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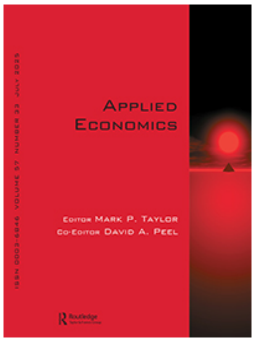


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# Convergence through sustainable development: can EU developing regions make it happen? firm-level counterfactual evidence via Machine Learning

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**ABSTRACT**

This work investigates whether EU cohesion policies aiming at environmental improvement and carbon reduction have an economic impact on adopters. By merging data from *Opencoesione*, with firms' information from *AIDA*, we look at the changes in firms' performance due to the sustainability-oriented technologies financed by the European cohesion funds during the 2007–13 programming period. We include firms that participated in pilot programs and received public incentives to upgrade their production plants with sustainable technologies, and we use Machine Learning (ML) techniques to identify the most appropriate counterfactuals for a multilevel DiD setting. Our results indicate a strong and positive policy effect on firms' profitability, with dissimilar dynamics for different levels of public support. Additionally, over time, the policy effect on treated firms tends to diminish, suggesting the possibility of a rebound effect where the gains in production efficiency and energy savings may be, at least partially, repurposed by firms to increase production (and profits) instead of reducing absolute emissions. This perfectly aligns with what one can expect from economic agents at the micro-level: firms' actions are guided by the search for ways to obtain profit increases. However, at the macro-level, policymakers should question if the policy design could be improved through the adoption of conditional subsidies or regulatory mechanisms that, by limiting emissions, could foster more environmental benefits.

**KEYWORDS**

EU cohesion policy; environmental and carbon reduction policy; technology adoption; supervised machine learning (ML) algorithms; discrete multilevel matching difference in differences; rebound effect

**JEL CLASSIFICATION**

C54; R11; Q58

## I. Introduction

Climate change is among the most pressing challenges of our time. In recent years, the ecological transition and the implementation of green technologies have been prioritized on several policy agendas. For instance, the Green Deal, introduced by the European Commission in December 2019, consists of a comprehensive set of actions aimed at reducing greenhouse gas (GHG) emissions in the EU by, at least, 55% by the year 2030 compared to 1990 levels.

In such a framework, the industrial strategy should be grounded in growing competitiveness and energy efficiency, under the assumption that 'innovative and climate-neutral re-industrialisation will create local jobs and ensure the competitiveness of the European economy' (European Parliament 2021, 6). Public interventions to mitigate human impacts on the environment align with this framework.

European cohesion policy plays a crucial role in encouraging regional adaptation to the new overall vision of a low-impact society. Indeed, one of its primary targets is to foster a greener and low-carbon economy by contributing to the long-term macroeconomic strategy of reducing territorial inequalities[1] through the development of lagging regions.

Therefore, understanding how contemporary EU environmental and carbon reduction policies work is, nowadays, fundamental. More importantly, the empirical research needs to investigate whether the recent direction of EU cohesion programs towards technology-led initiatives to support and encourage SMEs to invest in activities that optimize the use or reuse of water, energy, and materials is effective in reducing emissions and pollution. The effectiveness of such an actor-based strategy relies on the potential competitive

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[1]This policy is mainly implemented through three funds, the European Regional Development Fund (ERDF), the European Social Fund (ESF) and the Cohesion Fund (CF).

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advantage and firms' profitability gains connected with a more efficient use of energy and reduction in production costs. The existence of this advantage is key in the perspective of regional convergence by leveraging these gains in competitiveness.

However, the adoption of energy saving technologies by firms can often be held back by several barriers. Indeed, the international literature has opened a relevant debate on the energy efficiency gap (Jaffe and Stavins 1994) discussing the reasons why firms may be reluctant to invest in technologies which reduce their energy consumption. Conceptually, Cagno et al. (2013) provided a specific taxonomy of the main barriers, which may be technology-related, economic, behavioural, or organizational, as well as related to a lack of information, competences and awareness. The empirical literature demonstrated that adoption obstacles can be due to various factors including bureaucratic inefficiencies (DeCanio 1998). Public incentives for the implementation of energy saving technologies can be one of the strategies to overcome these constraints. Indeed, Cagno and Trianni (2013) showed, for a sample of Italian SMEs, that public funding is one of the main drivers for adoption together with potential long-run gains and external pressures linked, for instance, to energy prices.

A challenge in assessing the implications of improvements in firms' energy efficiency lies in accounting for the rebound effect, which arises when gains in production efficiency and energy savings are repurposed to increase production over time rather than reducing emissions overall.

Investigating the extent of the rebound effect is crucial for designing successful energy policies as this effect may constitute a crucial drawback of these specific public interventions (Amjadi, Lundgren, and Zhou 2022).

In this context, our empirical analysis focuses on assessing the microeconomic impact of the policies aiming at understanding the effects produced by different levels of public support.

In detail, we look at the changes in firms' performance due to the sustainability-oriented technologies financed by the European cohesion funds during the 2007–13[2] programming period. The 2007–13 programming period has been the first one to subsidize the implementation of sustainability-oriented technologies. In later programming periods, the subject received larger attention and is one of the main pillars of the 2021–27 cycle of cohesion policy. Recipients are composed of those firms that participated in pilot programs and received incentives by ERDF to upgrade their production plants with sustainable technologies. Such technologies, which favour a more efficient use of energy, contribute to an overall improvement of firms' profits, enhancing measurable benefits at the micro level.

In measuring these, we aim at providing an important contribution also in terms of methodological techniques and counterfactual identification. While it is very difficult to quantify the future impact of a policy, the literature has discussed several methods to assess the ex-post effectiveness of a past policy by comparing the outcome of the beneficiaries of the programs with the outcome that the same units would have experienced in the absence of the policy. Since the latter cannot be observed, we are in front of what the literature names as a missing data problem (Holland 1986). This is often addressed through quasi-experimental designs, where the objective of the evaluator consists of estimating a proxy of the missing outcomes mentioned above, using information on units that, despite being untreated, present similar characteristics to the treated ones before the treatment is assigned. The novelty of this paper, contributing to the literature on policy impact evaluation and policy learning (Cerulli 2021; Newman and Mintrom 2023), is the design of a counterfactual identification strategy based on Machine Learning (ML) regressor algorithms that go beyond the classical DiD or matching DiD framework, by employing a discrete multilevel Matching DiD framework. This approach allows to match more precisely treated units with untreated units based on the level of treatment, supporting the estimation of causal impacts for different levels of treatment.

In the context of this empirical design, we aim to investigate three research questions: i) do EU environmental and carbon reduction policies produce an economic impact on adopters? ii) what is the impact of different levels of

[2]The implementation of funded projects often takes place years after the conclusion of the programming period itself. The empirical section is designed to account for this delay in implementation.

public support for firms implementing green and carbon-reduction technologies in developing regions? Can subsidies potentially offset the disadvantages of these territories and support them towards a convergence path? iii) do these implementations have the potential to drive significant benefits for the environment?

Ideally, to answer all these questions, economic outcome measures should be used in conjunction with more environmental ones. Unfortunately, specific environmental variables are not available at the firm level. For this reason, we focus on more traditional economic measures and discuss their potential to translate into benefits for the environment. Our main outcome measure, *operating margins*, is defined as the profit that companies make on sales after paying for variable costs of production, such as wages and raw materials, but before paying interests or taxes.

Our results indicate a strong and positive policy effect, with different dynamics for different levels of public support and implementation. However, they also indicate that, in the short run, the effect on treated firms tends to diminish, suggesting the possibility of a rebound effect (Thiesen et al. 2008).

In this context, the analysed public policies are effective and have, indeed, the potential of reducing the environmental burden of the production system; however, this potential is offset by economic actors aiming at maximizing profits and production rather than reducing overall emissions. As we will argue later, the policymaker should consider the individual behaviour of economic actors while designing these types of policy.

The rest of the paper is organized as follows. Section II presents the theoretical framework and reviews relevant contributions in the literature. Section III describes the data, and the sources employed in the analysis as well as the territorial context of the study area. Section IV provides a detailed account of the identification strategy and methods developed for the paper. Finally, Section V presents the results of the Discrete Multilevel Matching Difference-in-Differences analysis with the identified counterfactuals that are also summarized in Section VI, alongside concluding remarks and policy suggestions.

## II. State of the art

### *A theoretical framework to evaluate the impact of EU environmental policy effectiveness*

Evaluating the impact of these EU climate policy programs could be done by measuring the difference in carbon emissions before and after. To achieve this, however, we would need a direct (or proxied) measure of carbon emissions at the micro (firm) level. Unfortunately, this information is not available.

While we don't have a direct measure on the environmental impact, the adoption of technologies and practices supported and incentivized by these programs (i.e. sourcing energy from renewable, installing renewable energy generators, carbon filters etc.) should produce a net positive impact on carbon emissions. Thus, in a context where global – public – problems are addressed through solutions mediated by local – private – actors, their active participation is a key element for the (environmental) success of the program. Focusing on the adoption, and its drivers, we can understand whether these policies can be effective or not.

