6 (most stringent policy or above the 90th percentile).

of countries, particularly the Nordic countries such as Sweden, Denmark, and Norway, have consistently implemented stringent market-based frameworks. Countries such as Brazil, Indonesia, Israel, and South Africa consistently fall below average in all categories, while Switzerland, Japan, and Finland rank among the most stringent.

We now turn to how environmental policy stringency has evolved over time. This descriptive overview highlights both common trends and important heterogeneity in national approaches, providing essential context for our later empirical analysis. Figure 1 illustrates the average EPS category scores from 1990 to 2020, highlighting distinct development patterns. Non-market-based policies experienced a sharp increase in the 1990s, technology support policies intensified in the early 2000s, and market-based policies grew steadily but more moderately. Over the last two decades, technology support policies have continued to expand, while the other categories have flattened. The patterns reflect persistent differences in policy priorities and highlight the importance of selecting treatment countries based on sustained long-term policy development rather than short-term stringency spikes. Such methodological choices will be elaborated on in more detail in the next section.

We further decompose the EPS index to identify which policy instruments contribute the most to each category's stringency score. This informs the selection of predictor variables in the SCM, as explained in the next section. Following Kruse et al. (2022), we calculate annual averages for each instrument within a category (recalling Table 1), express these as shares of the total category score, weight them accordingly, and aggregate over time to rank their influence. Appendix B.1 shows the development per category in a manner similar to

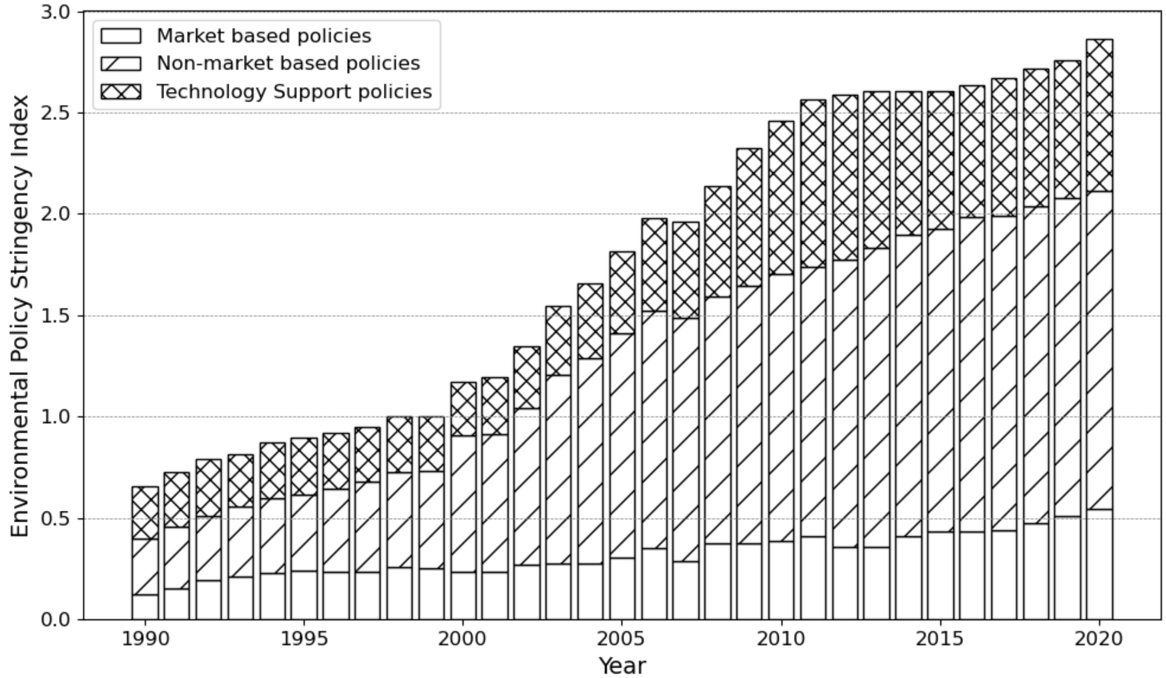


Figure 1: Average development of environmental policy stringency by category and overall EPS score (1990–2020, 35 countries). The figure highlights distinct score development trajectories for market-based policies, non-market-based policies, and technology support policies.

that of the total EPS mentioned above.

It is important to note that the fixed weights in Table 1 are determined by the OECD and remain constant by design. These weights reflect the structure of the index, assigning equal importance to policy instruments within each category. In contrast, the contributions presented in Appendix B.1 are data-driven and vary over time. They reflect the actual implementation of each policy instrument in various countries and years. These contributions result from the interaction between the fixed index weights and the observed stringency levels of each instrument across countries. For example, even if two instruments carry equal weights in the index, one may contribute more to the category score in a given year if its implementation is more stringent. This approach allows us to track how the relative influence of different instruments evolves over time, highlighting real-world policy shifts rather than fixed design parameters.

For market-based policies, diesel taxes contribute more than half of the category score, reflecting their broad adoption across countries. CO_2 certificates and taxes on the remaining pollutants contribute smaller, but steadily increasing shares over time, with countries such as Denmark, Norway, and France rapidly developing the policy frameworks for these instruments. For non-market-based policies, emission limit values are relatively evenly distributed across pollutants. Emission limit values for sulphur dominated in the early years by early adopters such as the United States and Switzerland, but they have since converged with those for NO_x, particulate matter, and SO_x as countries like Canada introduce increasingly stringent regulations. For technology support policies, R&D subsidies account for nearly half of the category score, while support for wind and solar adoption has grown in recent years, gradually balancing the category's composition, particularly in countries such as Japan and the Netherlands.

3.3 Macroeconomic Data

To assess the economic effects of the identified policy transitions, we use annual GDP growth rates from the World Bank's World Development Indicators. Specifically, the analysis draws on the indicator "GDP growth (annual %)"[1], which captures the year-on-year percentage change in real GDP at constant prices. This measure adjusts for inflation and is reported in each country's local currency, ensuring comparability over time across countries. Since it reflects relative growth rather than absolute economic size, this measure facilitates consistent cross-country comparisons, regardless of currency or population differences. Figure 2 presents the average GDP growth in 35 countries from 1990 to 2020, highlighting economic downturns during the 2008 financial crisis and the COVID-19 pandemic. Outside of these shocks, the average growth remained positive.

[1] series code: NY.GDP.MKTP.KD.ZG

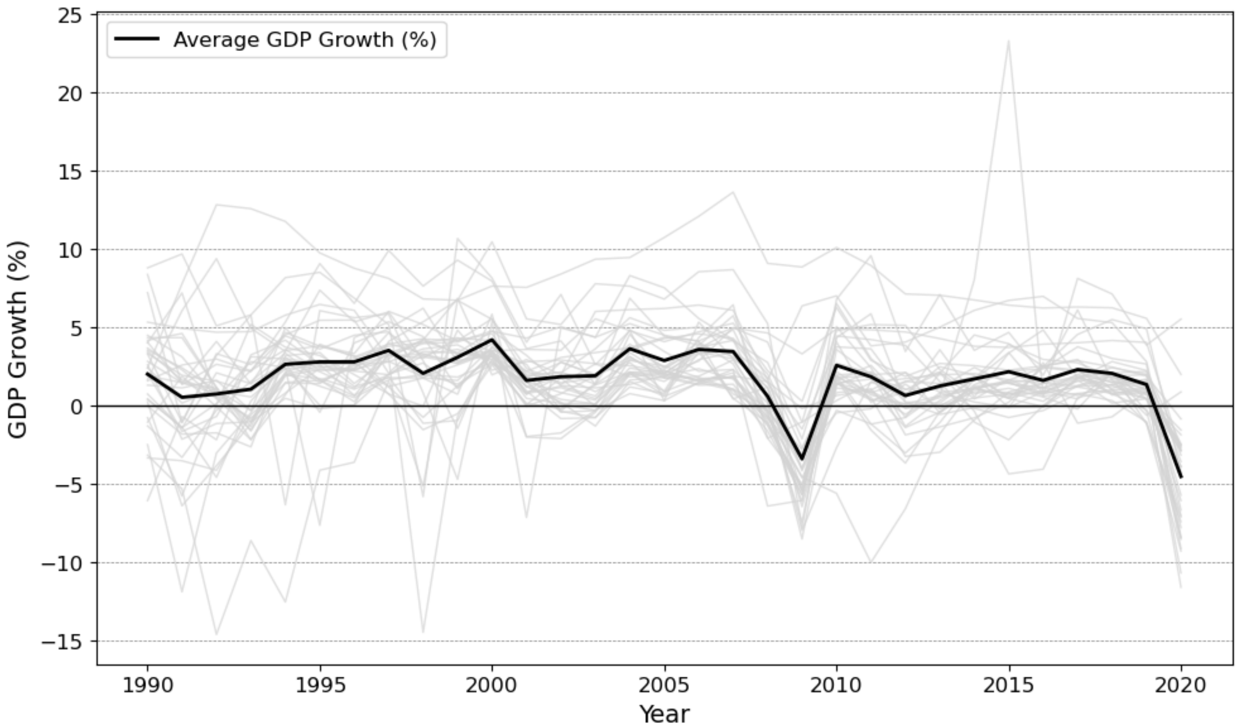


Figure 2: Average annual GDP growth across 35 countries from 1990 to 2020. The figure illustrates general growth trends over time, providing macroeconomic context for evaluating environmental policy developments.

4 Model

In this section, we first motivate the use of the SCM to assess the impact of environmental policy transitions on economic growth. We then outline the key components of the empirical implementation: the identification of treatment countries and event years, the selection of predictor variables, and the construction of the donor pool. Finally, we describe the implementation of in-space placebo tests, which provide the basis for statistical inference by benchmarking observed treatment effects against a distribution of placebo outcomes under the null hypothesis of no policy impact.

4.1 Synthetic Control Method

To evaluate the impact of more stringent environmental policies on a country's economy, we require a counterfactual: how the economy would have developed in the absence of the policy change. This is not observable once the policy has been implemented. A natural approach would be to compare the treated country with a single control country that has not undergone a similar policy shift. However, such comparisons are problematic because countries differ in many relevant dimensions, such as institutional structures, economic conditions, and baseline policy frameworks.

Instead, we apply the SCM introduced by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), which constructs a synthetic control version of the treated country from a weighted average of untreated countries (the donor pool). A technical derivation of the synthetic control estimator is provided in Appendix C.1. Since each country follows a distinct policy trajectory, it is reasonable to assume that the donor countries did not undergo the same policy transitions during the study period. They either do not undergo a comparable policy transition, do so at a different time, or experience changes of a different magnitude. By assigning optimal weights to donor countries based on a set of predictor variables, the synthetic control country closely replicates the treated country's economic performance in the pre-transition period. The post-transition divergence between the treated country and its synthetic counterpart then provides an estimate of the effect of the policy transition.

As discussed in Section 3, we use stringency scores for 13 policy instruments in 35 countries from 1990 to 2020. Each country follows a unique policy path. For the overall EPS index and its three main categories (market-based, non-market-based, and technology support policies), we identify ten treatment countries based on their highest average post-transition stringency scores in each category. The event year for each treatment country is defined as the year in which the steepest increase in that category's score occurs. Since the selected event year may differ between policy categories, even for the same country, the event year, predictor variables, and donor pool are all defined at the country-category level. The subsections that follow detail our data-driven approach to identifying these key inputs for the SCM, followed by the method used to statistically test the overall estimated effect.

4.2 Treatment Countries

This subsection describes the methodology used to identify treatment countries for each policy category. For each category, including the overall EPS, we select ten countries that exhibit the highest average stringency scores after their respective policy transitions. To better understand how countries achieved high stringency in each category, we refer to the detailed policy stringency scores discussed in Section 3. By focusing on the post-transition period, defined in terms of years, we exclude countries that experience only temporary spikes in policy stringency, ensuring that we capture those with sustained policy commitments. In the next section, we outline the methodology for constructing the post-transition event by specifying the event years for each treatment country. The definition of treatment countries and event years can therefore be determined simultaneously, as they rely on different criteria: the average policy score for identifying treatment countries and the year of the steepest increase in policy scores for determining event years.

Table 3 summarizes the ranking and average post-transition policy scores for the treatment countries in each category. The results highlight significant variation in policy development across countries. Some countries, such as Switzerland, France, and Luxembourg, consistently rank among the top performers in several categories, whereas others appear to specialize more narrowly. For each category, the corresponding tables in Appendix A.2 (Tables A.2, A.3, and A.4 for market-based policies, non-market-based policies, and technology support policies, respectively) show the disaggregated scores for each treated country. Countries not selected as treatment countries form the donor pool for constructing the synthetic control.

Sweden stands out in market-based policies through its comprehensive use of environmental taxes and a well-developed framework to support the adoption of renewable energy. Its leading position reflects an early recognition of the importance of price signals in environmental regulation. In particular, Sweden was the first country to introduce a carbon tax to incentivize cleaner energy use. Other countries in the top ranking, such as Norway, Den-

	EPS	MBP	NMBP	TECHS
1	Switzerland (3.97)	Sweden (3.72)	Canada (5.49)	Luxembourg (5.20)
2	Luxembourg (3.84)	Norway (3.19)	Italy (5.45)	Japan (4.70)
3	France (3.83)	Denmark (2.87)	Germany (5.31)	Switzerland (4.66)
4	Finland (3.74)	France (2.42)	Luxembourg (5.31)	France (4.45)
5	Norway (3.62)	United Kingdom (2.24)	Netherlands (5.29)	Finland (4.07)
6	Denmark (3.60)	Italy (2.10)	Korea, Rep. (5.28)	Italy (3.43)
7	Italy (3.52)	Switzerland (2.05)	Belgium (5.26)	Netherlands (3.41)
8	United Kingdom (3.38)	Finland (1.89)	Austria (5.16)	Austria (3.08)
9	Japan (3.34)	Hungary (1.69)	Switzerland (5.12)	Denmark (3.00)
10	Sweden (3.32)	Japan (1.66)	France (5.07)	Canada (2.85)

Table 3: Final list of treatment countries for each environmental policy category. Values in parentheses indicate the average policy stringency score during the post-transition period. EPS = Environmental Policy Stringency; MBP = Market-Based Policies; NMBP = Non-Market-Based Policies; TECHS = Technology Support Policies.

mark, and France, also employ extensive pollution taxation but tend to focus more narrowly on specific sectors or fuel types. What distinguishes the top performers from the donor pool in this category is not only the tax level but also the integration of market mechanisms, such as renewable certificate schemes, into a broader policy strategy.

For non-market-based policies, the differences in stringency scores are narrower, suggesting a more uniform international alignment around regulatory standards. The countries with the highest rankings adopt comprehensive regulatory frameworks that address multiple pollutants simultaneously. In contrast, lower-scoring countries tend to emphasize controls on specific pollutants, such as sulphur or particulate matter controls.

Technology support policies show greater variation in stringency scores between the top-ranked countries. Countries such as Luxembourg and Japan lead through a combined strategy of substantial public investment in clean energy innovation and strong support for the adoption of renewable energy. This reflects national targeted strategies adopted to promote innovation.

Together, these rankings reflect broader international trends in the evolution of environmental policies. Developed countries, particularly in the Nordic region, exhibit consistently high levels of policy stringency across categories. In contrast, countries in Latin America, the Middle East, and parts of Asia tend to adopt environmental policies more slowly. The gap appears to be widening, with early adopters building on past commitments and lagging countries struggling to catch up. Within Europe, this divergence is further reinforced by EU-wide regulatory frameworks, illustrating how sustained engagement with environmental policy can compound over time.

To assess the arbitrary choice of selecting ten countries for the treatment group, we have compared the average treatment effects between different group sizes. The results indicate negligible differences in estimated treatment effects, as they remain stable when the cutoff varies around ten countries.

4.3 Event Years

This subsection outlines the methodology used to define the event years for each treatment country and policy category. In our setting, the event corresponds to the year when a country initiates a transition toward more stringent environmental policies. As countries differ in past climate actions, national ambitions, emissions profiles, technological availability, and social, political, and institutional contexts, the timing of these transitions varies. We, therefore, adopt a data-driven procedure to determine the event year on a country-category basis.

We define the event year as the year in which the relevant policy category experiences the steepest increase in stringency. We implement this by calculating the average policy score before and after each possible event year and selecting the year that maximizes the difference between these two averages. This method ensures that we capture the year in which the shift toward more stringent policy is most pronounced.

Reliable SCM estimation requires a sufficiently long pre-transition period to fit the model (Abadie, 2021; Abadie and Vives-i-Bastida, 2022). Moreover, we also require a sufficiently long post-transition period to assess dynamic effects. Therefore, we restrict the event year to lie within an inner window of the data period, excluding the first and last ten years (1990–1999 and 2011–2020). This ensures at least ten pre- and post-transition observations

	EPS	MBP	NMBP	TECHS
1	Switzerland (2010)	Sweden (2003)	Canada (2003)	Luxembourg (2010)
2	Luxembourg (2010)	Norway (2007)	Italy (2006)	Japan (2010)
3	France (2004)	Denmark (2000)	Germany (2001)	Switzerland (2010)
4	Finland (2010)	France (2010)	Luxembourg (2001)	France (2006)
5	Norway (2007)	United Kingdom (2005)	Netherlands (2004)	Finland (2010)
6	Denmark (2003)	Italy (2004)	Korea, Rep. (2004)	Italy (2010)
7	Italy (2005)	Switzerland (2010)	Belgium (2003)	Netherlands (2007)
8	United Kingdom (2009)	Finland (2010)	Austria (2010)	Austria (2008)
9	Japan (2000)	Hungary (2008)	Switzerland (2007)	Denmark (2008)
10	Sweden (2000)	Japan (2003)	France (2003)	Canada (2006)

Table 4: Final list of treatment countries for each environmental policy category, with identified event years in parentheses. The event year refers to the year in which each country experienced the steepest increase in stringency within the respective category. EPS = Environmental Policy Stringency; MBP = Market-Based Policies; NMBP = Non-Market-Based Policies; TECHS = Technology Support Policies.

for each country-category combination. The technical derivations on the determination of the event years are provided in Appendix C.2.

Table 4 presents each country-category combination, along with their identified event years. Several correspond to major policy milestones. For example, Sweden's 2003 event year aligns with the launch of its green energy certificate system (Agency, 2004). Luxembourg's 2010 transition corresponds to expanded feed-in tariffs, regulatory tightening, and green R&D under the 2020 EU climate and energy goals, alongside similar policy shifts in France, Italy, Austria, and Finland (European Commission, 2010). Japan's 2010 shift reflects its "Green Innovation" strategy (Ministry of Economy, Trade and Industry, 2010). The UK's 2005 event marks its entry into the EU Emission Trading Scheme (European Parliament and Council, 2003), while Italy's 2006 transition coincides with new EU air quality and emission standards (Government of Italy, 2006; European Parliament and Council, 2008).

In this subsection, we outline the methodology used to construct the final SCM models for all treatment countries and policy categories. As described in Section 3.1, the data set includes a wide range of policy instruments. While each of these variables provides important information about a country's environmental policy development, their inclusion presents a core modeling challenge: the risk of overfitting. This issue is well documented in the existing literature (Abadie, 2021; Abadie and Vives-i-Bastida, 2022; Chen and Li, 2024). In our case, two key factors contribute to this risk.

First, the number of potential predictors is large relative to the available pre-transition periods. Since all event years are restricted to before 2011, each SCM model is calibrated on a maximum of 20 years. Including all 13 policy instruments as separate predictors would bring the predictor count close to or beyond the number of observations. As a result, the model risks capturing noise rather than the true underlying counterfactual. In this situation, the synthetic control might closely replicate the trajectory of the treated country in the pre-transition period, but only due to the unstable or extreme weights assigned to a small subset of donor units. This typically occurs when the treated unit lies near the boundary of the space spanned by the donor pool, known as the convex hull. The convex hull defines the full set of weighted combinations that can be formed from the donor units. When a treated unit falls outside this boundary, its characteristics cannot be replicated through a balanced mix of donors drawn from within the interior of this space. As a result, the model tends to assign large weights to a small subset of donor countries, increasing the risk of overfitting and reducing the robustness of the estimated counterfactual (Abadie, 2021).

A second risk factor is the size of the donor pool itself. With 25 potential control countries, the number of donors relative to the available time periods is again imbalanced, increasing the likelihood of unstable or spurious weight assignments (Abadie, 2021). To mitigate both risks, we implement two strategies.

First, we reduce the set of predictors to include only the most informative policy indicators. The selection of predictors is guided by the decomposition analysis in Section 3.2. Two policy instruments stand out in terms of their relative contribution: diesel taxes, which account for more than 50% of the market-based policies' score, and R&D subsidies, which contribute an average of 45% to the technology support policies' score. These are included as standalone predictors. To retain a broader policy context while avoiding overfitting, we include the aggregate scores for market-based policies, non-market-based policies, and technology support policies, alongside the two aforementioned individual policy instruments, resulting in a final set of five predictors. This combination captures both prominent individual effects and the overall policy environment, enabling reliable estimation while maintaining model parsimony.

Second, we cut the donor pool for each treated country by removing countries that are the least similar in terms of economic and policy profiles. Since event years vary, the number of pre-transition periods, denoted as T_0, also differs across countries. To maintain a consistent balance between the number of donor countries and pre-transition periods, we define the donor pool size dynamically using a ratio parameter ρ, which takes on three predetermined values: 0.5, 0.75, and 1.0. Smaller values of ρ imply smaller donor pools [2]. Donors are selected using a distance-based matching strategy. Appendix C.4 presents the technical derivations of the distance-based matching strategy.

For each treated country, we construct a vector z that includes all final policy predictors, as well as our outcome variable, GDP growth, measured over the pre-transition period. All variables are standardized to have a zero mean and unit variance between countries, ensuring comparability between different scales. We then calculate the Euclidean distance between the treated country c and each potential donor country d during the pre-transition period to measure their similarity [3]. For each treated country, donors are ranked by this distance, and the closest countries $k(\rho)$ are retained.

Each of the three values for ρ yield a separate SCM. To evaluate model performance, we compute the Root Mean Square Prediction Error (RMSPE), which measures how closely the synthetic control replicates the treated unit's outcome before the event [4]. Further technical

[2]The donor pool size $k(\rho)$ is defined as a fixed fraction ρ of the number of pre-transition periods T_0, formally expressed as $k(\rho) = \rho \cdot T_0$.

[3]The standardized Euclidean distance is calculated as $\ell(t, d) = \sqrt{\sum_{t=1}^{T_0} (z_{dt} - z_{ct})^2}$, where z_{dt} contains the standardized values of all predictors for donor country d at time t, and z_{ct} contains the corresponding standardized values of all predictors for treated country c.

[4]The Root Mean Square Prediction Error is defined as $\text{RMSPE}(\rho) = \sqrt{\frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1t}^I - Y_{1t}^{N,\rho} \right)^2}$,, where Y_{1t}^I is the observed outcome and $Y_{1t}^{N,\rho}$ is the synthetic outcome for donor ratio ρ.

details on RMSPE are provided in Appendix C.3. To determine the optimal donor size, we compare the performance of each SCM model using the RMSPE calculated over the pre-transition period. The value of ρ that minimizes the RMSPE is selected as the optimal donor pool size, denoted by ρ^*. If multiple values result in identical RMSPEs, the SCM model with the smallest donor pool is preferred. Additionally, the obtained RMSPE values across different values of ρ also serve as a robustness check. When these values are identical or negligible in difference, it suggests that the donor weight distribution remains stable across specifications, indicating that the estimates are not sensitive to the choice of the donor pool size.

Given the centrality of the tuning process in constructing reliable synthetic controls, the full set of RMSPE values by treated unit and donor pool size is reported in Table A.5 of Appendix A, providing a transparent view of the model calibration process. The results show that smaller donor pools often improve the fit of the model, although this is not universal. More importantly, the differences in RMSPE between donor pool sizes are generally negligible, indicating that our estimates are robust and that the risk of overfitting is mitigated. Figure B.4 in Appendix B.2 illustrates how varying donor pool sizes affect model performance for a transition in Denmark's technology support policies.

4.4 Placebo Tests

To evaluate whether the estimated total economic effects are statistically significant, we cannot rely on conventional standard errors or asymptotic approximations, as these are not suitable for SCM models. Instead, inference is based on resampling strategies that construct a distribution of placebo effects under the null hypothesis of no treatment (Abadie, Diamond, and Hainmueller, 2010; Abadie, Diamond, and Hainmueller, 2015). Placebo tests can be conducted either in-time, by shifting the date of the policy transition, or in-space, by reassigning the treatment to donor countries. We focus on in-space tests, as they provide a distribution of placebo effects that serves as the benchmark for evaluating the significance of the estimated total economic effects [5].

Methodologically, the steps are identical to the estimation of the actual treatment effects, except that the set of treatment countries is replaced by randomly selected donor countries of equal group size (ten in our case). The treatment effects from the placebo group are first computed at the country level, then averaged across the group, and finally accumulated over time. These accumulated average treatment effects represent the total economic effects of the donor group [6]. This aggregation ensures that the inference reflects the total group-level effect of the policy transitions rather than being driven by any single country.

To generate the placebo distribution, this procedure is repeated for 250 random draws, each time assigning treatment to a new group of donor countries. For each draw, the total economic effects in each year after the policy transition are computed, yielding a benchmark distribution against which the total economic effect from the treatment group can be evaluated. From this distribution, p-values are derived as the fraction of placebo effects at a given horizon that are at least as extreme as the observed effect [7].

This inference procedure avoids reliance on asymptotic theory and, instead, uses the empirical distribution of placebo outcomes to assess whether the observed treatment effects are unusually large in magnitude. Further technical details and derivations of this procedure are provided in Appendix C.5.

5 Results

This section presents the empirical findings of our SCM analysis. Separate models are estimated for each treatment country across all policy categories, as well as for the overall EPS index. As outlined in Section 4, the approach identifies treatment countries and event

[5] See Abadie, Diamond, and Hainmueller (2010) for the development of in-space placebos, and Abadie, Diamond, and Hainmueller (2015) for related inference approaches, including in-time placebos.

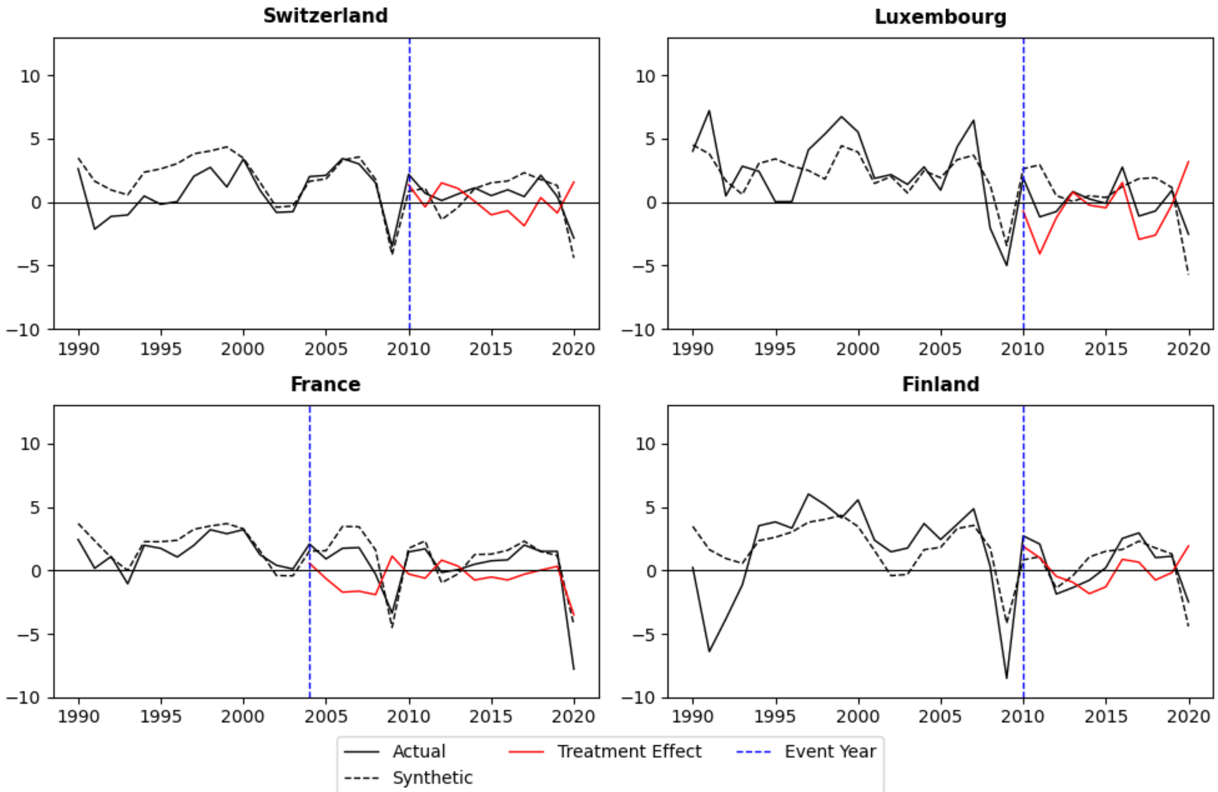
[6] Formally, if $\widehat{\tau}_{it}$ denotes the treatment effect for treated country i at time t, the group-average effect is $\bar{\tau}_t = \frac{1}{m}\sum_{i=1}^{m}\widehat{\tau}_{it}$, and the total economic effect is $\theta_t = \sum_{s=T_0}^{t}\bar{\tau}_s$, with θ_T denoting the final total economic effect in the last time period T.

[7] Formal definitions of the one-sided and two-sided p-values are provided in the Appendix C.5.

years, selects relevant predictors, and applies donor pool trimming to ensure robust estimation. The results are structured in five parts. First, we present country-level outcomes by policy category. Second, we aggregate treatment effects on a relative timeline to assess the broader economic impact of policy transitions. Third, we disaggregate these effects by policy category. Fourth, we evaluate the statistical significance of the total economic effects using in-space placebo tests. Finally, we assess model performance to validate the credibility of the estimated effects.

5.1 Country-Level Effects of Policy Transitions

Figure 3 shows the GDP growth paths for the ten treatment countries with the highest EPS scores after their policy transition takes place. Each panel represents a treatment country, where the solid black line traces actual GDP growth, the dashed line shows the synthetic control estimate, and the red line depicts the estimated treatment effect following the event year (marked by the vertical blue line), which corresponds to the steepest change in environmental policy stringency. This comparison illustrates how each country's economic trajectory evolved relative to a synthetic counterfactual scenario without the policy shift.


Switzerland
Luxembourg
France
Finland
10
5
0
−5
−10
1990
1995
2000
2005
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2020
Actual
Synthetic
Treatment Effect
Event Year

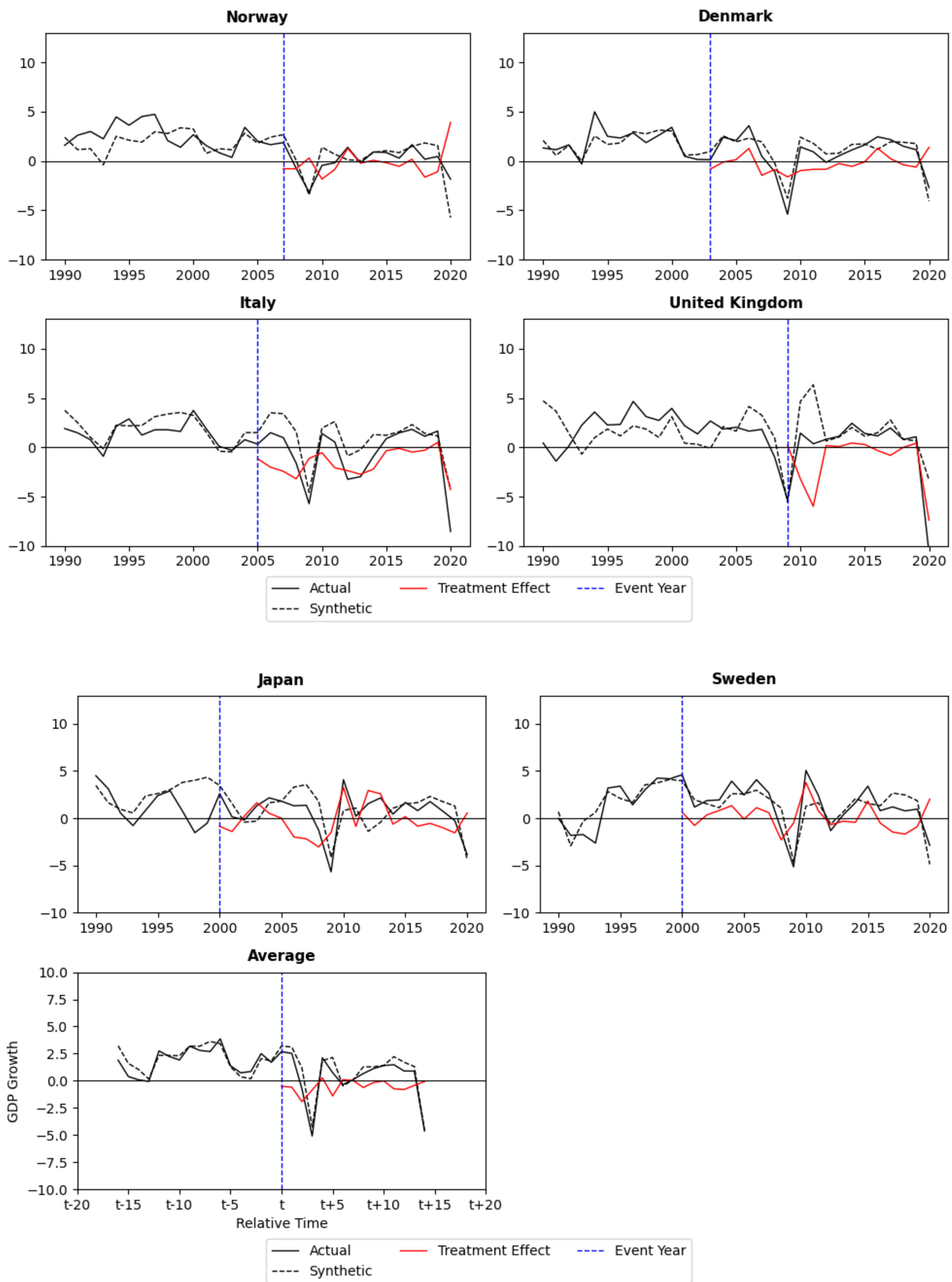


Figure 3: Country-level comparison of the observed outcome with the synthetic control, alongside the corresponding treatment effects for EPS policies. The solid black lines represent actual GDP growth; dashed lines show the synthetic control. The red line captures the estimated treatment effect after the policy transition event.