Conceptually, the environmental impact of these policies can be described as follow:

$$Cr = f(Te, Ar, Rc) \tag{1}$$

where:

$Cr$ is the achievable carbon reduction as a function of: $Te$, the effectiveness of the adopted technologies and practices in reducing carbon emissions;$Ar$ the adoption rate by economic agents, driven by microeconomic considerations; $Rc$ which represents sectoral and territorial dynamics within which economic activities are located.

Starting from the latter, the literature has widely highlighted the importance and the role of the sectoral and territorial contexts in enhancing firm-level productivity (see, among others, Ganau and Rodríguez-Pose 2023). However, the effectiveness at the firm level of public subsidies for local development is highly debated with overall mixed evidence (see, for instance, Du and Li 2019).

The effectiveness of the adopted technologies ($Te$) in reducing carbon emissions is extremely relevant from an environmental perspective. However, from the policymaker perspective this variable is in large part out of their control since, differences in effectiveness, depend on the material technology used.

If we were able to control for the technology level and sectoral/territorial context, the adoption rate $Ar$ can be considered the primary driver shaping the total reduction in emissions. Intuitively, the larger the participation, the larger the impact.

While economic agents, as citizens and policymakers, can be concerned with environmental pollutions and climate change, their actions are primarily driven by profits and gains. Therefore, the effectiveness of the policy, is driven by its potential to enhance profits for adopters. Assuming no policy impact on revenues, the adoption of energy saving technologies should produce a reduction in total costs and a consequent increase in profits.

From a theoretical point of view, we could expect that, if participation in these programs is an economically sound choice, the adoption rate by firms would be high. At the same time, higher adoption rates should correlate with substantial carbon emission reduction and the policy program a success. Following this framework, we investigate if the participation in these programs is economically profitable for firms and we follow firms' behaviour over time to observe how additional profits are used by firms.

## Literature review and contribution of the study

Our paper contributes to two main strands of economic literature contributing several elements of novelty. The first strand assesses the sustainability content of the European cohesion policy. The second evaluates the outcome of the energy-efficient technologies on firms' performance.

While most of the empirical literature on EU cohesion policy has mainly focused on quantifying its impact on regional growth, recent policy developments have increasingly incorporated environmental and climate objectives, in line with the European Green Deal. Balancing competitiveness with environmental sustainability calls for the design of interventions that mitigate the potential trade-off between economic growth and emissions reduction.

Some recent contributions have begun to explore the sustainability dimension of cohesion policy (see Santos et al. (2023) among others). Through firms may have an intrinsic motivation to reduce their impact on the environment (Arvanitis and Ley 2013), one of the main determinants of the adoption of energy-efficient technologies for economic agents is the possible gain in profitability (Liu and Xu 2025). If firms experience private gains from the implementation of these technologies, the adoption rate and the overall effectiveness of the programmes will rise.

Furthermore, several contributions showed that public stimulus may play a strong supporting role for the implementation of green technologies (Shao and Chen 2022) as well as for the reduction of firms' liquidity constraints to investments (Donati 2016).

Focusing on Italy, Cainelli, Mazzanti, and Zoboli (2011) found a short-run negative relationship between environmental innovations and growth by focusing on a sample of Italian service firms. Caragliu (2021) demonstrated a positive impact on firms' performance of policy support (in terms of White Certificates) on a sample of Italian companies operating in the paper and glass sector.

Therefore, the empirical evidence about the impact of the introduction of eco-innovations on firms' performance in Italy is not conclusive and needs further specific scrutiny.

Our contribution aims to fill the gap by assessing the ex-post firm-level causal impact of the introduction of energy-efficient technologies financed through European structural funds in Italy. By focusing on Italian lagging regions, our analysis emphasizes the potential of EU cohesion policy to foster environmental sustainability, balancing it with its key objectives of economic growth and, particularly, regional convergence.

However, the introduction of energy-saving technologies can have unintended environmental consequences, such as the rebound effect (or take-back effect) which was first conceptualized by Jevons (1866) and more recently studied by Greening, Greene, and Difiglio (2000), among others. Several studies found the existence of a rebound effect in different countries and sectors (see among others Berner, Lange, and Silbersdorff (2022) for Germany and Lu and Wang (2024) for China). Our analysis offers some considerations on the rebound effect, which, to our knowledge, have been scarcely examined in the context of energy-saving policies in Italy, especially for less developed regions.

## III. Data and study area description

We evaluate the ex-post impact on firms' performance of the energy-efficient technologies financed by the European cohesion funds during the 2007–13 programming period. While data are available also for the recently concluded 2014–2020 programming period, focusing on the previous one provides some benefits for the empirical framework. First, since expenditure takes place two or three years after the conclusion of the programming period, focusing on 2007–2013 programming period allows to include a longer post-implementation period. Secondly, as described in Section IV, the 2007–13 programming period was the first to directly promote subsidies for the adoption of sustainability-oriented technologies.

The empirical analysis concerns the main Italian regions belonging to the 'Convergence' Objective,[3] namely those with a per capita GDP lower than 75% of the EU average. By this way to investigate whether the considered carbon reduction policy may be an effective instrument towards regional convergence and environmental sustainability by providing adopters with a competitive advantage and mitigation in operating costs. In detail, we deal with firms operating in Apulia, Calabria, Campania, and Sicily regions in the Southern part of Italy. These regions concentrate the majority of funds and projects originating in the cohesion strategy (about 75 percent of the total allocations in the country).

Our counterfactual is also limited to firms operating in the same territories because they have to be exposed to a similar institutional environment and territorial context. The firm-level database was constructed starting from a detailed database providing information on all cohesion policy projects implemented in Italy. This database, named *'Opencoesione'*, is managed by the Italian Cohesion Policy Department (*Dipartimento per le politiche di coesione*), in collaboration with the Territorial Cohesion Agency (*Agenzia per la coesione territoriale*) and the State General Accounting Office (*Ragioneria generale dello Stato*). The source enabled us to monitor the progress of each cohesion project concerning both the execution and the spending flows. It encompasses the information on the overall cohesion expenditure in the two most recent (completed) programming periods (2007–13 and 2014–20) and it extends to the next (2021–27) period. The cohesion interventions are tracked with details concerning beneficiaries, location, spending sector, investment typology, payments as well as starting and completion dates.

Our sample includes 320 firms (Ltd and Co. Ltd) that participated in pilot programmes and received an incentive with the resources of the ERDF to upgrade their production plants with sustainable technologies. We selected the projects implemented within the 2007–13 programming period whose payments were entirely disbursed in the year 2016. This approach allowed us to capture a post-Great Recession period while still being able to gather data points for the years following the intervention. Firms implementing similar projects, or participating in any other cohesion project, in previous or later years, were excluded from the analysis.

The projects financed the introduction of sustainable technologies to improve energy saving, to mitigate energy costs and to reduce the pressure of the treated firms on the environment through cogeneration (electricity and heat), trigeneration (electricity, heat and cold), photovoltaic systems and other renewable sources.

In particular, the interventions fall under the following policy spending axes (priorities): 'Energy production from renewable sources' and 'Energy efficiency and system optimization'.

Through the VAT number, this sample of treated firms is linked to balance sheet information extracted from the AIDA[4] repository. This database is a primary source of data for our empirical analysis. In detail, we consider a panel of balance

[3] In that programming period also the region Basilicata belonged to that objective but with a 'phasing-out' status (transitory regime).
[4] AIDA (*Analisi Informatizzata Delle Aziende italiane*) is the digital repository of information on Italian companies.

sheet information for Italian firms operating in the study area over the period 2009–2019.

Firm level data have been carefully cleaned and tested for consistency to eliminate extreme outliers and gaps in the panel for the main variables. Variables were then winsorized by year over the whole study area to reduce the impact of outliers and standardized (Lian 2014). The resulting dataset is composed of 21,200 firms operating over 210 local labour systems (LLSs) in the four selected lagging Italian regions. The treated sample is composed of a total of 320 firms. Balance sheets provide relevant firm-level information capturing the dynamics of different firms. Information collected includes: i) *operating margins*, i.e. the main output in our empirical analysis, whose variation was used as a measure of the microeconomic impact of subsidies; ii) firm dimension measures. These include the *number of employees*, the *total assets* owned by a firm, and the *share of tangible assets* over the total assets of the firm; iii) Productivity measures. These include *value added per employee*, *return on investments (ROI)*, *total revenues from sales*; iv) profitability and financial stability measures. They include *total profits* and *debt to EBITDA ratio*. Finally, we have also collected information on firms' primary sector of operation, using the Nace rev.2 classification aggregated at the second digit, as well as on the NUTS-2 region in which the firm operates, by specifying its territorial environment (urban or rural).

Table 1 and 2 report relevant summary statistics and information of beneficiary firms compared to the average firm operating in the study area.

On average, beneficiary firms show different characteristics when compared to the other firms operating in the area. This is particularly evident when we focus on those variables connected to firms' size (number of employees, tangible assets). Beneficiary firms are substantially larger than most firms in the study area. These differences highlight the importance of a robust counterfactual identification strategy, addressing the specificities of treated firms to build an adequate control group.

Table 2 highlights that beneficiary firms mostly operate in urban areas (around 75%), which is consistent with the locational context of most firms in the area. A potential source of heterogeneity refers, instead, to the main sector of activity of beneficiary firms. While the incentive program under analysis is not directed to economic agents operating in specific industries, almost 80% of beneficiary firms, indeed, are active in manufacturing or wholesale and retail activities. By operating within different sectors, firms may produce dissimilar results in terms of revenues and/or operating margins. This can produce relevant heterogeneity in the policy impact results which should be addressed.

## IV. Empirical strategy

### *Machine learning strategy for counterfactual identification*

The main novelty of this paper, from a methodological perspective, lies in the ML strategy implemented for the identification of suitable

**Table 1.** Summary statistics, beneficiary firms vs all other firms in the area.

| Variable | | mean | std. | min. | max. |
|---|---|---|---|---|---|
| *Num. of Employees* | beneficiaries | 37.4 | 80.6 | 1 | 661 |
| | all other firms | 11.2 | 41.4 | 1 | 2,359 |
| *Tot. Tangible Assets* | beneficiaries | 2,759.7 | 4,599.1 | 1.6 | 41,925 |
| | all other firms | 1,124.1 | 8,109.2 | 1.2 | 586,540 |
| *Added Value* | beneficiaries | 1,820.3 | 3,459.6 | 25.6 | 26,907 |
| | all other firms | 491.8 | 2,387.4 | 0.3 | 142,097 |
| *Revenues from Sales* | beneficiaries | 8,790.3 | 15,109 | 41 | 105,449 |
| | all other firms | 2,387.6 | 13302 | 0.3 | 776,241 |
| *Operating Margins* | beneficiaries | 417.8 | 1,315.7 | −789 | 18,248 |
| | all other firms | 73.5 | 956.8 | −67,983 | 60,482 |
| *Debt/Ebitda Ratio* | beneficiaries | 4.2 | 10.2 | −59 | 115 |
| | all other firms | 2.6 | 23.1 | −987 | 526 |
| *Age* | beneficiaries | 22.5 | 11.1 | 11 | 87 |
| | all other firms | 25.6 | 11.3 | 11 | 129 |

*Source*: Authors' calculations on AIDA database.

Table 2. Territorial context and sector of operation of beneficiary firms vs all other firms in the study area.

| Variable | group | share of firms in class |
|---|---|---|
| **Urban-Rural** | | |
| Urban areas | benficiaries | 75.6% |
| | all other firms | 76.9% |
| Rural Areas | benficiaries | 24.6% |
| | all other firms | 23.1% |
| **Sector** | | |
| Agricolture | benficiaries | 0.9% |
| | all other firms | 5.9% |
| Mining and quarring | benficiaries | 3.1% |
| | all other firms | 2.2% |
| Manufacture | benficiaries | 39.7% |
| | all other firms | 14.3% |
| Construction | benficiaries | 2.8% |
| | all other firms | 15.9% |
| Wholesale and Retail | benficiaries | 40.9% |
| | all other firms | 40.8% |
| Info. and Comm. | benficiaries | 1.2% |
| | all other firms | 2.7% |
| Tech and Sci. Prof | benficiaries | 4.7% |
| | all other firms | 7.4% |
| Others | benficiaries | 6.7% |
| | all other firms | 10.9% |

*Source*: Authors' calculation on AIDA database.

counterfactuals. Such strategy has been developed to enhance the impact evaluation of complex policy scenarios in the case of significant sources of heterogeneity between treated and untreated units, and among treated units with varying levels of public support.

While dealing with the heterogeneity between treated and controls has long been one of the main concerns of the larger literature on quasi-experimental designs (Athey and Imbens 2017), only in more recent years scholars have started developing strategies to deal with heterogeneity of treatment. Most empirical contributions addressed this issue by implementing technical solutions focused on a more detailed identification of the treatment itself in the model. This led to the development of several advances over the Difference in Difference setting, from continuous treatment to heterogeneous treatments and dose response functions (De Chaisemartin and d'Haultfoeuille 2023; Nunn and Qian 2011). A drawback of these approaches is that, though the estimates can model the treatment heterogeneity, they still rely on a counterfactual group which is – at best – identified to be similar *overall* to the treatment group. Though widely used, conventional matching strategies show, indeed, important weaknesses (see among others, King and Nielsen 2019).

To deal with this, we designed a strategy that relies on the estimation of DiDs for multiple levels of treatment. The identification of the counterfactual group is performed leveraging a ML strategy to match different treatment level with untreated units which would have received the same treatment level, if they had participated in the policy.

The application of ML algorithms to perform matching operations, or to calculate propensity scores is not new (Lee, Lessler, and Stuart 2010). This is indeed recognized as the best practice in several fields (such as pharmaceutical, medical and computer science literature) and, recently, this approach has also been extended to economics (Cerulli 2021).

In our context, firm-oriented policies for carbon reduction and green transition have seen, in the 2007–2013 programming period, their first major implementation. Therefore, in that period, very few firms, especially in Southern Italy, had their attention focused on these types of issues. Our ML strategy exploits the existence of this awareness bias (Slonim et al. 2013) to identify control firms.

The identification strategy is detailed in full in Figure 2. The flowchart includes the whole empirical strategy which can be divided into four stages.

In the first stage (Figure 2, panel i) the real dose and the treatment levels are calculated for all treated units. This is done by leveraging information on the amount of funding received by each treated firm in 2016 from carbon reduction policy, divided the total tangible assets of firms in the pre-treatment period (as a proxy of firms' dimension). This normalizes the amount of funding on beneficiary firms' dimension, allowing to partially control for radically different types of interventions. Contextually, different treatment levels are identified using the quintile of the distribution of the dose.

The second stage (Figure 2, panel ii) is where ML algorithms come into play. Using the whole set of firms' characteristics described in Section III, a Random Forest Regressor [5] is modelled to estimate the potential dose for untreated firms. The specific regressor, composed of a non-parametric ensemble of decision trees (Breiman 2001), is chosen from a range of possible algorithms as the literature indicates it to be the most suitable for handling a large set of covariates (Lee, Lessler, and Stuart 2010). The model is

[5]This is detailed in Annex 1.

trained on a random subset of available observations (both treated and untreated) by feeding it with information on firm-level pre-treatment characteristics, whether they have received any funding, and the specific amount of funding received by those firms. Therefore, the algorithm learns to discern differences between treated-untreated firms and between smaller-larger doses. Through multiple iterations, the algorithm estimates and checks its accuracy, and we can adjust the weights, parameters, and most elements of the regressor accordingly. Once trained, the specific algorithm is used to estimate a potential dose for all units.

The accuracy of the final model is validated by running it on a set of previously unseen observations. This is a common validation strategy for ML where a random subset of observations is held out from the training and only used for final validation (Kohavi 1995). The final Random Forest regressor model shows a good fit, scoring an R-squared of 0.86. Its accuracy can be estimated by comparing the potential dose with the real dose for treated units; in doing so a pairwise Pearson's correlation is used to show that the two are highly correlated with a coefficient of 0.9464.

The identification of a suitable counterfactual for the causal impact analysis is performed in the third stage (Figure 2, panel iii) and makes use of the predicted potential dose.

Out of the 21,200 firms, only 1,920 (320 of which are treated units) show a potential dose larger than 0. All observations with a potential dose of 0 are discarded from the analysis, they would have not participated in the program anyway. The remaining 1,600 untreated units are divided between treatment levels using the same boundaries of the quintile distribution of the real dose (Table 3).

These counterfactuals are used in the DiD in stage four (Figure 2, panel iv) to estimate the outcome that treated units would have experienced in the absence of the policy. Details of the Discrete Multilevel Matching Difference-in-Difference model employed are discussed below in section 4.2.

Before that, the goodness of each identified counterfactual group (and its similarity with the related treatment group) is evaluated by testing the covariate balancing between each two groups and their differences in *operating margins* (the main output) in the pre-treatment period. The results of these tests are reported in Annex 2 Table A1 (covariates' balance and overall goodness of fit), Figure A2 and Table A2 (parallel trend in the pre-treatment period). The significant reduction of standardized bias (almost 20% reduction in bias) between treated and controls, due to the identification, support – as discussed in Annex 2 - the credibility of our results and the effectiveness of the identification strategy.