The results illustrated in Figure 3 show that the treatment effects differ substantially across countries. The United Kingdom and France, for example, exhibit immediate negative economic effects after transitioning to more stringent environmental policies, suggesting that short-term adjustment costs, such as compliance expenses, shifts in investment, or sectoral disruptions, may initially weigh on economic growth. Since these estimates reflect transitions in the composite EPS index, the observed effects may arise from one or more underlying policy categories (market-based instruments, non-market-based regulations, or technology support measures), depending on each country's specific policy composition. Conversely, countries like Switzerland and Sweden experience relatively mild short-term economic impacts, indicating smoother integration of policy changes with minimal disruption. Over the longer term, countries such as Norway and Japan show signs of economic recovery following initial negative economic impacts, consistent with a pattern where short-term adjustment costs diminish and lead to longer-term economic benefits from environmental policy stringency.

This heterogeneity in country-level effects is consistent with findings in the broader literature and reflects a range of underlying factors. For instance, the differences in the scope and depth of policy transitions play an important role: some policy transitions are limited to specific instruments, while others involve more comprehensive shifts across multiple policy categories (Goulder and Parry, 2008; Stavins, 2010). Timing is also critical, since policy transitions coinciding with recessions or energy price shocks tend to further increase short-term costs (Burns and Tobin, 2016; Burns, Eckersley, and Tobin, 2020). In addition, the economic structure of a country plays a role: countries with larger emissions-intensive sectors or higher fossil-fuel dependency are more exposed to negative economic impacts, while service-based or diversified economies adjust more smoothly (Jorgenson and Wilcoxen, 1990; Jaffe, Peterson, et al., 1995).

Taken together, these patterns clarify the variability in economic responses to environmental policy transitions. Similar heterogeneous responses can be observed for the remaining

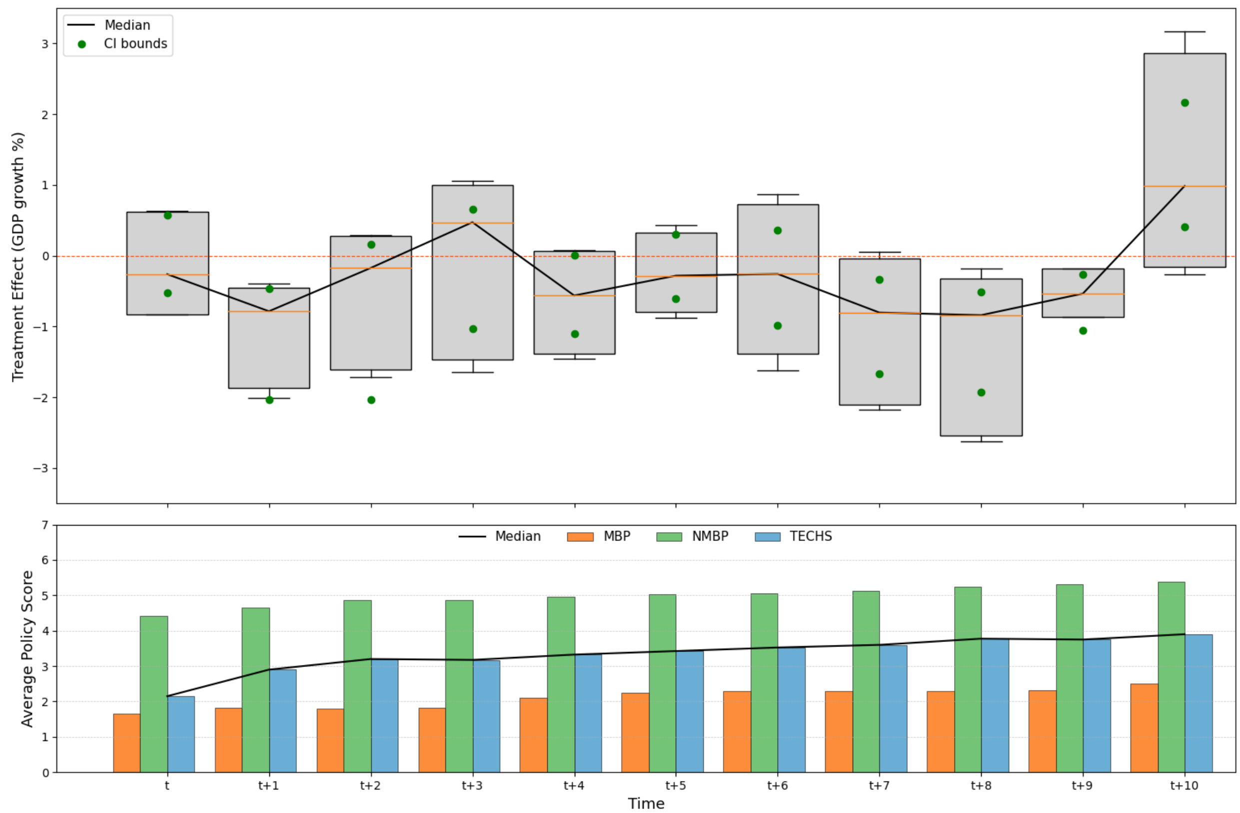


Figure 4: Aggregated estimated GDP growth effect following EPS-based policy transitions. The upper panel shows boxplots of the treatment effects over time with a 90% confidence interval ($\alpha = 0.10$); the lower panel presents the average scores of each policy category across the treatment countries. MBP = Market-Based Policies, NMBP = Non-Market-Based Policies, TECHS = Technology Support Policies.

policy categories, with detailed country-level results reported in the Appendix B.3. To further understand these patterns, we aggregate the treatment effects along a relative time scale.

5.2 Aggregate Effects of Composite EPS Index

Figure 4 aggregates treatment effects for transitions in the overall EPS index along a relative timeline centered on the event year (year zero). The upper panel presents boxplots summarizing the distribution of GDP growth effects, and the lower panel shows the average policy stringency scores by category for treated countries, reflecting the policy stringency associated with the transitions.

Immediately after the policy transition, the upper panels indicate that the average economic impact is negative in the second year, consistent with short-term adjustment costs documented by Palmer, Oates, and Portney (1995), Jaffe, Peterson, et al. (1995), and Botta and Koźluk (2014), such as temporary losses in competitiveness (market-based policies), compliance expenditures (non-market-based policies), or technology adaptation (technology support). This negative effect persists over the medium term, indicating ongoing integration costs. By approximately ten years post-transition, the economic impact becomes positive and statistically significant, suggesting a full economic recovery. The lower panel shows that all policy categories generally continue to strengthen over time, with the total EPS score increasing by around 50% on average within ten years, confirming sustained policy commitments in the long term.

5.3 Policy Category Disaggregation

In order to understand how specific categories of environmental policy instruments contribute to the overall EPS effect, we separately analyze the treatment effects for each policy category. These disaggregated results for market-based policies, non-market-based policies, and technology support policies are reported in Appendix B.4 (Figures B.8, B.9, and B.10, respectively), using the same format as the composite EPS index in Figure 4 above. Below, we summarize the key patterns that emerge from these results.

The results for countries that have transitioned to more stringent market-based policies (see Figure B.8 in Appendix B.4) indicate that the economic effects are generally insignificant in the early years, with the exception of the fourth year, which shows a negative impact. The results do not provide evidence of any long-term economic recovery.

The lower panel shows that the overall market-based policy score does not continue to increase after the policy transition, driven by mixed trends among the underlying policy instruments: diesel and NO_x taxes remain relatively high or increase slightly, whereas SO_x taxes and energy certificate schemes tend to stabilize or decline. This stagnation suggests a lack of sustained policy reinforcement in the market-based category. These findings align with the literature showing that governments may scale back or delay environmental taxes during economic downturns to alleviate short-term burdens (Burns and Tobin, 2016; Burns, Eckersley, and Tobin, 2020; OECD, 2017). Without continued strengthening, initial reform impacts may not translate into longer-run economic changes.

The results for countries that have transitioned to more stringent non-market-based policies (see Figure B.9 in Appendix B.4) indicate immediate negative economic effects, directly at the event year when the sharp increase in policy stringency takes place (lower panel). After the initial rise of nearly all non-market-based instruments, policy stringency continues to increase more gradually, while economic effects remain neutral to negative in the medium term and tend to persist negatively in the long term. Goulder and Parry (2008), Oates and Portney (2003), and Palmer, Oates, and Portney (1995) argue that such persistent negative effects may arise when sectors face high compliance costs and limited flexibility in adjusting to regulatory requirements, particularly under non-market-based instruments such as performance standards and technology mandates.

The results for countries that have transitioned to more stringent technology support policies (see Figure B.10 in Appendix B.4) indicate the most pronounced short-term economic costs among all policy categories, followed by a gradual recovery, continuing to generate economic losses, over time. These initial costs likely reflect adjustment costs such as delayed R&D returns, capital reallocation, and production restructuring, as documented in the environmental economics literature (Jaffe, Peterson, et al., 1995; Goulder and Parry, 2008; Jaffe, Newell, and Stavins, 2003; Popp, Newell, and Jaffe, 2010). Technology policies like public R&D funding, renewable energy subsidies, and innovation incentives often require upfront spending before benefits materialize (Johnstone, Haščič, and Popp, 2010; Acemoglu et al., 2012), consistent with the gradual positive trend in economic effects observed in the long term here (Ambec et al., 2013; Albrizio, Kozluk, and Zipperer, 2017).

The lower panel indicates a rapid increase in the stringency of all three technology support policy instruments shortly after the transition, peaking around five years before slightly declining. This pattern suggests that initial commitments to stronger technology support policies may weaken over time, unlike regulatory policies, which tend to show more persistent strengthening after transitions. The variation in how the stringency of different technology support policies evolves over time reflects broader uncertainty regarding their long-term implementation. This aligns with earlier findings from the literature that governments may face constraints in maintaining consistent support for innovation policies, potentially limiting their sustained impact (Johnstone, Haščič, and Popp, 2010).

5.4 In-Space Placebo Tests on the Aggregated Economic Effects

We evaluate the magnitude and statistical significance of the total economic effects of the treatment countries using in-space placebo tests, following the approach outlined in Section 4.4. To formulate a hypothesis about the expected economic effects after each policy transition, we first need to derive the total economic effects of each treatment group across each policy category. Figure 5 summarizes these results: The solid lines represent the estimated effects over time, and the shaded bands indicate the 90% confidence intervals.

The estimates show that all policy transitions cause negative total economic effects over the entire time horizon. Among them, EPS and technology support generate the most persistent economic losses. Non-market-based and market-based policies also result in economic losses, but their estimated effects generally remain within the bounds of statistical uncertainty. Some signs of economic recovery emerge in the longer term for EPS and market-based policies, yet these effects are too limited to translate into sustained overall economic growth.

These findings motivate a test of the null hypothesis of no economic effects against the one-sided alternative of negative total economic effects (hereafter: economic losses). The in-space placebo tests not only assess the significance of the overall impact but also allow us to evaluate whether the effects are significant during specific periods, thereby offering insights into short-, medium-, and long-term dynamics [8].

[8]Formally, we test $H_0: \ \theta_{1t} = 0$ against the one-sided alternative $H_1^L: \ \theta_{1t} < 0$, where θ_{1t} denotes the

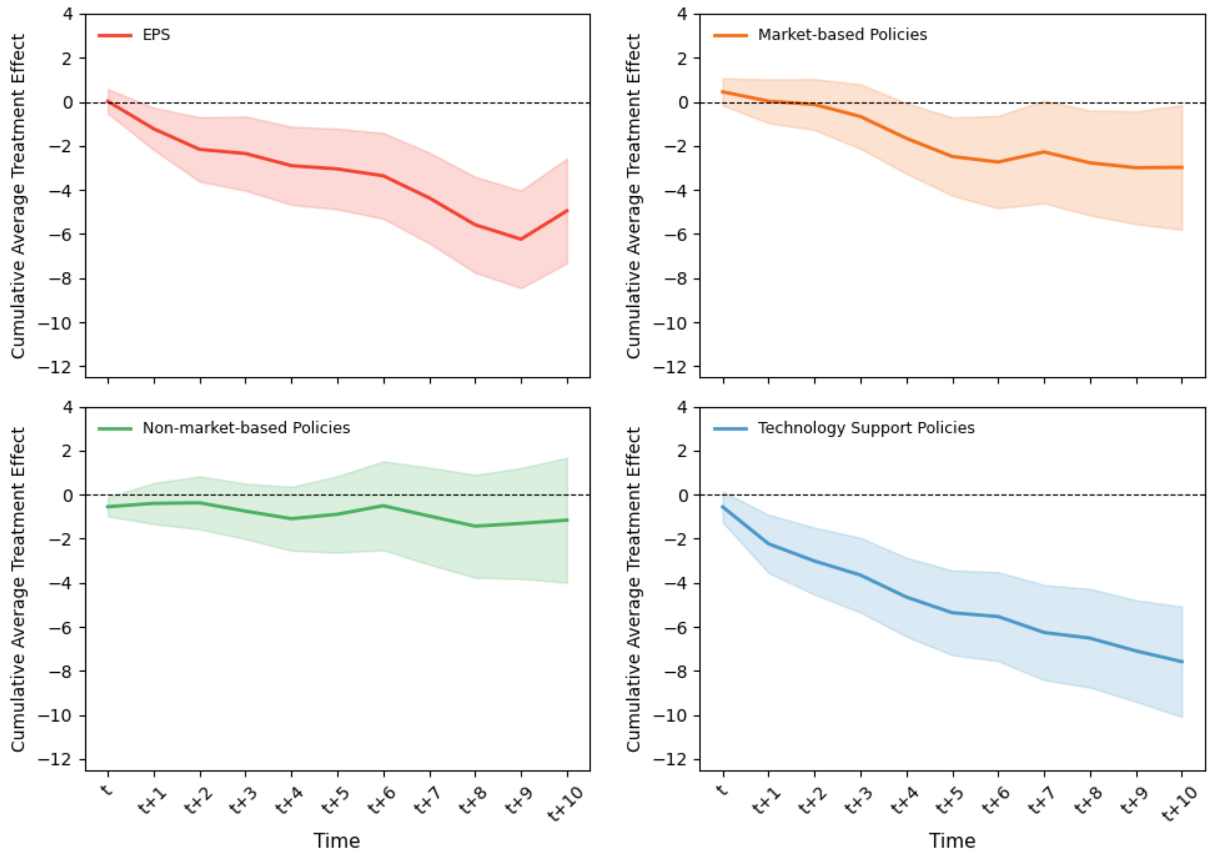


Figure 5: Cumulative average treatment effects for each policy transition. Solid lines show the cumulative average treatment effects across the ten treatment countries; shaded regions represent the 90% confidence interval ($\alpha = 0.10$).

Figure 6 reports the results of placebo tests. For each policy category, the left panels compare the total economic effects of the treatment countries (black line) with the distribution of placebo effects (gray lines), based on 250 random draws. The reported left-sided p-value corresponds to the total economic loss at the end of the time horizon [9]. The right panels display the corresponding left-sided p-values for each year following the policy transition. Histograms of the placebo distributions are provided in Appendix B.5.

Technology support policies show the largest and most consistent economic losses over the entire time horizon, with p-values below 5% in each year after the policy transition, accumulating to an overall economic loss of 7.6%. EPS transitions also produce large economic

total average treatment effect at time t.

[9]Following Abadie, Diamond, and Hainmueller (2010), we evaluate the significance of the total effects using the p-value at the final time horizon, denoted by θ_T.

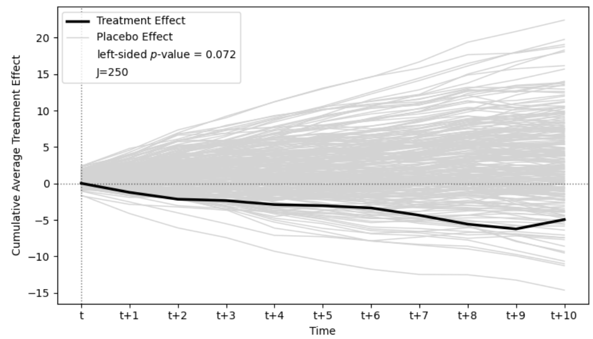
losses, significant at a minimum of 10%, except for the policy transition year, which results in a total economic loss of 4.9%. In contrast, market-based and non-market-based policy transitions are insignificant for almost all years. Taken together, these findings highlight the heterogeneous economic consequences of different types of policy transitions, with technology support policies and EPS standing out as the primary drivers of long-term economic losses.