**Table 3.** Distribution of treatment and control groups observations between treatment levels.

| | Treatment | Control | Total |
|---|---|---|---|
| First Quintile (1–20% of the Dose) | 64 | 144 | 208 |
| Second Quintile (21–40% of the Dose) | 64 | 628 | 692 |
| Third Quintile (41–60% of the Dose) | 64 | 166 | 230 |
| Fourth Quintile (61–80% of the Dose) | 64 | 577 | 641 |
| Fifth Quintile (81–100% of the Dose) | 64 | 85 | 149 |
| All | 320 | 1600 | 1920 |

## Discrete multilevel matching difference-in-differences

The short/medium-term microeconomic impact of different levels of public subsidies in green and carbon reduction technologies for firms and businesses is measured via an extended Difference-in-Differences design. Specifically, the paper employs a Discrete Multilevel Matching Difference-in-Differences (Fricke 2017) with multiple, ordered, treatment levels identified from a continuous dose, measuring the intensity of public financing received by each firm (public funding received by the firm in 2016 for green and CE policy over total tangible assets of the firm).

Within each treatment level, and its counterfactual, the standard specification of a DiD model is applied:

$$Y_{it} = a + bTreat_i + cPost_t + d * (Treat_i * Post_t) + \ldots + e_{it} \quad (2)$$

where $Y_{it}$ is the outcome measure for units in the treatment level $i$ at time $t$, $Treat_i$ is a binary variable that indicates if units in group $i$ are treated ($Treat_i = 1$) or untreated ($Treat_i = 0$). $Post_t$ is a further binary variable that refers to time, which assumes a value equal to 1 after the treatment and equal to zero before the treatment; finally, $e_{it}$ represents an error term.

We focus on $d$, which measures the difference-in-differences estimate of the treatment effect. Our identification strategy allows for a more in-depth analysis considering each treatment level separately with its own counterfactual group. Indeed, for each treatment level, a separate DiD model estimates the treatment effect for that specific, ordered, treatment level compared to their counterfactual group identified by a potential dose of similar intensity.

To ensure consistency of the results and remove sources of uncontrollable heterogeneity, all firms participating in similar policies but receiving funds in different years have been excluded from the analysis. Moreover, firms participating in other public programs (i.e. receiving public financing for other R&D projects) have also been excluded from the analysis.[6]

The Discrete Multilevel design has been selected to estimate the impact of different levels of implementation and types of technologies implemented. Indeed, the amount of public aid requested could be influenced by the scope of the intervention, its cost, the number of interventions, or a combination of these factors. Although we lack detailed information about the implementation on a firm-by-firm basis, different levels of implementation can be estimated from the amount of funding received for it. This is achieved by formulating a 'treatment dose', which is calculated by dividing the amount of aid received by the size of the firm, i.e. total tangible assets. The microeconomic impact is measured, at the firm level, as the Average Treatment Effect on the treated (ATT) within each treatment level (quintiles) on firms' *operating margins*. The *operating margin* measures how much profit a company makes on a dollar of sales after paying for variable costs of production, such as wages and raw materials, but before paying interest or tax. In the context of measuring the impact of implementing new technologies, using *operating margins* as outputs allows us to directly measure the impact of these technologies and production or operating changes in the immediate aftermath (medium-short impact). Considering that treated units have been selected for implementing green transition and CE technologies, changes in *operating margins* are assumed to be brought by either increased production efficiency and/or a decrease in energy cost or requirement. In the short-medium term of the study, and before the 'rebound effect' can settle, changes in *operating margins* for treated units directly correlate with environment benefits due to increased efficiency in production and energy use.

Finally, to test how long this impact could last before the rebound effect would settle and increases in *operating margins* could be redirected towards increasing production or reducing other costs, the paper also implements a more time sensitive analysis via a Trajectory Balancing (Hazlett and Xu 2018) using the same treatment levels and control groups.[7] The flexibility of Trajectory Balancing allows us to easily follow the ATT over time which – in turn – can indicate us whether and when the rebound effect settles down.

## V. Results and description

### *Economic impact of carbon reduction and green transition technologies implementation*

In our empirical analysis, each treatment group is composed of a (ordered) quintile of the real dose. The average change in the outcome variable, *operating margins*, after the treatment, is compared with values before the treatment and with the changes in the control group. This Difference-in-Differences model produces an ATT which is interpreted as the direct effect of the implementation of carbon reduction and green transition technologies by treated firms. The results of the Discrete Multilevel Matching Difference-in-Differences are reported in Table 4. The design of the model includes robust and clustered (by primary sector) standard errors, and several covariates controlling for firms' differences within the treatment group: number of employees, added value per employee, total revenues from sales, total assets, share of tangible assets, return on investments, profits, debt to EBITDA ratio, a dummy variable indicating the primary sector in which the firm operates and

[6]This is done by identifying beneficiary firms of cohesion programs during the 2007–2013 and 2014–2020 programming period.
[7]Trajectory Balancing is an interesting technique halfway between a Difference-in-Differences design and a Synthetic Control analysis.

Table 4. Discrete Multilevel Matching Difference-in-Differences results.

| Quintiles: | 1st (<20%) | 2nd (21–40%) | 3rd (41–60%) | 4th (61–80%) | 5th (> 81%) |
|---|---|---|---|---|---|
| ATT (Oper. Margins) | 0.0644 | 0.0920* | 0.288* | 0.257** | −0.0702 |
| | (0.0548) | (0.0499) | (0.150) | (0.0916) | (0.188) |
| Observations | 416 | 1,384 | 460 | 1,282 | 298 |
| R-squared | 0.871 | 0.700 | 0.623 | 0.636 | 0.664 |
| Mean control t(0) | −0.00810 | −0.0406 | 0.581 | −0.0584 | −0.387 |
| Mean treated t(0) | 0.000839 | 0.0382 | 0.587 | −0.00878 | −0.246 |
| Diff t(0) | 0.00894 | 0.0788 | 0.00569 | 0.0496 | 0.141 |
| Mean control t(1) | 0.0377 | −0.0172 | 0.651 | −0.197 | −0.344 |
| Mean treated t(1) | 0.111 | 0.154 | 0.945 | 0.110 | −0.273 |
| Diff t(1) | 0.0733 | 0.171 | 0.294 | 0.306 | 0.0706 |

Robust standard errors in parentheses ***$p<0.01$, **$p<0.05$, *$p<0.1$.

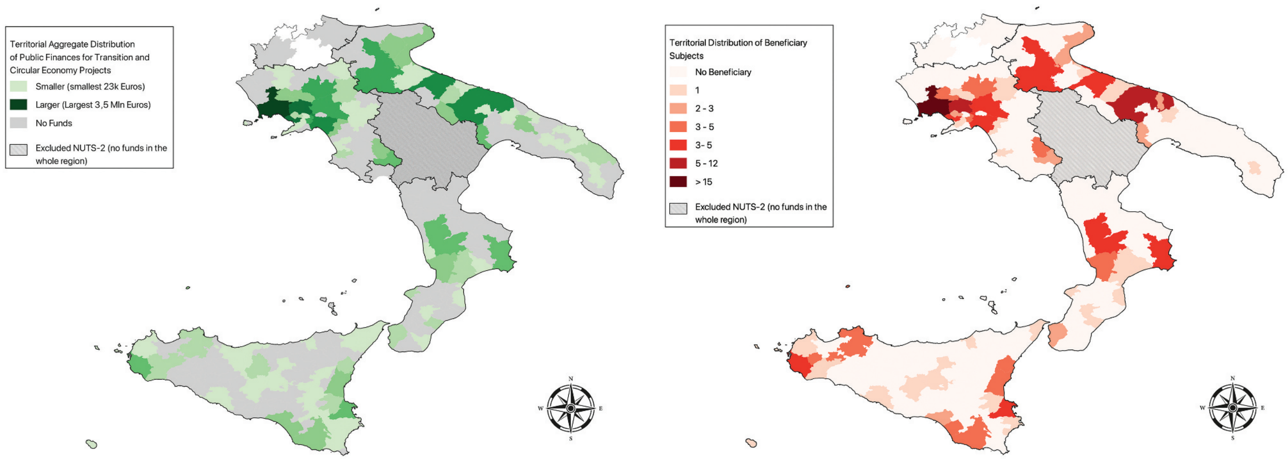


Figure 1. Spatial distribution of public funds (left) and beneficiary (right) by local labour systems (LLS).

a dummy variable indicating the region in which the firm is localized.

The main result of the analysis is the estimated DiD coefficient, the ATT for the output variable *operating margins*. In particular, the ATT is always greater than zero, except for the last quintile, suggesting an overall positive impact of the policy. When we focus on the central part of our distribution (columns 2, 3, and 4), findings suggest a larger and statistically significant effect of the policy. The largest ATT is found for the third quintile (0.288) and the second largest in the fourth (0.257). The coefficient for the fifth quintile, containing treatment firms that received the largest sums for their dimension, is negative although it is not statistically significant and shows the largest standard error in the analysis. Figure 3, below, reports the ATT for all groups (quintiles) in graphical form.