5.5 Model Fit

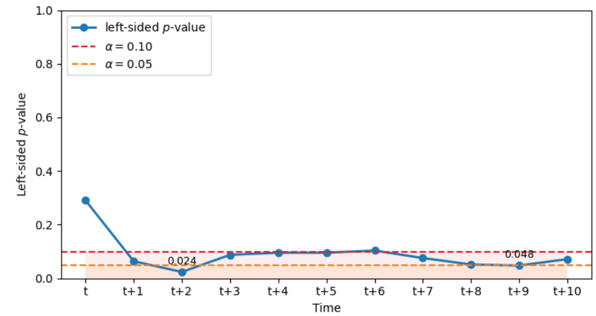
Finally, model performance is evaluated using the root mean squared prediction error (RMSPE), scaled by the total GDP growth in the corresponding pre- and post-transition periods. This scaling expresses RMSPE relative to the magnitude of economic change, making comparisons across countries with different growth patterns more meaningful. Lower scaled RMSPE values indicate a stronger pre-transition fit and greater confidence in the synthetic control as a valid counterfactual.

As shown in Table A.6 of Appendix A.4, the scaled RMSPE values are generally low, indicating a good model fit across treatment countries and policy categories. In some cases, such as Luxembourg, higher scaled RMSPE values arise when economic growth in the relevant periods is close to zero or negative. Under these conditions, even moderate absolute errors can produce large scaled values, which do not necessarily indicate poor predictive performance. Overall, higher RMSPE values tend to occur during periods of economic crisis when structural breaks or idiosyncratic shocks reduce the SCM's ability to accurately approximate GDP growth. Such deviations are evident in country-level plots (e.g., Figure 3 for EPS, and Figures B.5, B.6, and B.7 in Appendix B.3 for the individual policy categories). These results, suggesting that discrepancies reflect country-specific responses to macroeconomic shocks that cannot be fully captured by the donor pool, are consistent with findings in Billmeier and Nannicini (2013). Thus, they highlight limitations in replicating crisis dynamics rather than indicating poor SCM performance.

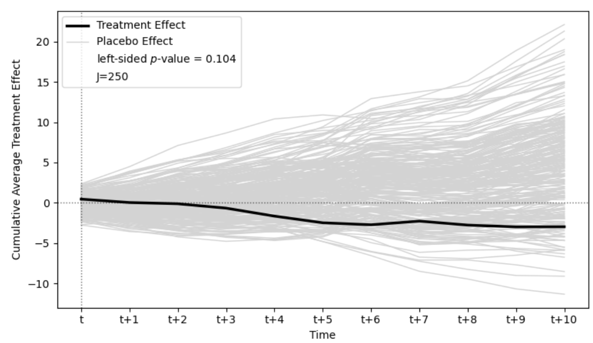
Taken together, these results indicate that the SCM performs well in replicating pre-



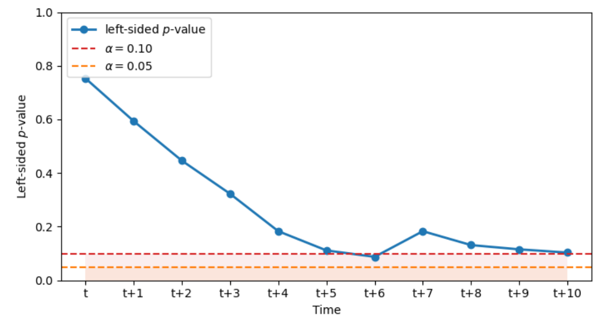
(a) EPS (Placebo distribution)



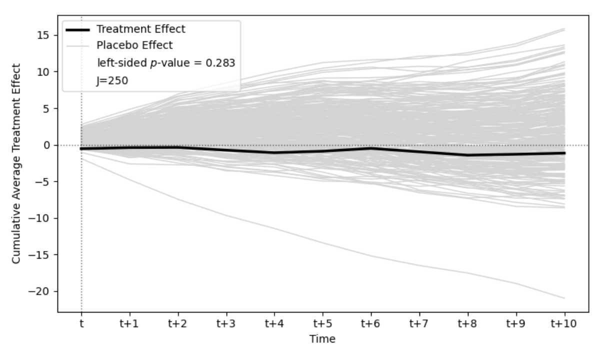
(b) EPS (left-sided p-values)



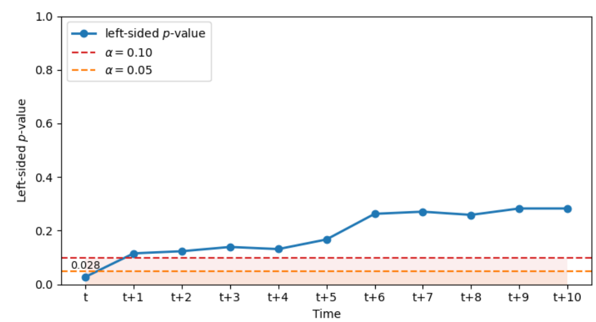
(c) Market-based policies (Placebo distribution)



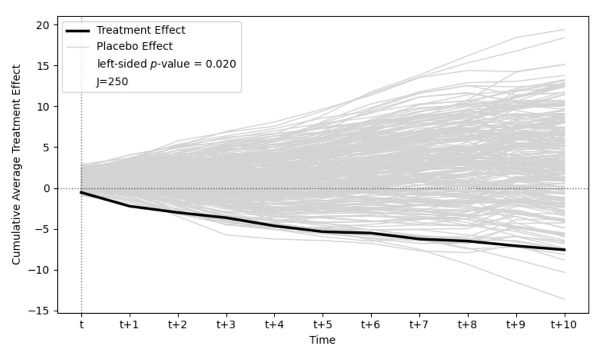
(d) Market-based policies (left-sided p-values)



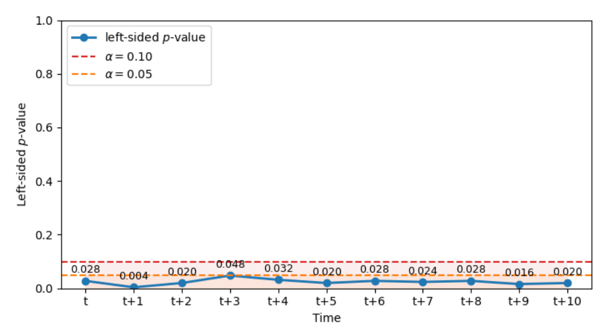
(e) Non-market-based policies (Placebo distribution)



(f) Non-market based policies (left-sided p-values)



(g) Technology support policies (Placebo distribution)



(h) Technology support policies (left-sided p-values)

Figure 6: In-space placebo test results. Left panel illustrates the distribution of placebo effects against the treatment effects for each policy category. The reported p-value corresponds to the significance level in the final time horizon. The right panel illustrates the development of the left-sided p-values, derived from the placebo distributions, after the policy transitions.

transition GDP growth across countries and policy categories. Deviations that arise, particularly during economic crises, appear to reflect external shocks rather than shortcomings in model specification. This supports the validity of the estimated treatment effects, especially during stable periods.

6 Conclusion

We have examined the economic effects of environmental policy transitions across market-based, non-market-based, and technology support policies, along with their aggregate effect captured by the environmental policy stringency (EPS) index, using a heterogeneous and multidimensional dataset of policy stringency scores. Moving beyond single-country case studies, we have developed a uniform synthetic control method (SCM) framework that can be applied across all countries and policy categories. Our methodology standardizes the identification of treatment countries, event years, predictor variables, and donor pools and incorporates in-space placebo tests to formally assess the magnitude and significance of the estimated total economic effects. Our framework enables direct cross-country comparisons of different policy transitions while accounting for variations in timing, design, and national context. A key contribution of this study is to have carried out a comprehensive comparison across a wide range of policy instruments and countries.

First, our results show that the annual economic effects of policy transitions vary significantly by category and over time. In the short term, most transitions impose modest to significant annual costs, especially for non-market-based and technology support policies. These findings may reflect compliance burdens, capital reallocation, and innovation lags (Jaffe, Peterson, et al., 1995; Palmer, Oates, and Portney, 1995; Goulder and Parry, 2008). Technology support policies incur the highest costs, consistent with their high investment needs and delayed returns (Jaffe, Newell, and Stavins, 2003; Acemoglu et al., 2012; Johnstone, Haščič, and Popp, 2010). In the long term, effects diverge. Non-market-based and market-based policy transitions do not produce any significant losses. Technology support policy transitions, on the other hand, continue to generate economic losses. EPS policy transitions also consistently generate economic losses, except for the last year in our time horizon, indicating that more time is required for the economic gains to materialize.

To assess whether these effects translate into significant economic losses, we perform in-space placebo tests. The results show that technology support policies generate the largest losses, with GDP declining by 7.6% in the last observed year after the policy transition. EPS transitions also lead to significant, though smaller, losses of 4.9%. For EPS, a longer transition period may be required for the effects to translate into growth, as losses diminish toward the end of the horizon. In contrast, technology support policies show no clear decline in losses over time. In contrast, market-based and non-market-based policies show no significant long-term effects. These findings highlight the heterogeneous economic responses to environmental policy transitions and demonstrate that, although short-term losses can be substantial, stricter market-based and non-market-based policies do not inherently constrain long-term economic performance.

Future research could explore the transitional economic effects of specific environmental instruments in greater detail. Countries that adopt more specialized strategies, focusing on a narrower set of instruments, may experience different economic outcomes than those pursuing broader policy implementations. Moreover, while this study focuses on countries with relatively advanced policy frameworks, it is equally important to examine economies with less developed or emerging frameworks. For these countries, identifying the most effective strategy, whether based on specialization or broader adaptation, could help improve the balance between environmental goals and economic performance. If a specialized set of policy instruments were to yield better outcomes, future work should assess which combination of policies has the highest or lowest economic impact in both the short and long term. Finally, this study focuses exclusively on GDP as the measure of economic growth, while environmental policies may also have broader macroeconomic impacts, such as on inflation, employment, fiscal outcomes, and social welfare. Examining these effects would provide a more comprehensive understanding of the economic consequences of environmental policy transitions.

In conclusion, our findings provide important implications for policy makers. Although short-term economic concerns can discourage countries from seeking more ambitious environmental reforms, our results suggest that such transitions can be compatible with long-term sustainable growth, depending on the category of policies pursued. Policy makers should therefore not be deterred from adopting more stringent environmental policy frameworks, as these do not necessarily imply persistent economic costs.

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Appendices

A Supplementary Tables

A.1 Country Abbreviations

Abbreviation	**Country Name**
AUS	Australia
AUT	Austria
BEL	Belgium
BRA	Brazil
CAN	Canada
CHL	Chile
CHN	China
DNK	Denmark
FIN	Finland
FRA	France
DEU	Germany
GRC	Greece
HUN	Hungary
ISL	Iceland
IND	India
IDN	Indonesia
IRL	Ireland
ISR	Israel
ITA	Italy
JPN	Japan
KOR	Korea
LUX	Luxembourg
MEX	Mexico
NLD	Netherlands
NZL	New Zealand
NOR	Norway
PRT	Portugal
RUS	Russia
ZAF	South Africa
ESP	Spain
SWE	Sweden
CHE	Switzerland
TUR	Turkey
GBR	United Kingdom
USA	United States

Table A.1: List of countries included in the analysis. These 35 countries are used to construct the SCM models. The sample is restricted to countries for which both environmental stringency and economic growth data are available over the full period from 1990 to 2020.

A.2 Policy Scores of Treatment Countries by Category

Rank	Country	MBP	CO_2 Tax	Diesel Tax	NO_x Tax	SO_x Tax	CO_2 Cert.	RE Cert.
1	Sweden	3.722	6.000	3.778	6.000	0.000	1.778	4.778
2	Norway	3.190	6.000	3.929	6.000	0.000	1.786	1.429
3	Denmark	2.873	2.762	3.810	3.143	6.000	1.524	0.000
4	France	2.424	2.545	4.182	3.000	3.091	1.727	0.000
5	Poland	2.406	1.000	3.250	2.813	2.000	1.875	3.500
6	United Kingdom	2.240	1.438	5.125	0.000	0.000	2.688	4.188
7	Italy	2.098	0.000	4.294	4.235	1.588	1.882	0.588
8	Switzerland	2.045	5.273	5.091	0.000	0.000	1.909	0.000
9	Finland	1.894	5.273	3.909	0.000	0.000	1.727	0.000
10	Hungary	1.692	0.000	3.385	3.231	1.615	1.923	0.000

Table A.2: Overview of market-based policy scores for selected treatment countries. MBP = Market-Based Policy instruments. CO_2 = Carbon Dioxide. NO_x = Nitrogen Oxides. SO_x = Sulfur Oxides. CO_2 Cert. = CO_2 Certificate Trading Schemes. RE Cert. = Renewable Energy Certificates. Each policy indicator is scored from 0 to 6, where higher values reflect stronger or more stringent market-based instruments.

Rank	Country	NMBP	ELV Sulphur	ELV NO_x	ELV PM	ELV SO_x
1	Canada	5.486	4.833	5.778	5.556	5.778
2	Italy	5.450	5.800	5.467	5.067	5.467
3	Germany	5.313	5.600	5.000	5.750	4.900
4	Luxembourg	5.313	5.600	5.000	5.750	4.900
5	Netherlands	5.294	5.706	4.882	5.706	4.882
6	Korea, Rep.	5.279	5.706	4.765	5.706	4.941
7	Belgium	5.264	5.667	4.778	5.722	4.889
8	Austria	5.159	6.000	5.000	4.636	5.000
9	Switzerland	5.125	5.857	5.214	6.000	3.429
10	France	5.069	5.667	4.778	4.944	4.889

Table A.3: Overview of non-market-based policy scores for selected treatment countries. NMBP scores reflect the stringency of non-market-based pollution control instruments. ELV = Emission Limit Value. ELV Sulphur, ELV NO_x, and ELV PM represent regulatory limits on sulphur oxides, nitrogen oxides, and particulate matter in vehicle emissions, respectively. Scores range from 0 to 6, with higher values indicating stricter standards.

Rank	Country	TECHS	AS Solar	R&D Subsidies	AS Wind
1	Luxembourg	5.205	5.818	5.455	4.091
2	Japan	4.705	4.091	4.909	4.909
3	Switzerland	4.659	4.818	4.000	5.818
4	France	4.450	4.000	5.267	3.267
5	Finland	4.068	0.000	5.909	4.455
6	Italy	3.432	5.000	2.182	4.364
7	Netherlands	3.411	3.643	2.643	4.714
8	Austria	3.077	1.923	3.154	4.077
9	Denmark	3.000	2.000	4.077	1.846
10	Canada	2.850	2.267	3.533	2.067

Table A.4: Overview of technology support policy scores for selected treatment countries. TECHS scores range from 0 to 6, where higher values reflect stronger national policy support for clean technology. AS = Adoption Support. R&D = Research and Development subsidies. "AS Solar" and "AS Wind" refer to instruments supporting adoption of solar and wind technologies, respectively.

A.3 Pre-Transition RMSPE Across Different Donor Pool Sizes

Category	Country	Pre-transition RMSPE			$\mathbf{k}(\rho^*)$
		$\rho = 0.50$	$\rho = 0.75$	$\rho = 1.00$	
EPS	Switzerland	1.714*	1.714	1.714	10
	Luxembourg	2.183	2.067	2.064*	20
	France	1.177	0.960*	0.960	10
	Finland	2.743*	2.743	2.743	10
	Norway	1.453*	1.454	1.456	8
	Denmark	0.969	0.848*	1.171	9
	Italy	1.248	1.249	1.027*	15
	United Kingdom	2.299	2.335	2.274*	19
	Japan	2.672*	2.672	2.672	5
	Sweden	1.312	1.292*	1.638	7
MBP	Sweden	1.964	1.469*	1.469	9
	Norway	1.546	1.454*	1.524	12
	Denmark	0.946*	0.959	0.960	5
	France	1.208*	1.208	1.208	10
	United Kingdom	2.627	2.609	2.408*	15
	Italy	1.279	1.278	1.223*	14
	Switzerland	1.714*	1.714	1.714	10
	Finland	2.743*	2.743	2.743	10
	Hungary	3.779*	4.118	4.029	9
	Japan	2.389*	2.389	2.389	6
NMBP	Canada	1.043*	1.043	1.055	6
	Italy	0.980	1.593	0.925*	16
	Germany	1.504*	1.991	2.027	5
	Luxembourg	2.716*	2.800	2.801	5
	Netherlands	1.094	0.922*	1.316	10
	Korea, Rep.	3.477	3.389*	3.400	10
	Belgium	1.030*	1.051	1.119	6
	Austria	1.036	0.928	0.911*	20
	Switzerland	1.418	1.417*	1.471	12
	France	0.938	0.996	0.863*	13
TECHS	Luxembourg	2.275	2.138*	2.138	15
	Japan	1.535*	1.630	1.627	10
	Switzerland	1.437	1.398*	1.398	15
	France	0.780	0.691	0.690*	16
	Finland	2.688	1.771*	1.771	15
	Italy	1.021*	1.027	1.237	10
	Netherlands	0.991*	1.002	0.992	8
	Austria	0.804	0.804	0.515*	18
	Denmark	0.738*	0.755	1.019	9
	Canada	1.004	1.004	0.984*	16

Table A.5: RMSPE values across different donor pool sizes for each treatment country per policy category. Each column reports the RMSPE obtained when the donor pool is restricted to a fixed proportion ρ of the pre-transition period length T_0. $k(\rho^*)$ indicates the number of donors selected based on the lowest pre-transition RMSPE. Asterisks (*) indicate the lowest RMSPE per country.