Visualized as a continuous function, the ATTs of different (ordered) treatments suggests that the relationship between different levels of subsidies and their impact on firms' *operating margins* assumes an inverted 'U' shape. This is especially true in the interval where our entire dose is statistically significant (i.e. both upper and lower bounds lie above zero). The existence of a maximum has an important economic interpretation: larger subsidies are correlated with a larger (and more statistically significant) impact until a certain threshold (that coincides with the middle group, the third quintile). Once the threshold is reached, the effect of the policy, despite being still positive and significant, starts decreasing. Economically, we interpret this as evidence of an 'optimal amount' of subsidies in terms of policy effectiveness.

## *Spatial, sectorial, and territorial heterogeneity of the impact*

While the first set of results confirms the existence of a positive impact of carbon reduction and green transition public policies aimed at firms, Figure 4 helps us to better understand the spatial dimension and the distribution of this impact.

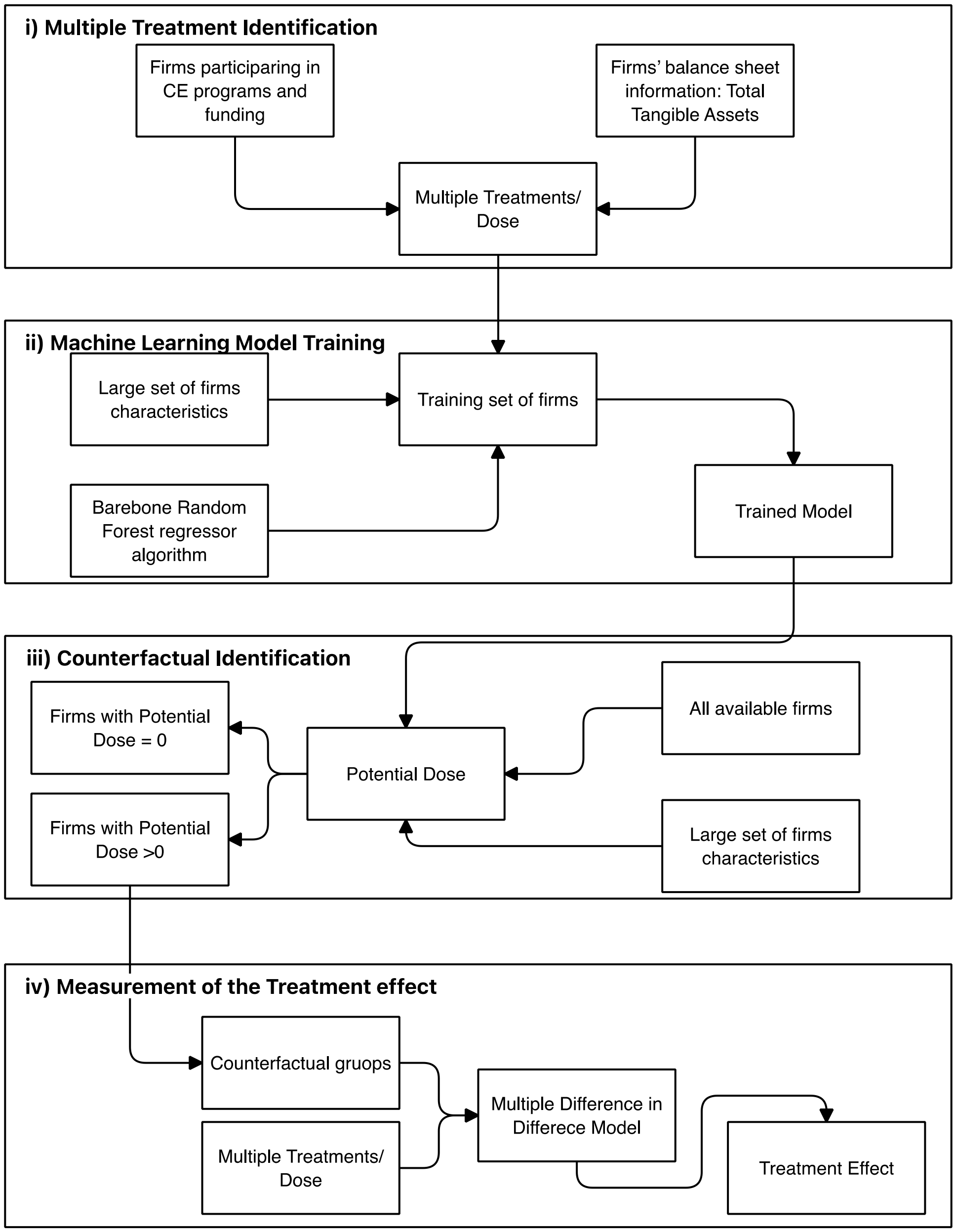


**Figure 2.** Flowchart of the empirical strategy.

In this figure, ATTs of all groups are averaged by Local Labour Systems to show the territorialization of the impact. Figures 1 had shown how funds and beneficiaries are mostly concentrated in and around urban areas, especially larger ones (i.e. Napoli, Bari, Palermo). Figure 4 shows a different pattern where the territorially averaged ATTs for several rural and peripheral LLSs are positive, larger than those of several urban and peri-urban LLSs. In this context, especially, public policies could make very relevant differences.

Conversely, being localized in central and urban LLSs could partially off-set potential benefits for firms implementing these technologies. This could be in part because of the presence of larger infrastructure (i.e. the potential gain in energy cost saving is smaller) and in part due to a more dynamic and competitive environment. Such possible heterogeneity of impact due to the localization is investigated further by running the model on sub-groups of firms operating in urban areas or, separately, in peripheral areas. Results are shown in

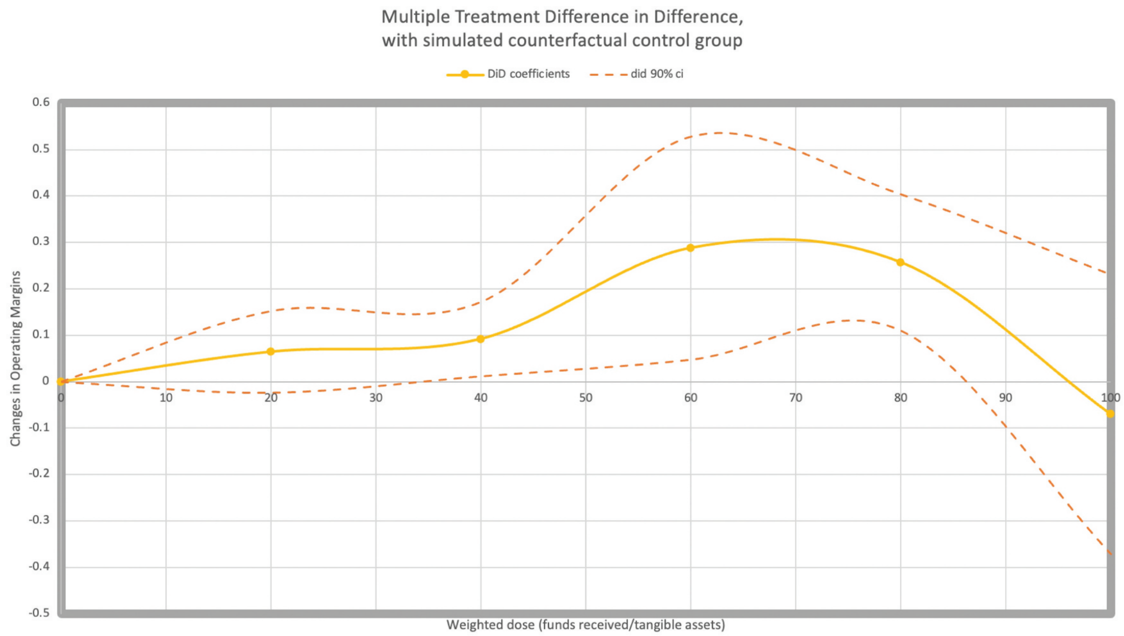


**Figure 3.** Model quintiles. Source: authors' elaboration.

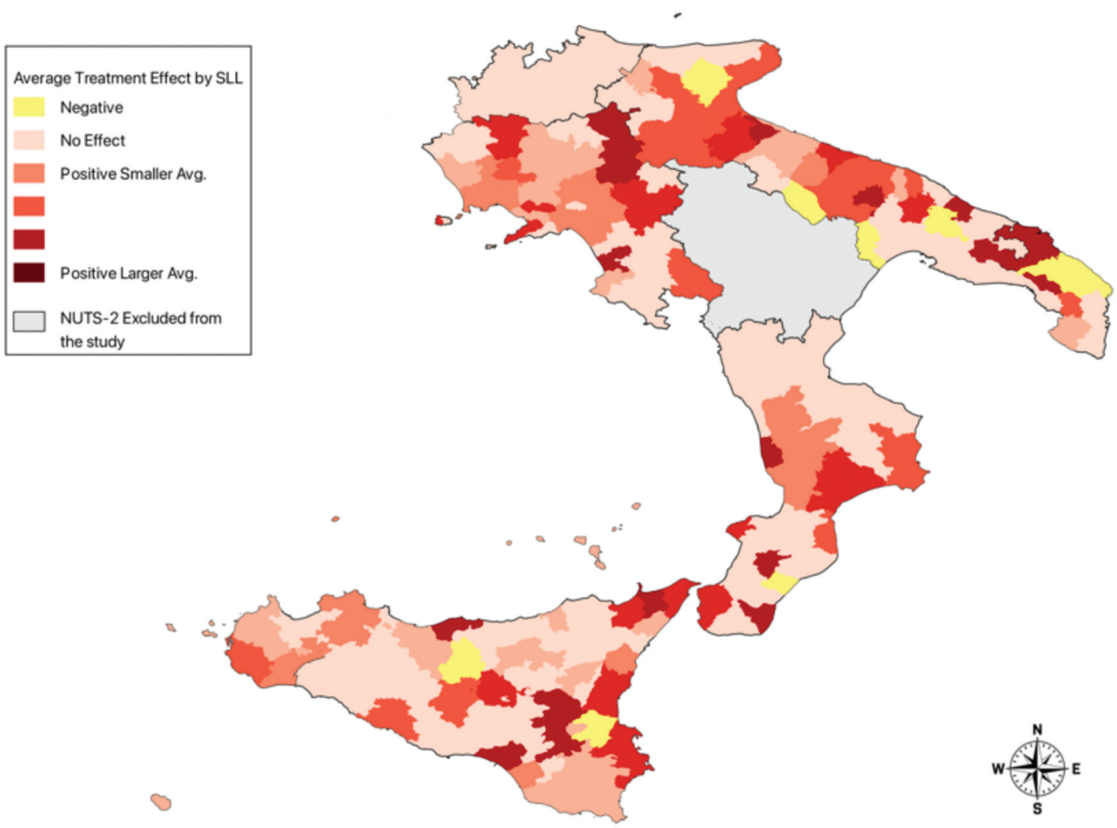


**Figure 4.** Average of ATTs by local labour systems in the study area. Source: authors' elaboration.

graphical form below while coefficients for all subgroups are reported in Annex 3 (Tables A3 and A4).

Coherent with the prevalent localization of firms in the study area, most beneficiary firms (around 75%) operate in an urban context. In these contexts,

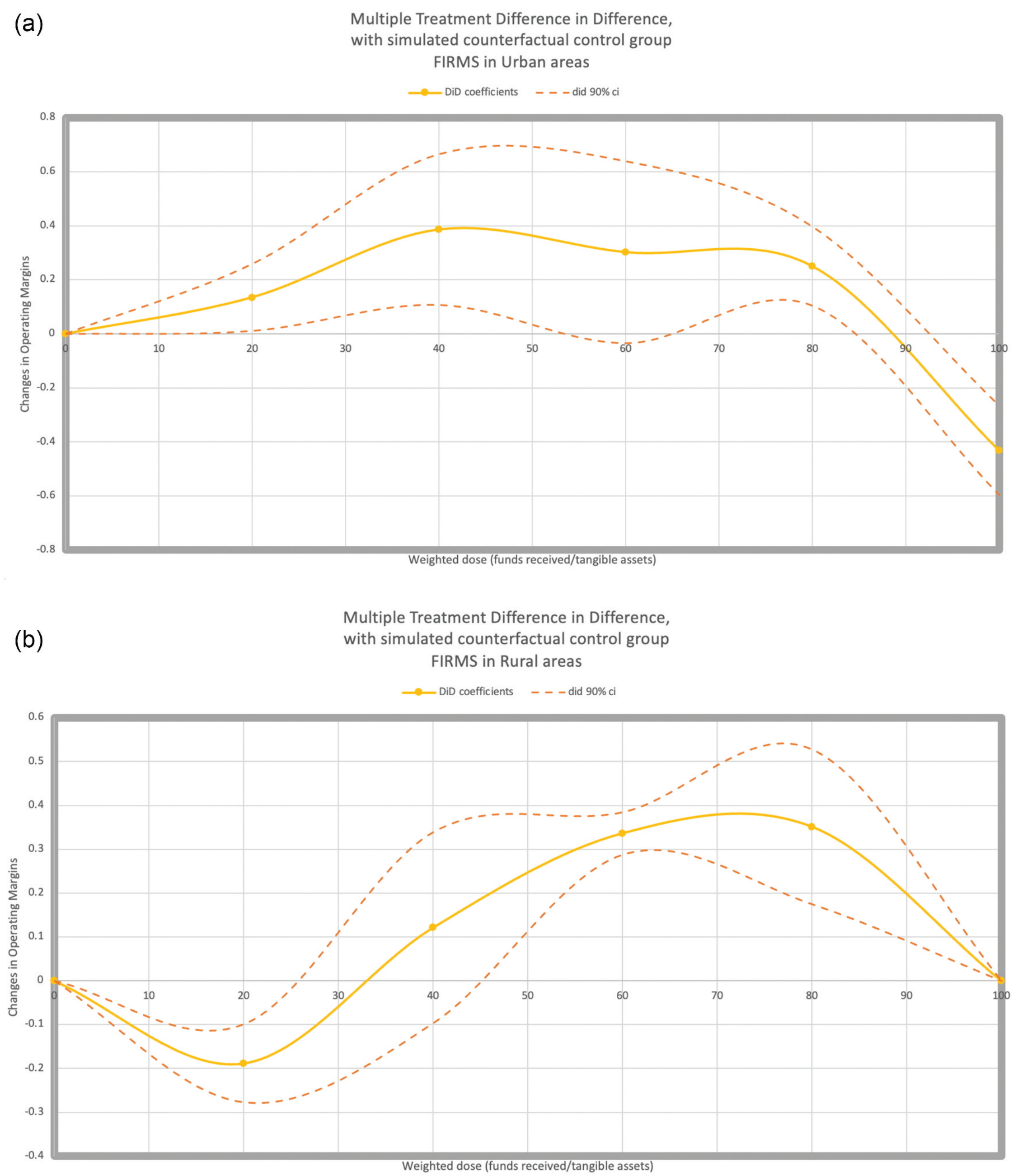


**Figure 5.** Localization heterogeneity. Urban and peripheral areas.

as shown in Panel (a) of Figure 5, different levels of subsidies impact firms' *operating margins* by following the same inverted 'U' shape identified in the general model, therefore providing robustness to the previous results. Indeed, for firms operating in urban contexts, larger subsidies show a larger impact on *operating margins* up until a threshold and then show diminishing, if not negative, returns. The situation is partially dissimilar for firms operating in rural contexts, instead. Within these contexts, the inverted 'U' shape relationship is exacerbated as show in Panel (b) of Figure 5. The left tail of the distribution reports negative ATTs suggesting how the window of optimal amount of subsidies might be smaller and more concentrated towards the centre of the distribution. In rural context firms not only might risk diminishing returns for bigger projects and larger subsidies, but this might also be true for