A.4 SCM Model Performance per Category

Category	Country	Pre RMSPE	Post RMSPE	RMSPE ratio
EPS	Switzerland	0.109	0.178	0.652
	Luxembourg	0.040	13.559	1.010
	France	0.047	0.242	1.299
	Finland	0.085	0.199	0.442
	Norway	0.034	1.595	0.950
	Denmark	0.034	0.075	1.070
	Italy	0.049	-0.177	1.953
	United Kingdom	0.062	-0.838	1.281
	Japan	0.220	0.129	0.621
	Sweden	0.098	0.048	1.065
MBP	Sweden	0.070	0.067	0.961
	Norway	0.034	1.851	1.101
	Denmark	0.045	0.061	1.041
	France	0.052	0.518	0.988
	United Kingdom	0.075	2.537	1.067
	Italy	0.061	-0.151	1.305
	Switzerland	0.109	0.178	0.652
	Finland	0.085	0.199	0.442
	Hungary	0.123	0.119	0.665
	Japan	0.163	0.170	0.731
NMBP	Canada	0.053	0.133	1.136
	Italy	0.044	-0.118	1.494
	Germany	0.074	0.153	1.975
	Luxembourg	0.070	0.164	0.781
	Netherlands	0.030	0.068	0.971
	Korea, Rep.	0.040	0.040	0.576
	Belgium	0.042	0.074	0.825
	Austria	0.026	0.681	1.455
	Switzerland	0.096	0.163	0.834
	France	0.042	0.216	1.313
TECHS	Luxembourg	0.042	16.709	1.202
	Japan	0.098	0.138	0.837
	Switzerland	0.089	0.151	0.678
	France	0.029	0.322	1.011
	Finland	0.055	0.275	0.947
	Italy	0.063	-0.368	2.452
	Netherlands	0.026	0.155	0.998
	Austria	0.014	-1.844	3.317
	Denmark	0.022	0.218	1.016
	Canada	0.039	0.312	1.156

Table A.6: Pre- and post-transition fit of the SCM models for each category. Scaled RMSPE (Root Mean Square Prediction Error) values express the prediction error relative to total GDP growth in the respective pre- and post-transition periods, providing a measure of fit that accounts for differences in economic magnitude. The RMSPE ratio is calculated as the post-transition RMSPE divided by the pre-transition RMSPE.

B Supplementary Figures

B.1 Policy Score Development per Category

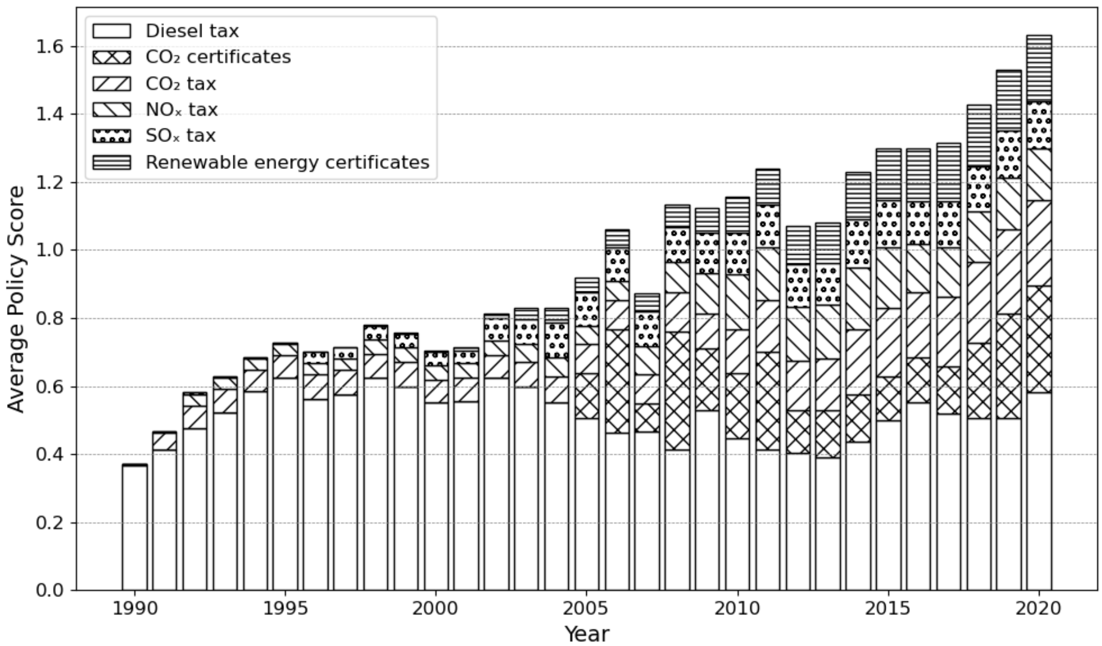


Figure B.1: Development of market-based policies across all 35 countries over the sample period 1990-2020.

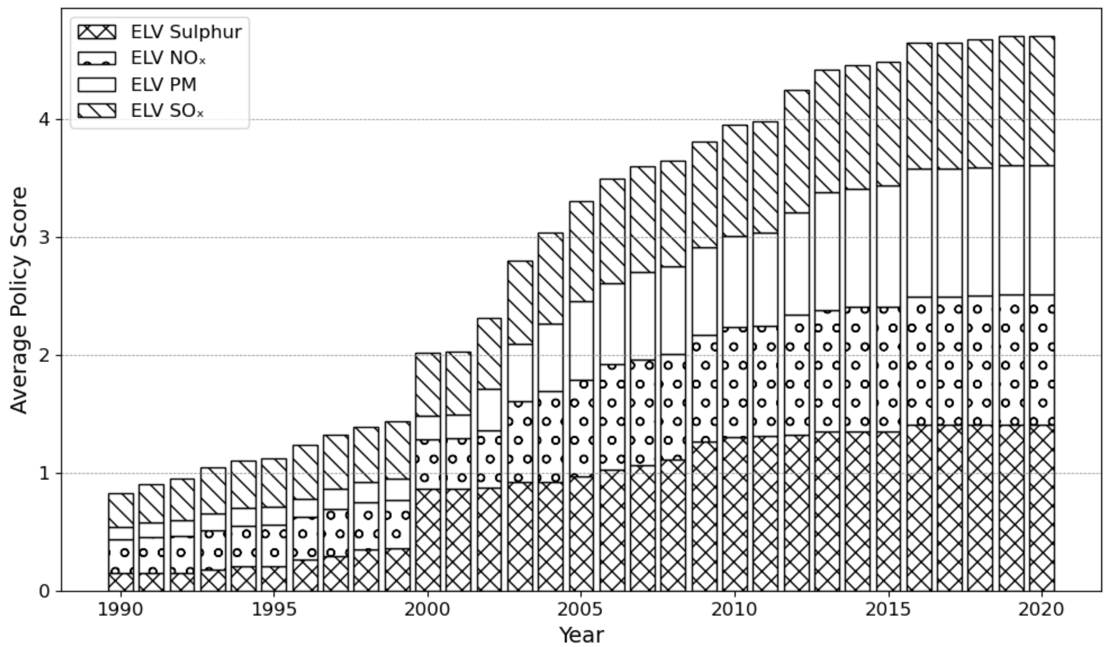


Figure B.2: Development of non-market-based policies across all 35 countries over the sample period 1990-2020.

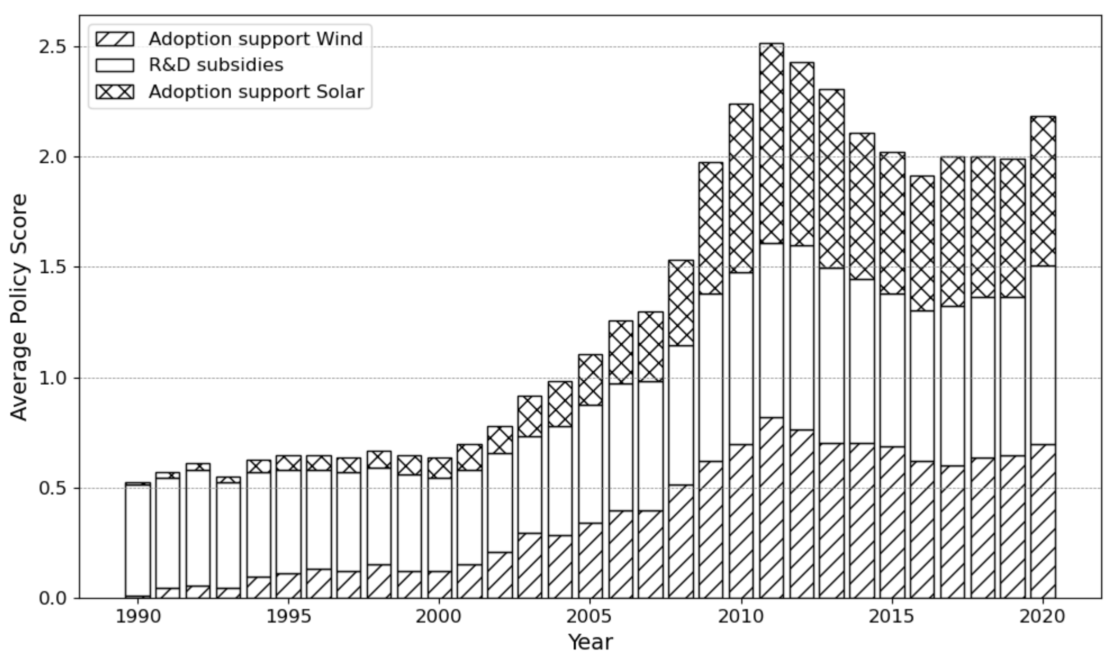


Figure B.3: Development of technology support policies across all 35 countries over the sample period 1990-2020.

B.2 Model Performance for Different Donor Pool Sizes

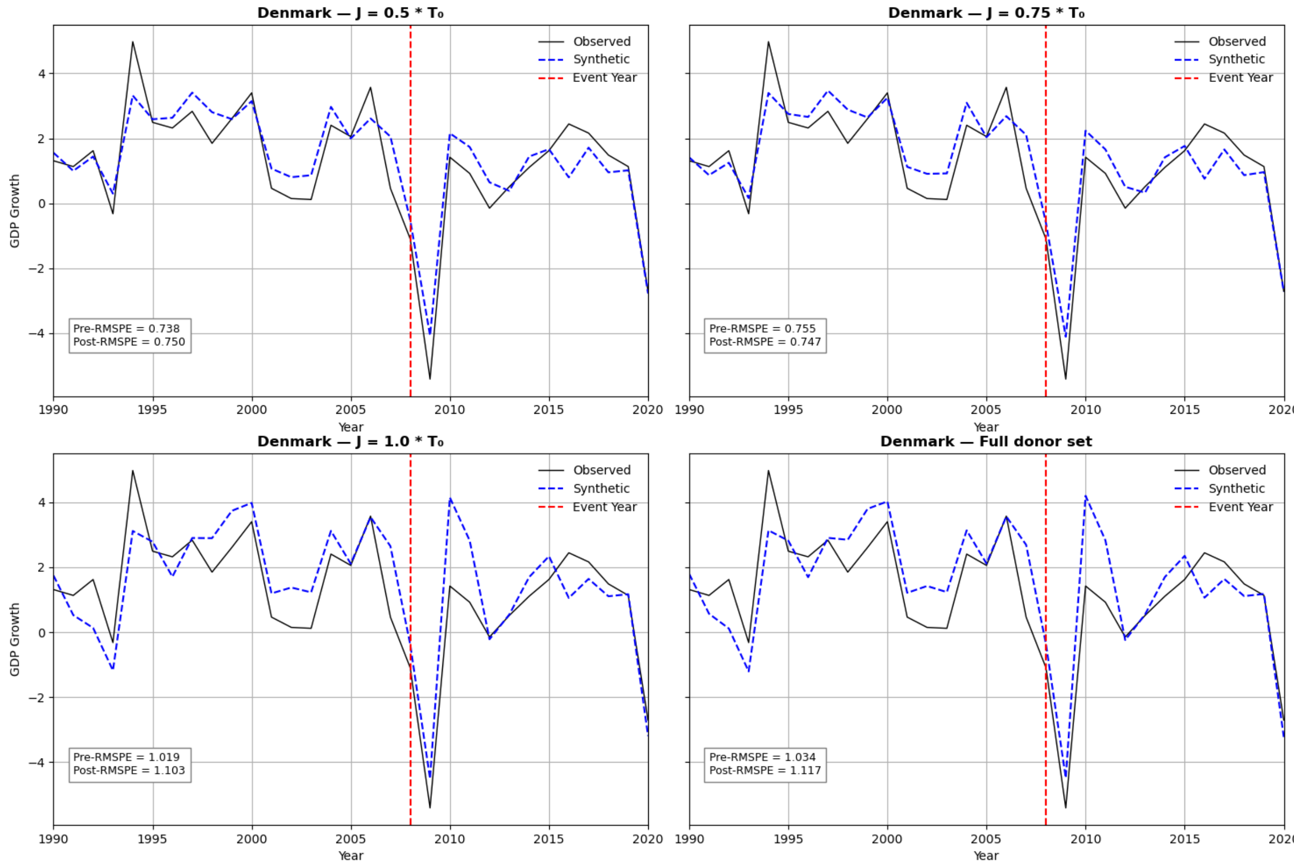
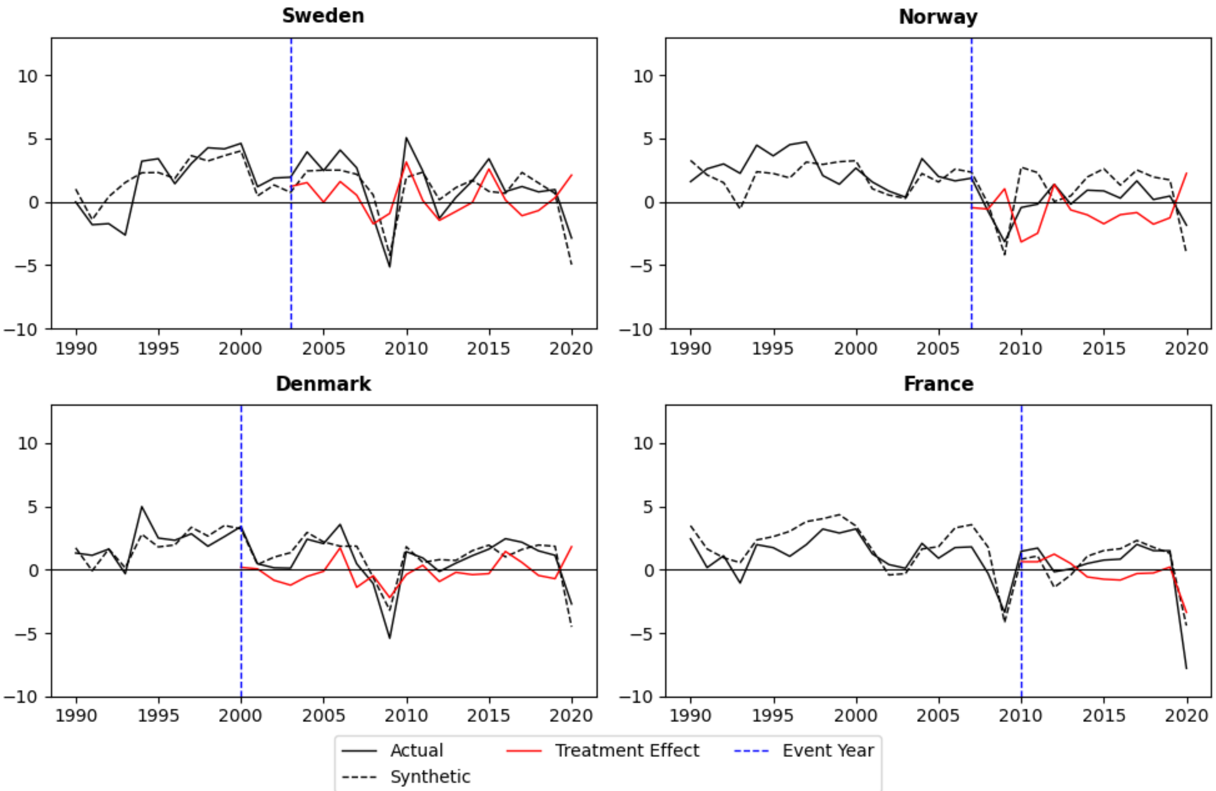
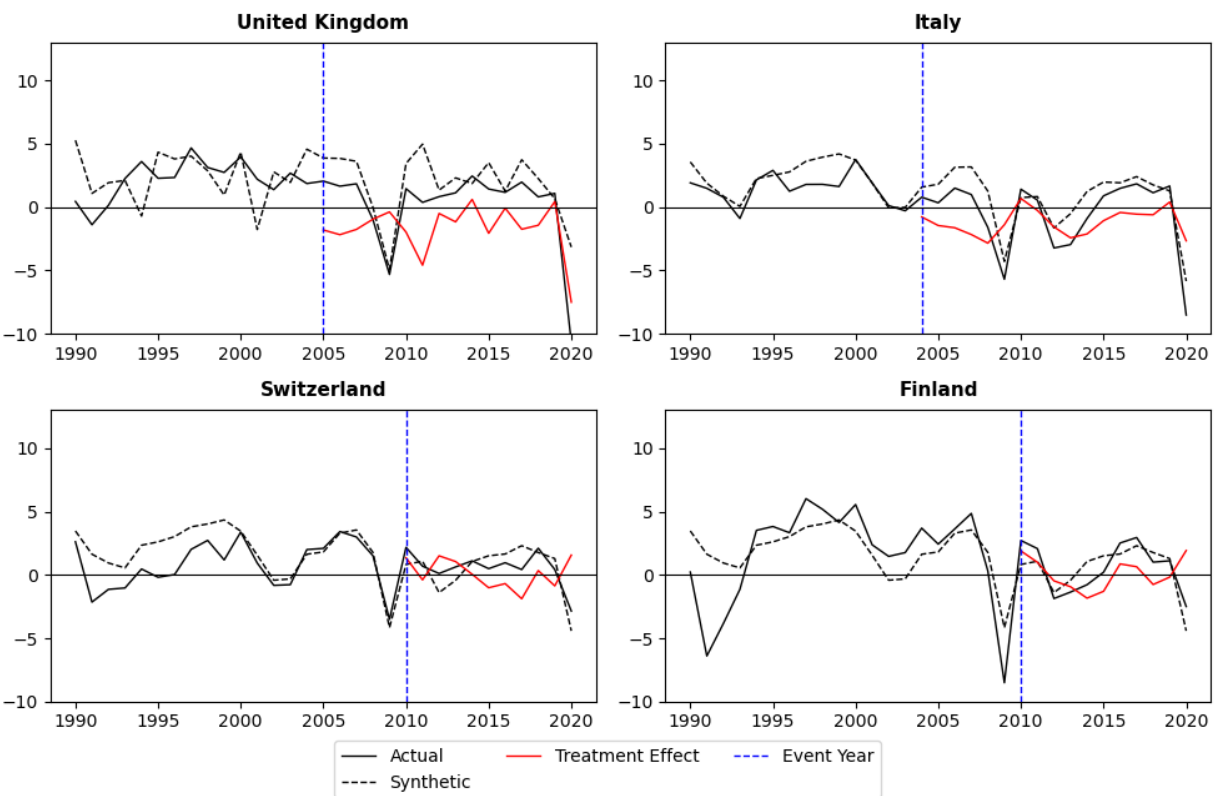


Figure B.4: Robustness check: Impact of donor pool size on SCM model performance for technology support policies in Denmark. Reducing the donor pool improves pre-transition fit and changes the estimated treatment effect, supporting the use of trimming strategies.

Figure B.4 presents four SCM models for Denmark's technology support policies, each based on a different donor pool size. Models using smaller, more selective donor pools show a closer match to the observed GDP growth in the pre-transition period. This improved fit results in more stable post-transition estimates, which is also reflected in the corresponding post-RMSPE values.

B.3 Country-Level Effects of Policy Transitions per Category





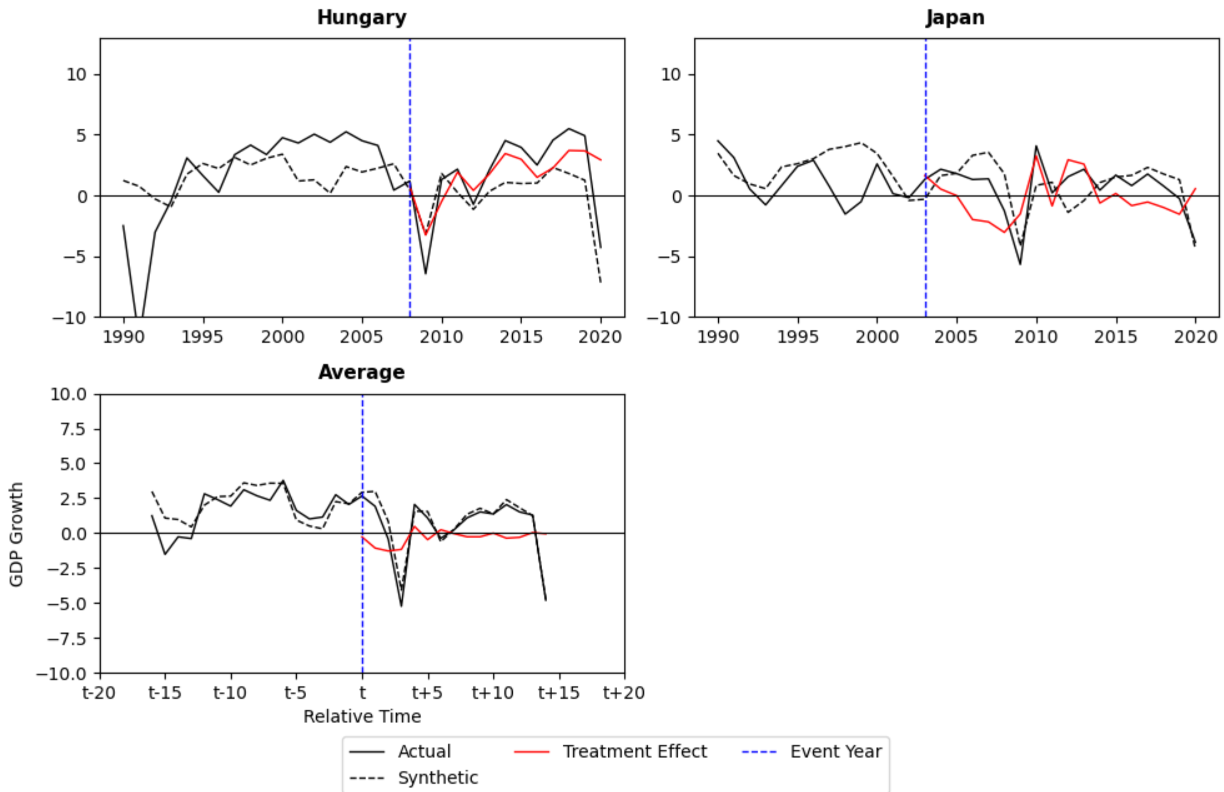
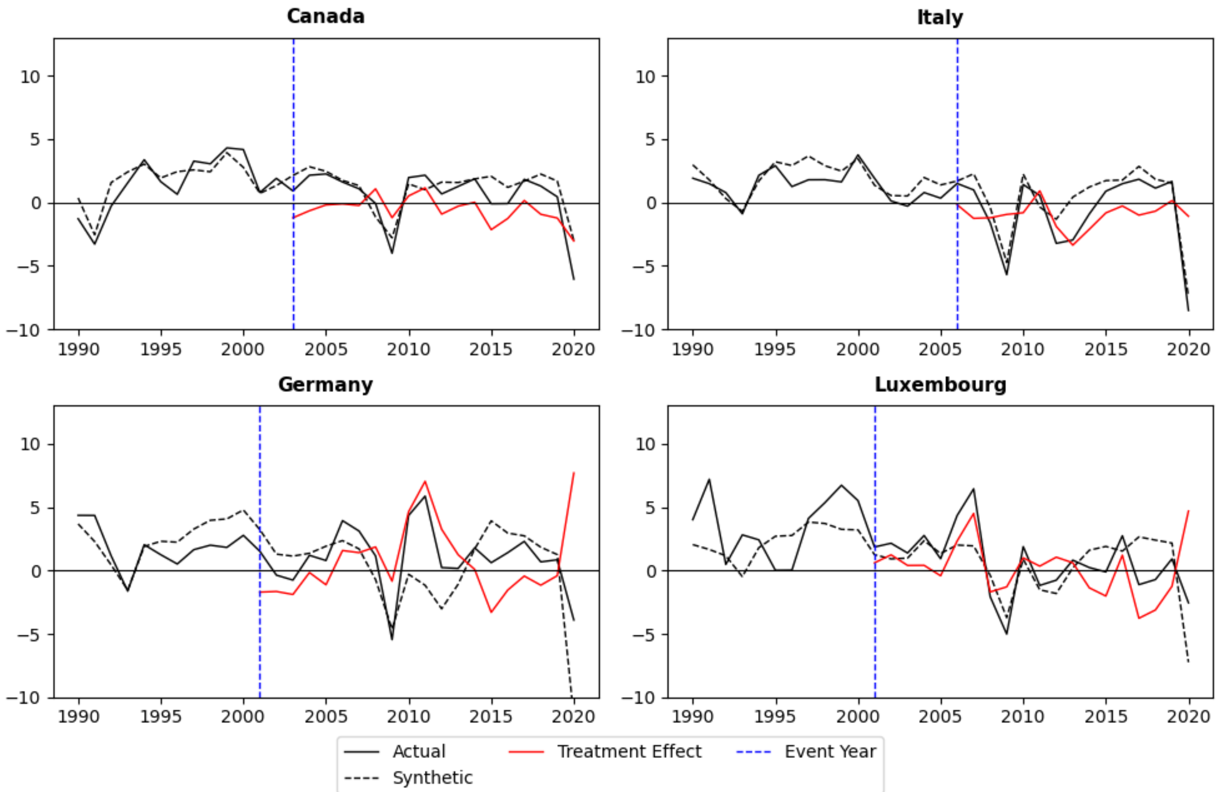
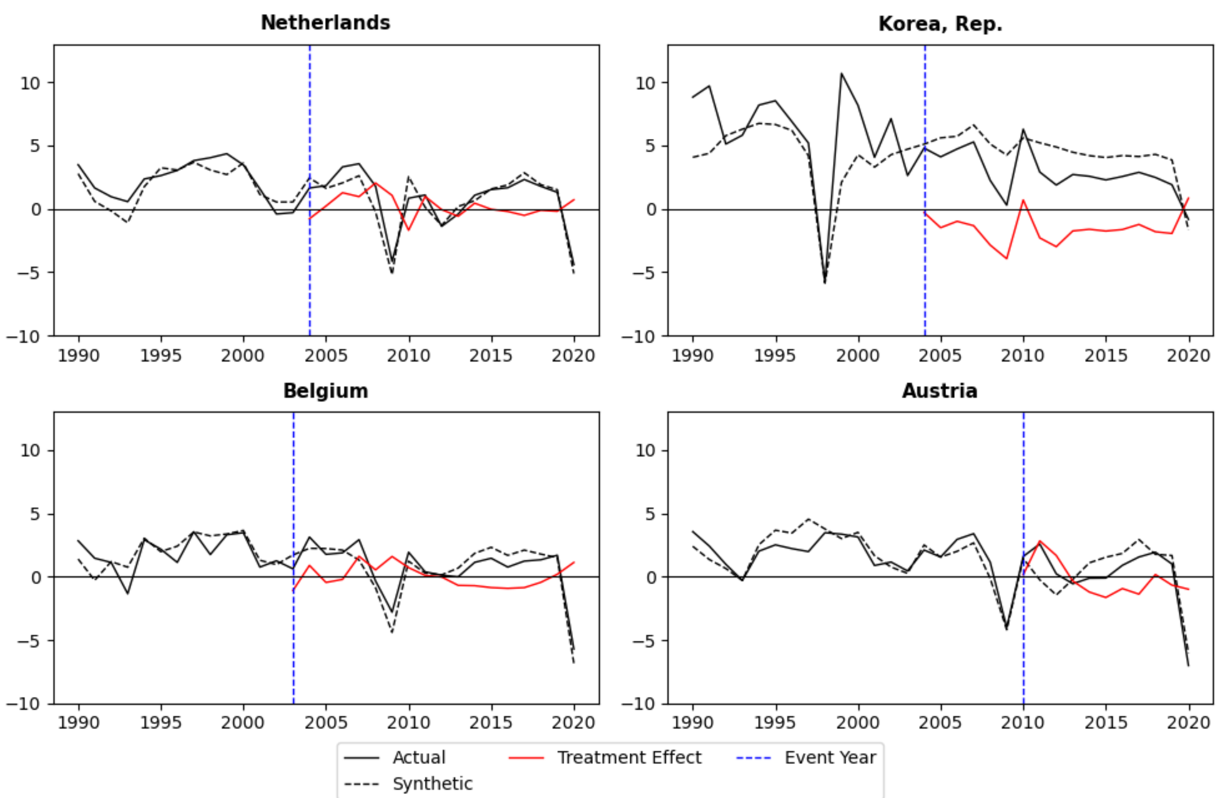


Figure B.5: Country-level comparison of the observed outcome with the synthetic control, alongside the corresponding treatment effects for market-based policies. The solid black lines represent actual GDP growth; dashed lines show the synthetic control. The red line captures the estimated treatment effect after the policy transition event.


Canada
Italy
Germany
Luxembourg
Actual
Synthetic
Treatment Effect
Event Year


Netherlands
Korea, Rep.
Belgium
Austria
Actual
Synthetic
Treatment Effect
Event Year