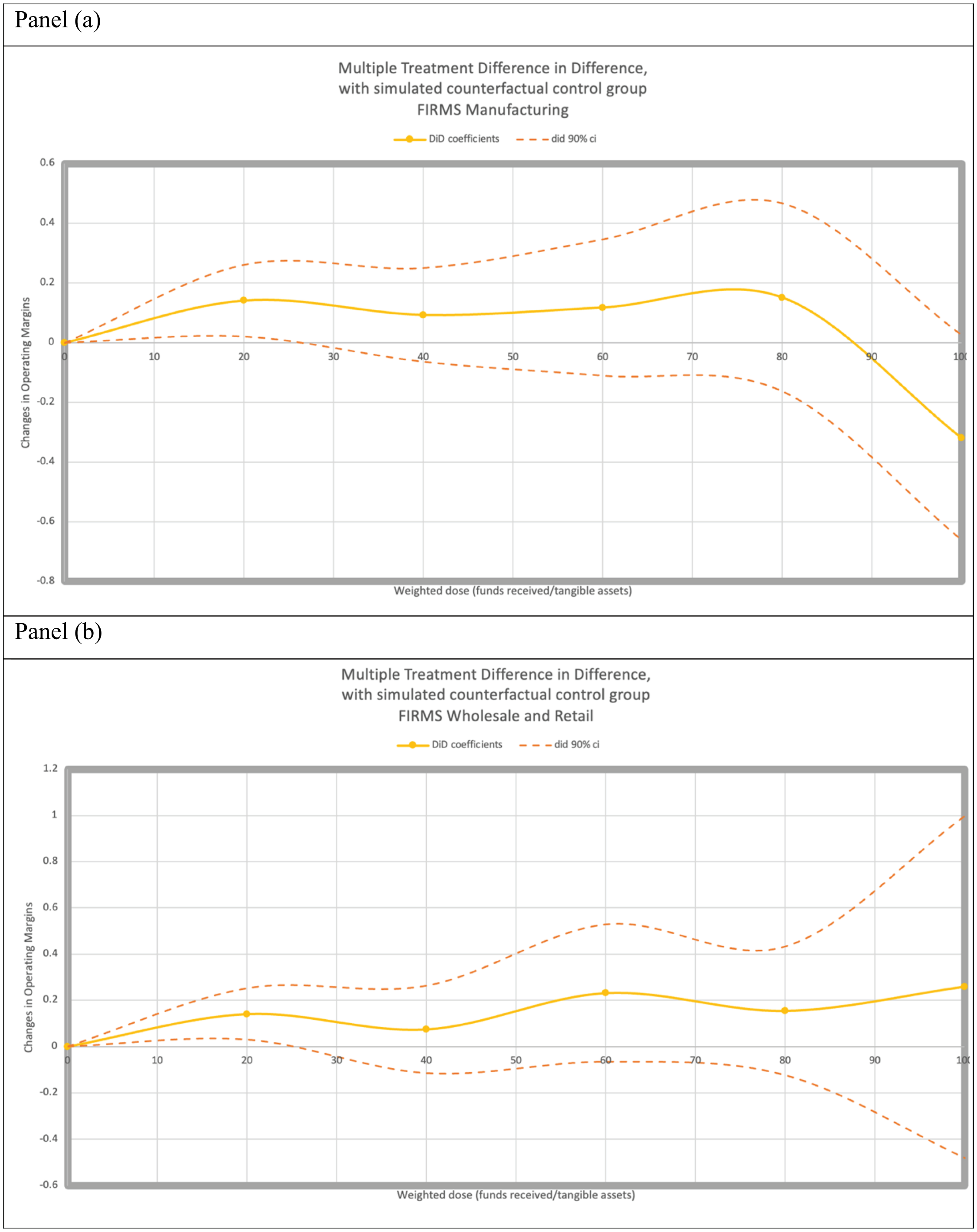


**Figure 6.** Impact heterogeneity, sectors.

smaller projects and subsidies. This makes extremely important a careful planning based on firms' endowment and assets.

A second, important, possible source of heterogeneity, highlighted by the summary statistics provided in Table 2, is the main sector of activity. Indeed, almost 80% of beneficiary firms operate either in manufacturing activities or wholesale and retail activities. Different dynamics and possible biases due to the sectorial composition are investigated by running the DiD model on subgroups of beneficiary and non-beneficiary firms operating in the same sector. Tables with the complete results are available in Annex 3 (Tables A5 and A6).

Overall, results indicate that – as already accounted for in the counterfactual identification strategy – the sector of firm's activity is relevant for the impact measurement. As shown in Panel (a) of Figure 6 results for firms operating in manufacturing activities exhibit an increasing impact up to the fourth quintile and a marked drop in the fifth quintile. This is consistent with the interpretation given to the main results. A different situation occurs for firms operating in wholesale and retail activities. Results of the counterfactual analysis shown in Panel (b) of Figure 6 report that at an increase of received subsidies corresponds an increase of the impact on beneficiary firms. Visualized as a continuous function, the ATTs for beneficiary firms in this sector is constant, if not slightly growing. Results indicate a different dynamic here without the presence of an optimal amount of subsidies.

In conclusion, the main results, i.e. the presence of a general inverted 'U' shape relationship between the intensity of the treatment and the impact on *operating margins* are confirmed and supported by testing the model over different sources of heterogeneity. Only firms operating in wholesale and retail activities display a different dynamic from the rest and do not show a non-linear shape.

### *Environmental impact and rebound effect*

As previously mentioned, environmentally oriented policies targeting economic actors can suffer from what is known, in the literature, as the *rebound effect* (Thiesen et al. 2008). Scholars noted how, especially in the environmental field, there is a reduction in expected gains from the implementation of technologies that increase the efficiency of resource use, due to behavioural or other systemic responses. We must stress that the existence of a rebound effect is perfectly in line with the prescription of economic theory in terms of optimizing behaviour of economic agents. Indeed, while environmental awareness can produce positive corporate images and brand identities, the primary aim of firms and businesses is and remains that of generating profits.

Related to our specific case, the existence of a rebound effect would suggest that higher production efficiency, and energy-savings produced by the implementation of carbon reduction and green transition technologies, are soon repurposed – for example – to raise the total production.

To test for the emergence of the rebound effect, the same treatment groups and counterfactuals are inputted in a Trajectory Balancing model, which, similarly to a Synthetic control method, flattens observation to the mean (for both treated and controls) and allows to follow the treatment effect over time. On average, results are consistent with those of the Discrete Multilevel Matching Difference-in-Differences,[8] with larger and more significant ATTs for the third and fourth quintiles. The main difference in terms of average results is the ATT of the fifth quintile, which, with the Trajectory Balancing model, is positive instead of negative but not statistically significant and still with the largest overall standard error. Compared to the Discrete Multilevel Matching Difference-in-Differences, data are strongly weighted[9] and, similarly to a Synthetic Control method, this model allows us to follow the treatment effect over time.

Despite the post-treatment data series not being extremely long (just four years), they cover all available years before the emergence of the COVID-19 pandemic and the subsequent economic and environmental shock. Most graphs of Figure 7 show signs of diminishing returns over time, after the implementation of carbon reduction and green transition technologies in the year 2016. This is particularly evident in the third and fourth quintiles since, towards the end of the series, the treatment effect tends to shrink down. The result supports the idea of the existence of a rebound effect where the gains from implementing carbon reduction and green transition technologies are redistributed after a short time period to maximizing production and profits. While the economic impact of the policy on adopters is clear and the correlated energy-use savings should also induce a reduction in carbon emissions, the existence of

[8]Tabled results are available in Annex 3, Table A7.
[9]This is noticeable in the graphs by how means in the pre-treatment periods are weighted and forced to be equal between treatment and control groups leading to a pre-treatment effect equal to 0.

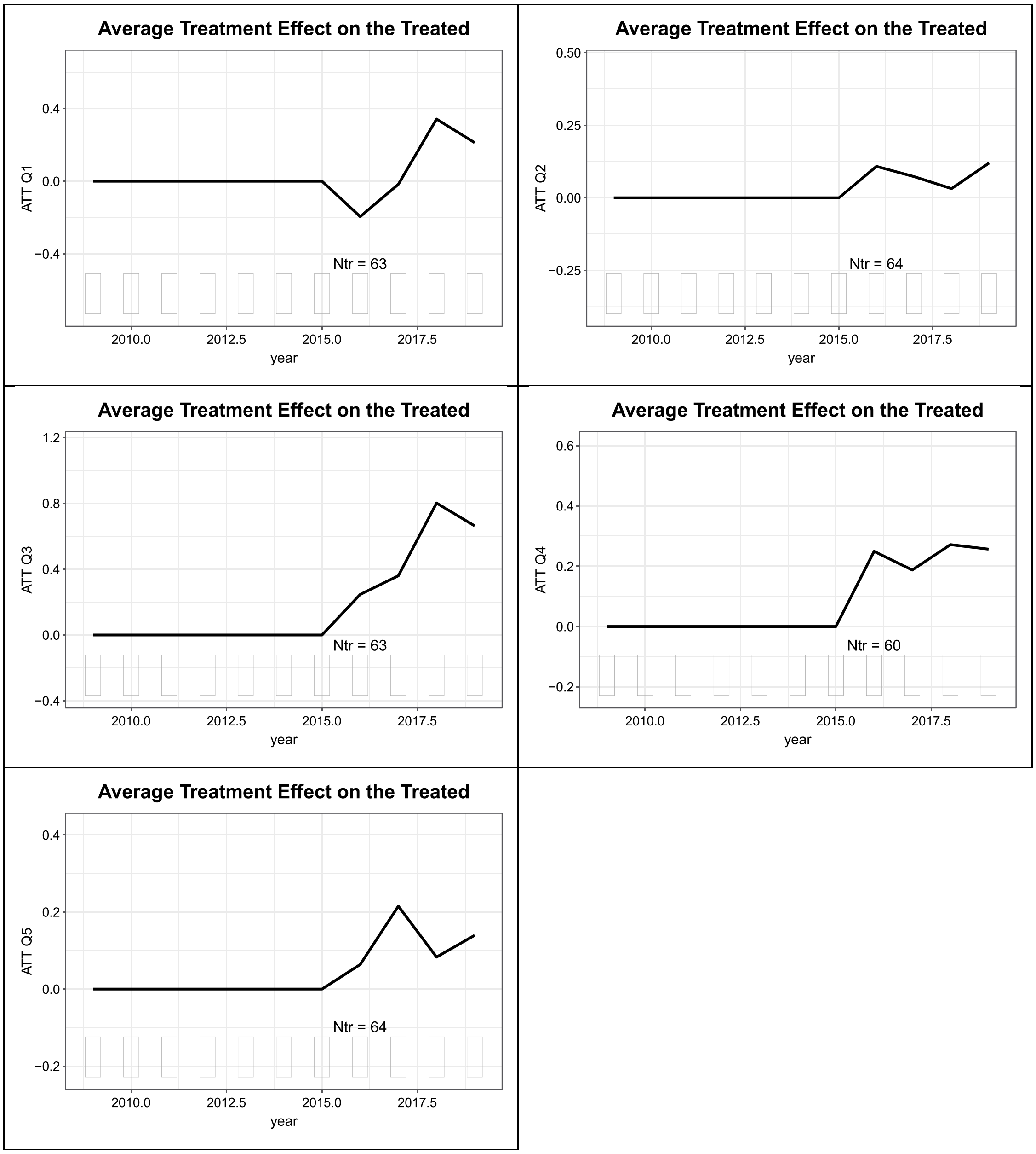


**Figure 7.** Treatment levels impact over time.

this rebound effect over time suggests that the eventual positive environmental impact could be only a temporary.