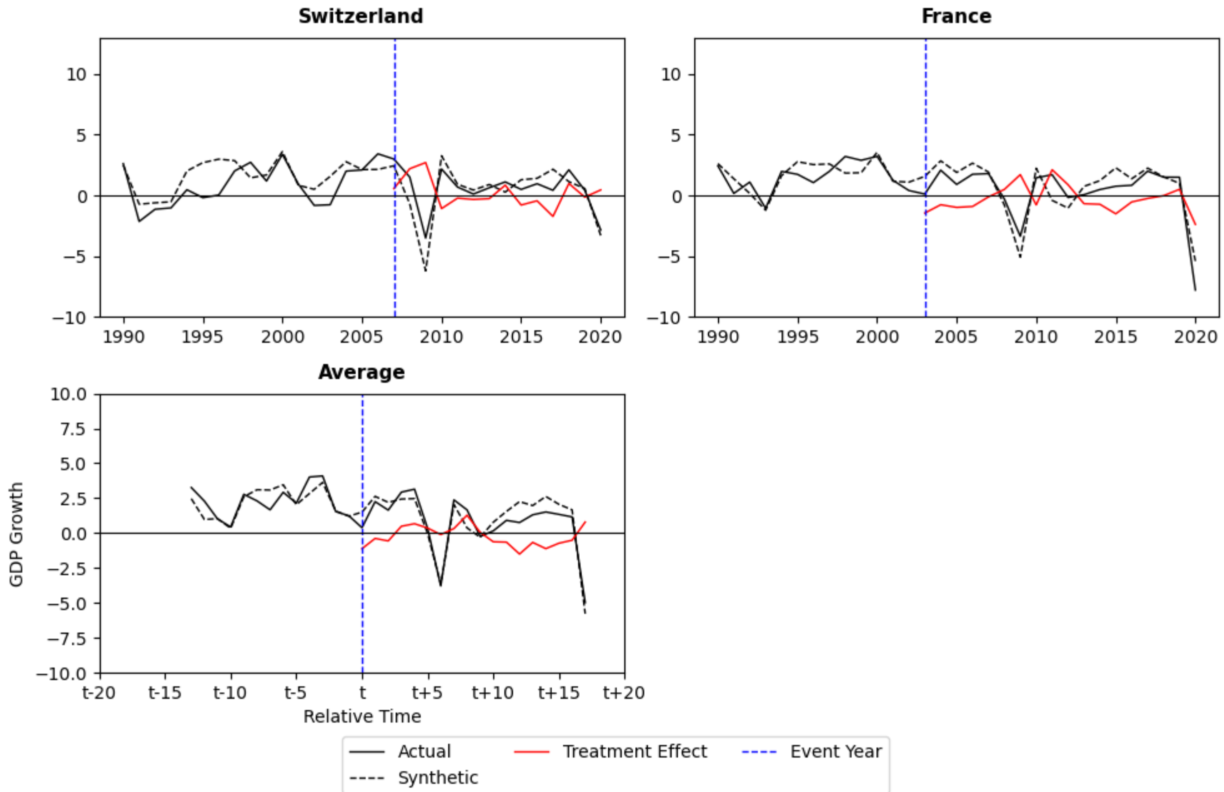
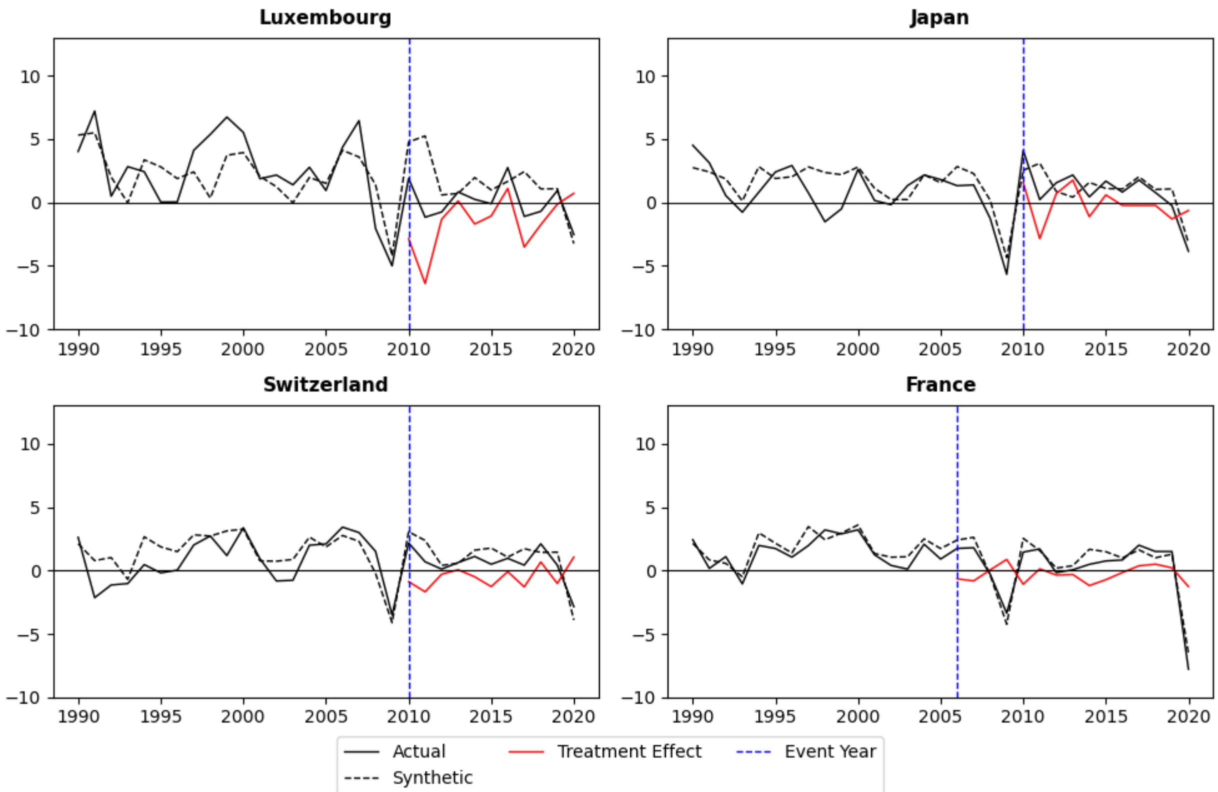
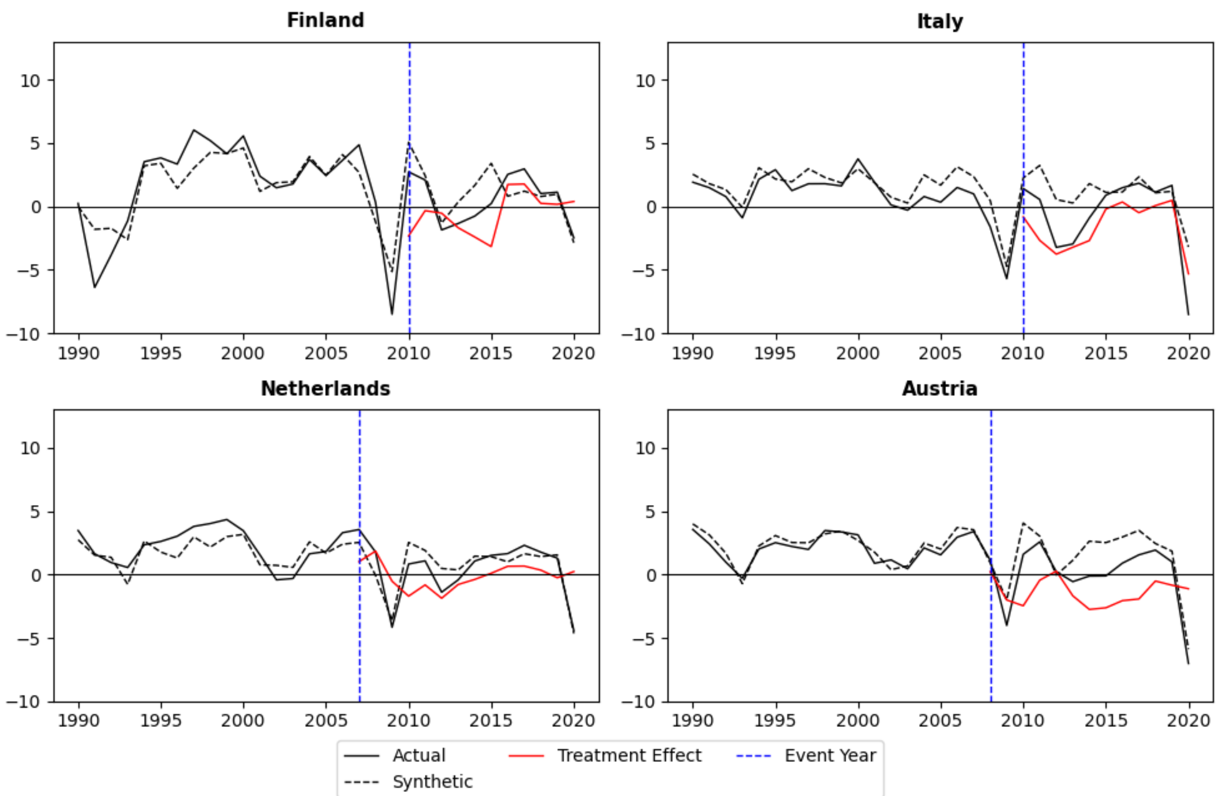


Figure B.6: Country-level comparison of the observed outcome with the synthetic control, alongside the corresponding treatment effects for non-market-based policies. The solid black lines represent actual GDP growth; dashed lines show the synthetic control. The red line captures the estimated treatment effect after the policy transition event.


Luxembourg
Japan
Switzerland
France
10
5
0
−5
−10
1990
1995
2000
2005
2010
2015
2020
Actual
Synthetic
Treatment Effect
Event Year


Finland
Italy
Netherlands
Austria
10
5
0
−5
−10
1990
1995
2000
2005
2010
2015
2020
Actual
Synthetic
Treatment Effect
Event Year

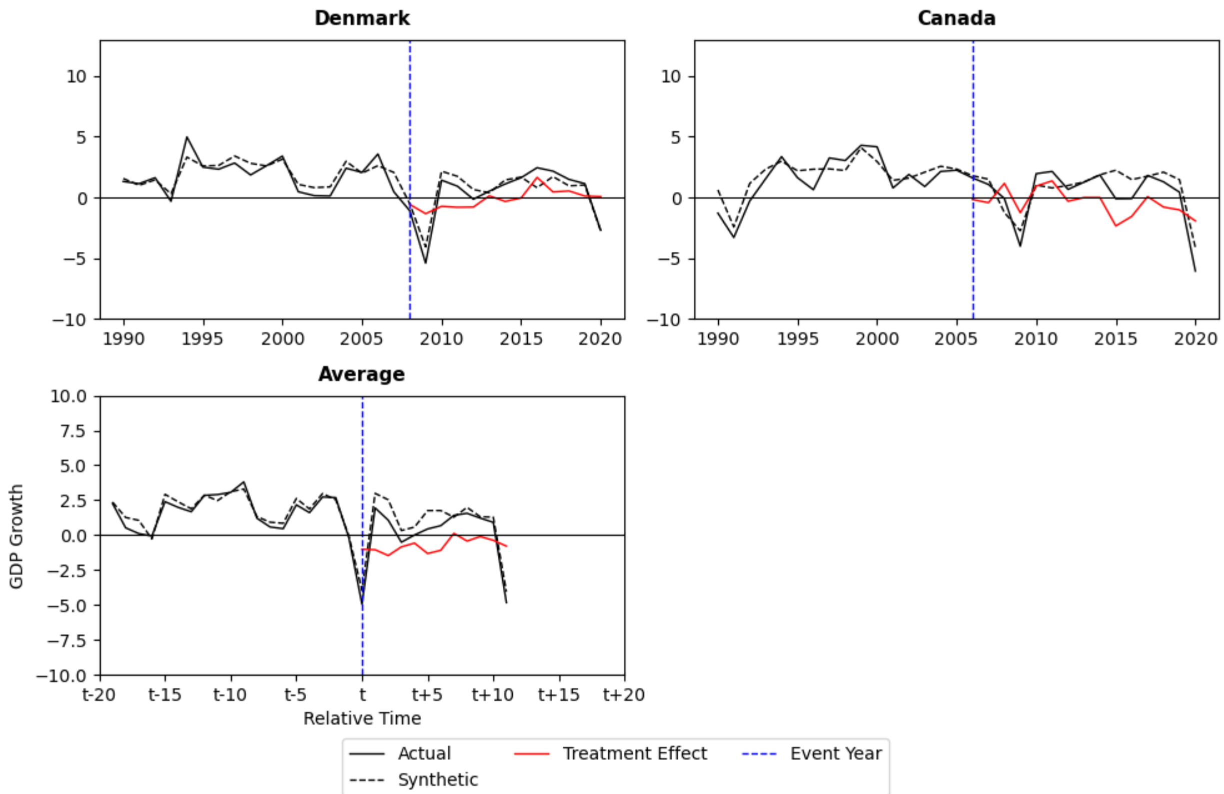


Figure B.7: Country-level comparison of the observed outcome with the synthetic control, alongside the corresponding treatment effects for technology support policies. The solid black lines represent actual GDP growth; dashed lines show the synthetic control. The red line captures the estimated treatment effect after the policy transition event.

B.4 Aggregated GDP Growth Effects per Category

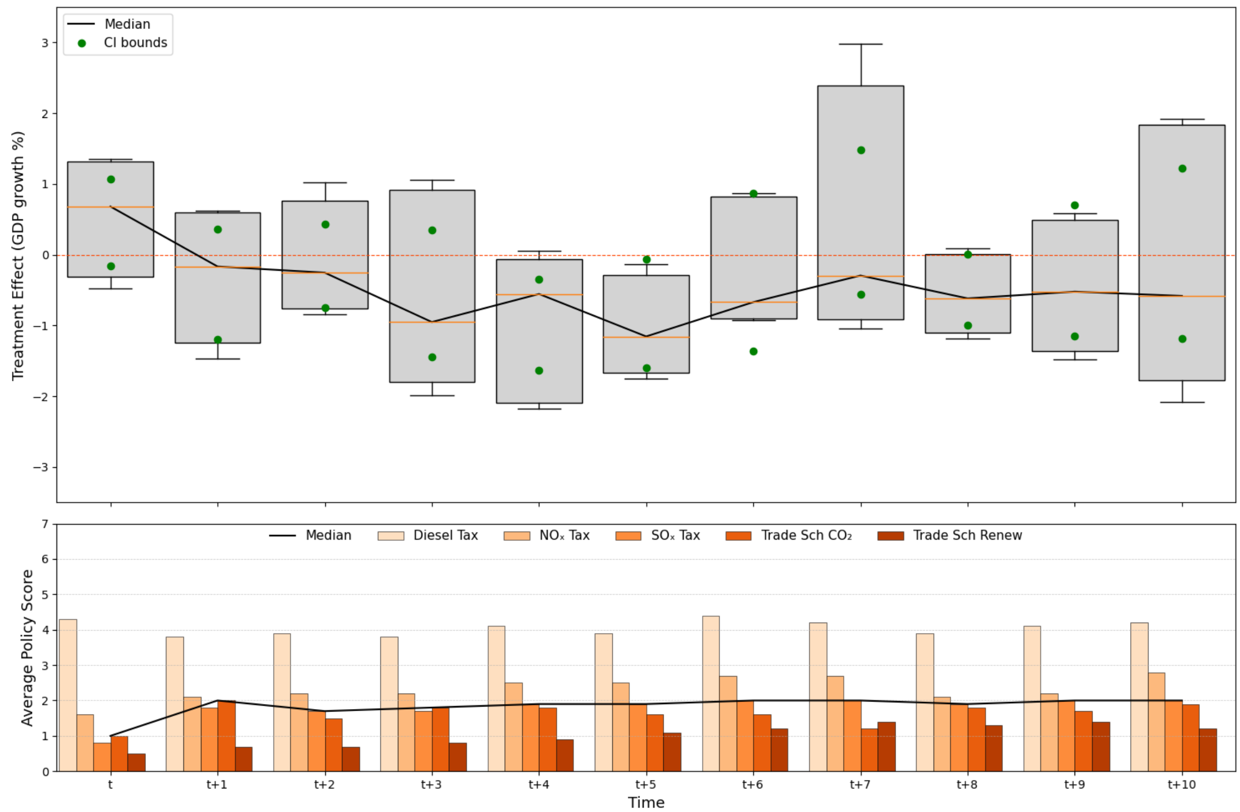


Figure B.8: Aggregated estimated GDP growth effect following market-based policy transitions. The upper panel shows boxplots of the treatment effects over time with a 90% confidence interval ($\alpha = 0.10$); the lower panel presents the average scores of each policy category across the treatment countries.

Note: Policy instruments include Diesel Tax, NO_x Tax, SO_x Tax, and CO_2 and Renewable Energy Certificate Trading Schemes.

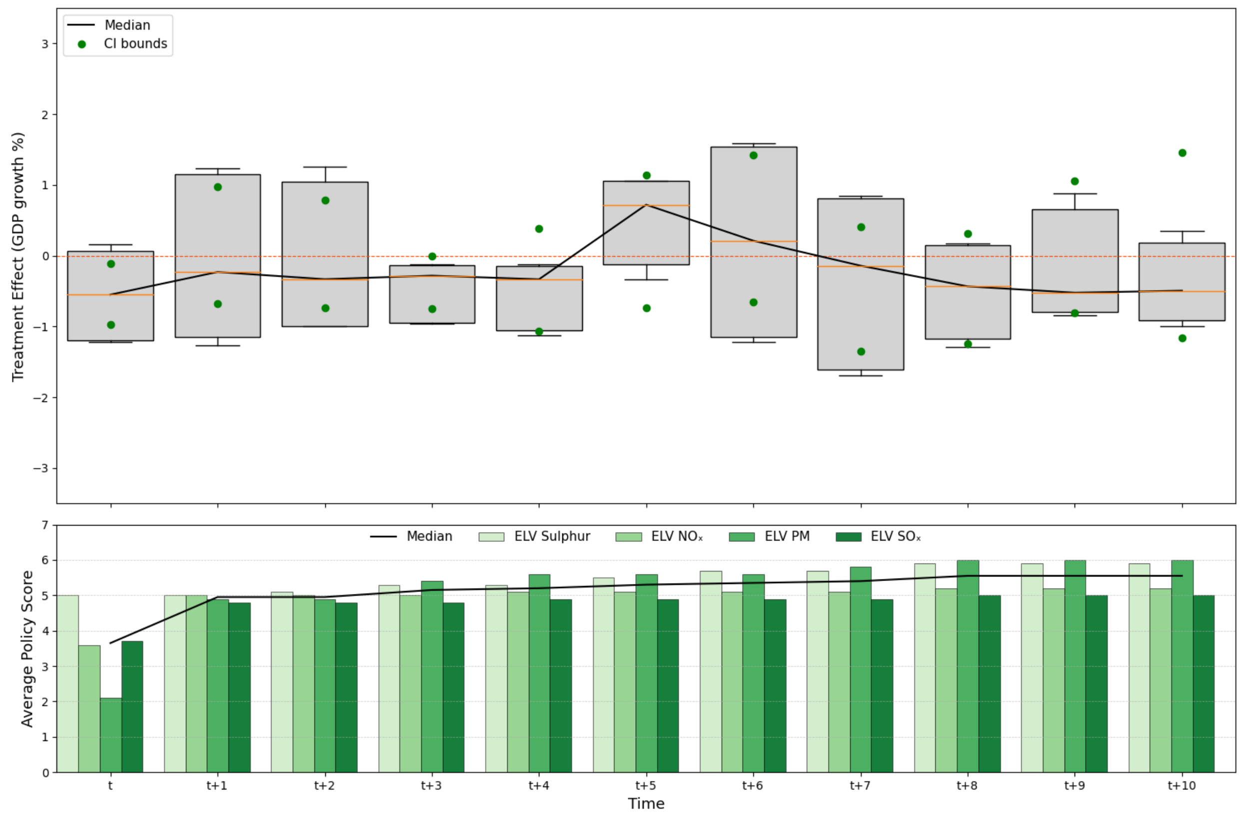


Figure B.9: Aggregated estimated GDP growth effect following non-market-based policy transitions. The upper panel shows boxplots of the treatment effects over time with a 90% confidence interval (α = 0.10); the lower panel presents the average scores of each policy category across the treatment countries.

Note: ELV = Emission Limit Values. Instruments include ELV Sulphur, ELV NO_x, ELV PM (Particulate Matter), and ELV SO_x.

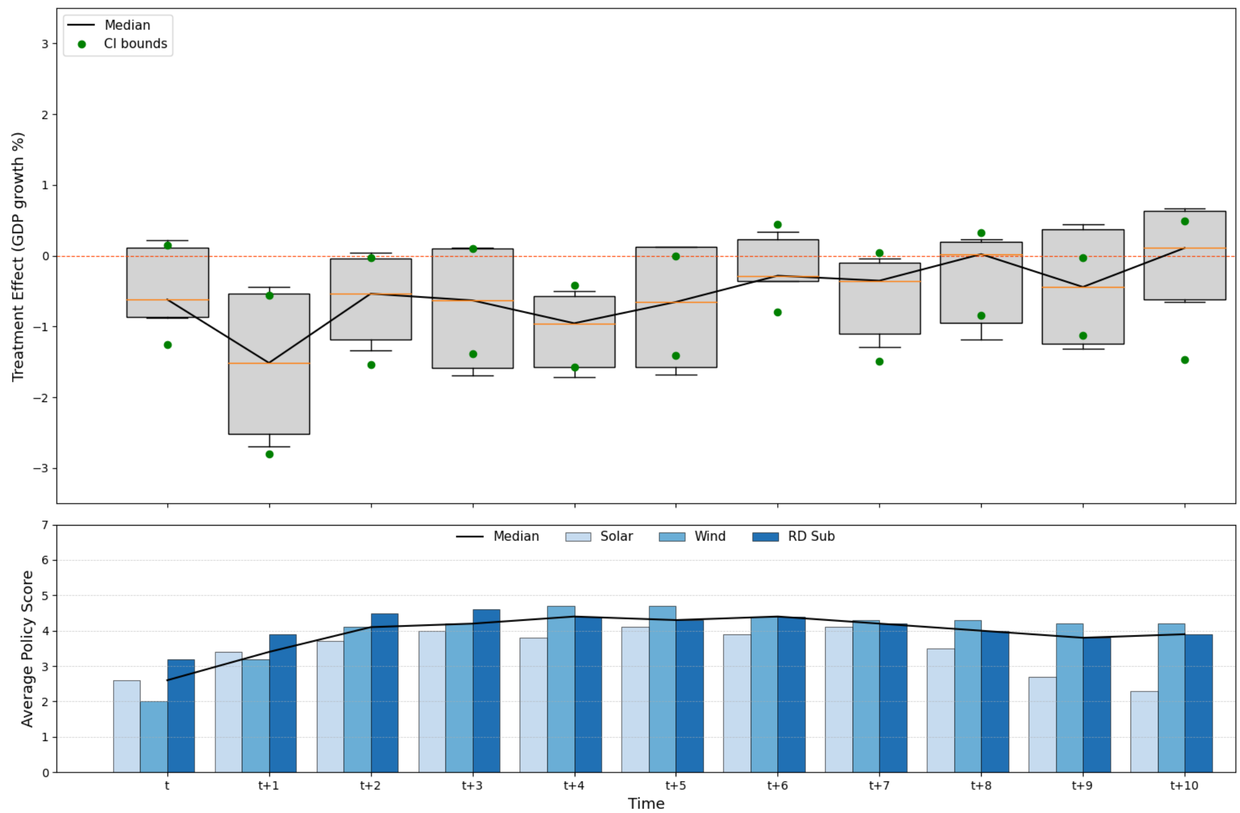
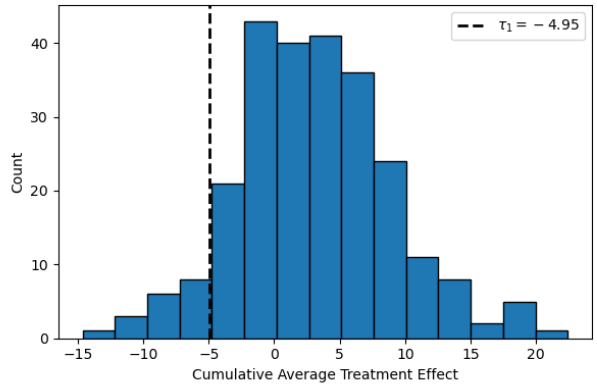


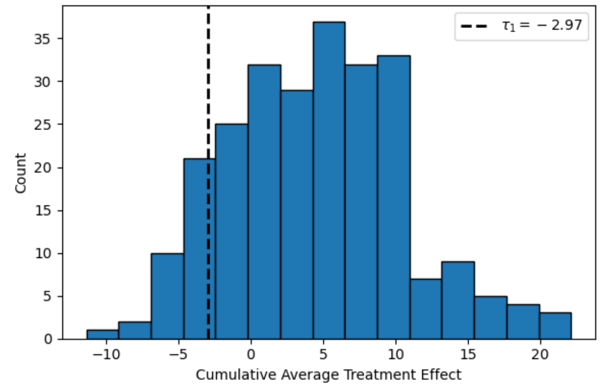
Figure B.10: Aggregated estimated GDP growth effect following technology support policy transitions. The upper panel shows boxplots of the treatment effects over time with a 90% confidence interval ($\alpha = 0.10$); the lower panel presents the average scores of each policy category across the treatment countries.

Note: Policy instruments include Solar (renewable energy support for Solar), Wind (renewable energy support for Wind), and R&D Sub (Public research and development expenditure on low-carbon energy technologies).

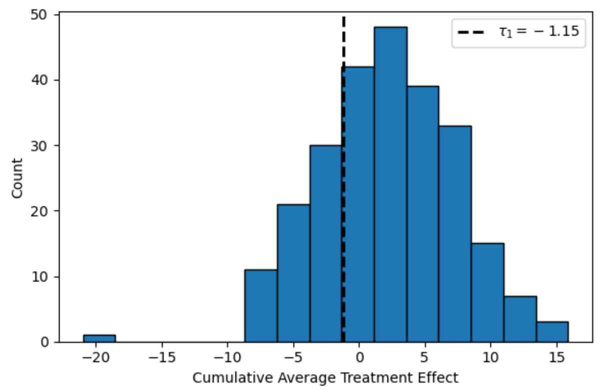
B.5 Histogram of Placebo Distributions



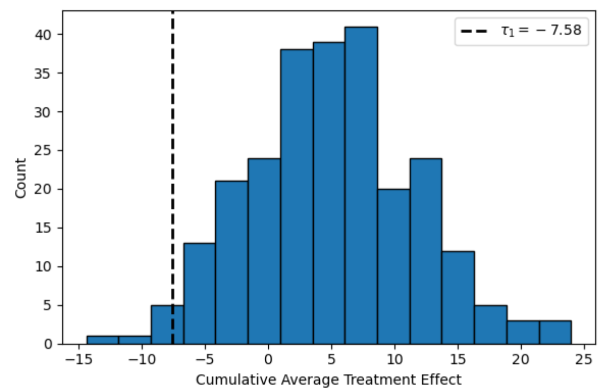
(a) EPS



(b) Market-based policies



(c) Non-market-based policies



(d) Technology support policies

Figure B.11: Histograms of the placebo distributions for EPS, market-based policies, non-market-based policies, and technology support policies, each with 250 draws ($K = 250$). The vertical dashed line denotes the observed cumulative average treatment effect, τ_1, of the treatment group in each category.

C Technical Appendix

C.1 Synthetic Control Estimator

Let Y_{it}^N denote the outcome that would be observed for unit i in the absence of the policy event, for $i = 1, \ldots, J+1$, over the time periods $t = 1, \ldots, T$ with the policy event occurring at $T_0 < T$. Let Y_{1t}^I represent the outcome for the treated unit when exposed to the intervention. We assume no treatment effect before the event, such that $Y_{1t}^I = Y_{1t}^N$ for all $t \leq T_0$.

Now assume the first unit ($i = 1$) is considered treated, while the remaining units ($i = 2, \ldots, J+1$) constitute the donor pool. The treatment effect in the post-event period ($t > T_0$) is then defined as

$$\hat{\tau}_{1t} = Y_{1t}^I - Y_{1t}^N. \tag{C.1}$$

Because Y_{1t}^I is observed, to estimate $\hat{\tau}_{1t}$, we only need to estimate the synthetic outcome Y_{1t}^N. This represents a weighted combination of the outcomes of the donor units:

$$\widehat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt} \tag{C.2}$$

where $\mathbf{W} = (w_2, \ldots, w_{J+1})'$ are nonnegative weights that sum to one.

The weights are chosen such that the pre-event characteristics of the treated unit closely match those of the synthetic control. Let $\mathbf{X}_1$ denote the predictor vector for the treated unit and $\mathbf{X}_0$ the corresponding matrix for the donor units. The optimal weights $\mathbf{W}$ are obtained by minimizing

$$(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}), \qquad t < T_0 \tag{C.3}$$

where $\mathbf{V}$ assigns the relative importance to the predictor variables. The optimal choice of $\mathbf{V}$ minimizes the Mean Squared Prediction Error (MSPE) of the outcome variable in the pre-event period (Abadie, Diamond, and Hainmueller, 2010).

With the optimal weights $\mathbf{W}^*$, the estimated treatment effect is

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \qquad t > T_0 \tag{C.4}$$

C.2 Event Year Determination

Fix a policy stringency category p (market-based, non-market-based, technological support) and let S_{jt}^p denote the corresponding stringency score for unit j in the year t. Define a time window $t = 1, ...T$ and restrict the candidate event years to an inner window:

$$\mathcal{W} \;=\; \{\tau_{\min}, \ldots, \tau_{\max}\} \subseteq \{1, \ldots, T\} \quad (\text{e.g., } \tau_{\min} = 2000,\ \tau_{\max} = 2010). \tag{C.5}$$

For any candidate $\tau \in \mathcal{W}$, define the pre- and post-averages as

$$\mu_{j,\text{pre}}^{(p)}(\tau) = \frac{1}{|\{t_{\min} \leq t \leq \tau - 1\}|} \sum_{t=t_{\min}}^{\tau-1} S_{jt}^{(p)}, \qquad \mu_{j,\text{post}}^{(p)}(\tau) = \frac{1}{|\{\tau + 1 \leq t \leq t_{\max}\}|} \sum_{t=\tau+1}^{t_{\max}} S_{jt}^{(p)}, \tag{C.6}$$

and the change measure

$$\Delta_j^{(p)}(\tau) \;=\; \mu_{j,\text{post}}^{(p)}(\tau) \;-\; \mu_{j,\text{pre}}^{(p)}(\tau). \tag{C.7}$$

The event year for unit j under category c is chosen as the maximum increase between the post- and pre-event averages:

$$\gamma_j^{*(p)} \;=\; \arg\max_{\tau \in \mathcal{W}} \; \Delta_j^{(p)}(\tau) \tag{C.8}$$

C.3 Distance-Based Matching for Donor Pool Trimming

For each unit j and time t, let z_{jt} denote the vector of predictors and outcomes included in the matching procedure, standardized to have a zero mean and a unit variance across countries.

The similarity between the treated country c and a donor country d is measured by the Euclidean distance:

$$\ell(c,d) = \sqrt{\left(\sum_{t=1}^{T_0} \|z_{ct} - z_{dt}\|^2\right)} \tag{C.9}$$

where $\|\cdot\|$ denotes the Euclidean norm. Donor countries are ranked by $\ell(c,d)$, with smaller values indicating greater similarity.

The number of countries included in the donor pool, denoted by $k(\rho)$, depends on (i) a fixed trimming parameter $\rho \in \{0.50, 0.75, 1.00\}$ and (ii) the length of the pre-event period T_0 of the treated unit:

$$k(\rho) = \rho \cdot T_0 \tag{C.10}$$

The $k(\rho)$ donors with the smallest distance $\ell(c,d)$ are then retained to construct the synthetic control. The optimal donor pool is selected by minimizing the pre-event RMSPE (see Section C.4).

C.4 Root Mean Squared Prediction Error (RMSPE)

The Root Mean Squared Prediction Error (RMSPE) measures the lack of fit between the outcome of the treated unit and its synthetic counterpart. For the treated unit $j = 1$ with outcome Y_{1t}, and synthetic outcome $\sum_{j=2}^{J+1} w_j^* Y_{jt}$ from the donor pool $j = 2, ..., J+1$ (see Section C.1), the pre-event RMSPE is defined as

$$\text{RMSPE}^{\text{pre}} = \sqrt{\left(\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t}^{I} - \sum_{j=2}^{J+1} w_j^{*} Y_{jt}\right)^2\right)} \tag{C.11}$$

Similarly, the post-event RMSPE is defined by replacing the summation range $t = 1, \dots, T_0$ with $t = T_0 + 1, \dots, T$.

C.5 In-Space Placebo Tests

We now extend the setup from a single treated country (Section C.1) to a group of treated countries for each policy category. Let $i = 1, \dots, J + 1$ index all the countries in the sample, where $N := J + 1$ denotes the treatment countries in the sample. Define the set of treated countries as $\mathcal{T} \subset \{1, \dots, N\}$, of size $|\mathcal{T}| = m$ (in our application $m = 10$), and let the donor pool be its complement $\mathcal{D} = \{1, \dots, N\} \setminus \mathcal{T}$. For each treated country $i \in \mathcal{T}$, let $\widehat{\tau}_{it}$ denote its treatment effect at time $t = T_0, \dots, T$. The group-average treatment effect at horizon t is

$$\bar{\tau}_t = \frac{1}{m}\sum_{i=1}^{m} \widehat{\tau}_{it} \tag{C.12}$$

The corresponding total economic effects θ_t, expressed as the group-level average cumulative effect, are

$$\theta_t = \sum_{t=T_0}^{T}\left(\frac{1}{m}\sum_{i=1}^{m}\widehat{\tau}_{it}\right) = \sum_{s=T_0}^{T} \bar{\tau}_s \tag{C.13}$$

We refer to θ_T as the final economic effect in the last year T.

Placebo randomization (in-space). Under the sharp null H_0 (no effects), treated labels are exchangeable with donors [10]. Draw K random placebo groups of size m from $\mathcal{D}$:

(i) For each draw $k = 1, \dots, K$, sample a set of donor countries $\mathcal{G}^{(k)} \subset \mathcal{D}$ with $|\mathcal{G}^{(k)}| = m$

[10] See Abadie and Gardeazabal (2003) for the original SCM application and Abadie, Diamond, and Hainmueller (2010) for the in-space placebo procedure. See also Abadie, Diamond, and Hainmueller (2015) for related inference and in-time placebos.

(ii) For each donor country $d \in \mathcal{G}^{(k)}$, take its *own* event year τ_d as the pseudo-event, re-estimate the treatment effects $\widehat{\tau}_{dt}^{(k)}$ using the donor set $\mathcal{D}$, and compute the corresponding group-average treatment effects $\bar{\tau}_t^{(k)}$

(iii) Compute the placebo group's total economic effect, denoted as

$$\theta_t^{(k)} = \sum_{s=T_0}^{T} \bar{\tau}_s^{(k)} \tag{C.14}$$

This delivers a placebo distribution $\{\theta_t^{(k)}\}_{k=1}^K$ for each t.

Hypothesis testing For each $t = \{T_0, \ldots, T\}$, we test whether the total economic effects of our treatment countries statistically deviate from zero, such that

$$H_0: \ \theta_t = 0 \quad \text{vs.} \quad H_1^L: \ \theta_t < 0, \ \ H_1^R: \ \theta_t > 0, \ \ H_1^{\text{two}}: \ \theta_t \neq 0. \tag{C.15}$$

Let $\{\theta_t^{(k)}\}_{k=1}^K$ be the placebo distribution at time t from J placebo draws. From there, we can form the p-values at time t as

$$\begin{aligned}
\text{two-sided } p(t) &= \frac{1 + \sum_{k=1}^K \mathbf{1}\left(|\theta_t^{(k)}| \geq |\theta_t|\right)}{1+K}, \\
\text{right-sided } p(t) &= \frac{1 + \sum_{k=1}^K \mathbf{1}\left(\theta_t^{(k)} \geq \theta_t\right)}{1+K}, \\
\text{left-sided } p(t) &= \frac{1 + \sum_{k=1}^K \mathbf{1}\left(\theta_t^{(k)} \leq \theta_t\right)}{1+K}.
\end{aligned} \tag{C.16}$$

Small left-sided (right-sided) values indicate θ_t are significantly below (above) zero. The statistical significance of the total accumulated economic effects is evaluated using the p-value of the final cumulative effect, θ_T.