## *Limitations and robustness checks*

Alongside the lack of a direct measure of the environmental impact of these policies – due, as discussed, to data availability – the main limitation of the study, and to the generalizability of results, is found in the – relatively – small treated sample size. The treatment group is composed of 320 firms, out of around 20,000 considered in the study. Part of the reasons for such a small sample size, i.e. participation bias, and their consequences for the counterfactual design are described and addressed in the previous section. To best characterize firms, the analysis incorporates a large set of firms' characteristics to capture the specificities of treated firms and develop a compelling counterfactual. Despite the effort and the methodological attention to this key element, it is important to notice that there will always be the chance of leaving out some characteristics and dynamics which – in turn – could produce some source of endogeneity and correlate with the error term. Unfortunately, this aspect is quite common for these types of analysis, where the estimated counterfactual, despite similar, can never be, for its nature, identical to the treated group. While we are confident that all possible and manageable sources of endogeneity are controlled for and managed, there are a few key elements for which data are not available; most notably, the human capital and skill level of workers and the managerial ability of owners and managers.

Besides the additional results and analysis described in the results section and reported in Annex 3 concerning the running of the DiD model on subgroups of sector and territorial context, several other robustness and sensitivity checks have been performed to ensure the credibility of the results. First, Annex 4 tests the possible heterogeneity due to firms' size by running the model on subgroup of only medium (Table A8) and smaller firms (Table A9). Results show only small variations.

Testing the robustness of results to our selected specification, Table A10 of Annex 5 shows the results of the main model while also including Inverse Probability Weights (IPWs) produced via kernel matching. Moreover, Table A11 shows results for different treatment levels, identified dividing the samples into quartiles instead of quintiles.

Annex 4 also reports the results of a falsification test and a confirmation test. The latter consists in running the model on the whole sample (Table A12), without quintiles distribution. For the falsification test, instead, the main Discrete Multilevel Matching Difference-in-Differences model is run changing the year in which the treatment occurs. As shown in Table A13, all results of the falsification test are not significant. Taken together, such extended collection of sensitivity and robustness tests are all in line with our main results and support their reliability and credibility.

## VI. Concluding remarks

In this work, we investigated whether EU environmental and carbon reduction policies do have an economic impact on adopters. This paper's research objectives are rooted in the European policy strategy, which aims to promote development and regional convergence by leveraging sustainable development and innovation. These objectives are in line with the requirements of the Green Deal that aims at reducing greenhouse gas (GHG) emissions in the EU by, at least, 55% by the year 2030 compared to 1990 levels. Such macro-economic issues are, necessarily, mediated by local economic actors who adopt and implement the policy. Local economic agents, firms and businesses do not necessarily share the same concerns about the environment, managing climate change, reducing pollution, and fostering regional convergence. Primarily, their actions are driven by profits and potential gains. In such a framework, macroeconomic objectives such as sustainable development, environmental benefits and regional economic convergence can only be reached if economic agents' objectives at the micro-level (in our specific case firms' profitability), align. But, because of the rebound effect, the policymaker needs to intervene in the economic system to achieve its macro-level objectives through specific mitigation strategies.

In our empirical analysis, due to the lack of availability at the firm level of specific environmental measures, we focused on firms' performance due to the sustainability-oriented technologies financed by the European cohesion funds during the 2007–13 programming period. We considered firms that received an incentive through the resources of the ERDF to upgrade their production plants with sustainable technologies. Our main outcome measure, *operating margins*, was defined as the profit that companies make on sales after paying for variable costs of production, such as wages and raw materials, but before paying interest or tax. Through the application of an empirical strategy based on ML algorithms to identify the most appropriate counterfactuals, our results indicate a strong and positive effect, for which the public policy is directly responsible, with different dynamics for different levels of public support and implementation. Specifically, we discussed how the relationship between different levels of subsidies and their impact on firms' *operating margins* presents an inverted 'U' shape. This can be economically interpreted in terms of the existence of an 'optimum dose' of public subsidies: larger subsidies are correlated with a larger (and more statistically significant) impact until a certain threshold (that coincides with the middle group - third quintile). Once this threshold is reached, the effect of the policy, despite being still positive and significant, starts decreasing.

We discussed also how, in the short run, the effect on treated firms tends to diminish, suggesting the possibility of a *rebound effect* where the gains in production efficiency and energy savings are repurposed by firms to increase production (and profits) instead of reducing absolute emissions.

In detail, while it is clear, from our empirical analysis, that firms adopting carbon reduction technologies experienced cost-savings, the dynamic Trajectory Balancing model has shown that such savings are partially re-invested to raise production levels. This is perfectly in line with what one can expect from an economic agent at the micro level: firms' actions are certainly guided by the search for ways to obtain profit increases.

From a policy perspective, this is extremely interesting, highlighting both strengths and weak points of the sustainable development strategy and how it could, indeed, foster regional economic convergence.

Our study shows that, in a short-term from the implementation, adoption can substantially reduce costs and, following our framework, emissions. Keeping production levels constant could then translate into an absolute reduction of carbon emissions. However, the increase in production efficiency may also allow firms and businesses to raise production levels (*rebound effect*) severely limiting potential environmental benefits. The general propensity to prioritize profit and growth over emission reduction shows the inherent weakness of actor-based policy and the difficulty to translate micro-level actions into macro-level impacts. To ensure some level of environmental impact policymakers should develop strategies mitigating the rebound effect.

Strategies that could work, combined with the existing actor-based programs, could include both regulatory actions (i.e. cap limits to production level growth in the years following interventions) or further progressive incentives based on actual carbon emission reduction. Future research will focus on the combined effect of actor-based programs and stringent regulatory action to better understand mediation dynamics and, more specifically, direct environmental impact.

We also acknowledge other limitations of this work, such as the small sample size of policy recipients, as well as their location in a limited area of Italy. Enlarging the analysis to further European regions would allow a comparison among different experiences and a better generalizability of findings. Data availability also limits the scope of the analysis. A longer data series could provide more insights into medium- and long-term dynamics and behaviours and would allow to test more effectively test the impact of the rebound effect to develop mitigation strategies. We leave these objectives to future implementations.

## Disclosure statement

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## References

Amjadi, G., T. Lundgren, and W. Zhou. 2022. "A Dynamic Analysis of Industrial Energy Efficiency and the Rebound Effect: Implications for Carbon Emissions and Sustainability." *Energy Efficiency* 15 (54). https://doi.org/10.1007/s12053-022-10059-4.

Arvanitis, S., and M. Ley. 2013. "Factors Determining the Adoption of energy-Saving Technologies in Swiss Firms: An Analysis Based on Micro Data." *Environmental &*

*Resource Economics* 54 (3): 389–417. https://doi.org/10.1007/s10640-012-9599-6.

Athey, S., and G. W. Imbens. 2017. "The State of Applied Econometrics: Causality and Policy Evaluation." *Journal of Economic Perspectives* 31 (2): 3–32. https://doi.org/10.1257/jep.31.2.3.

Berner, A., S. Lange, and A. Silbersdorff. 2022. "Firm-Level Energy Rebound Effects and Relative Efficiency in the German Manufacturing Sector." *Energy Economics* 109. https://doi.org/10.1016/j.eneco.2022.105903.

Breiman, L. 2001. "Random Forests." *Machine Learning* 45 (1): 5–32. https://doi.org/10.1023/A:1010933404324.

Cagno, E., and A. Trianni. 2013. "Exploring Drivers for Energy Efficiency within Small- and medium-Sized Enterprises: First Evidences from Italian Manufacturing Enterprises." *Applied Energy* 104:276–285. https://doi.org/10.1016/j.apenergy.2012.10.053.

Cagno, E., E. Worrell, A. Trianni, and G. Pugliese. 2013. "A Novel Approach for Barriers to Industrial Energy Efficiency." *Renewable and Sustainable Energy Reviews* 19:290–308. https://doi.org/10.1016/j.rser.2012.11.007.

Cainelli, G., M. Z. Mazzanti, and R. Zoboli. 2011. "Environmentally Oriented Innovative Strategies and Firm Performance in Services. micro-Evidence from Italy." *International Review of Applied Economics* 25 (1): 61–85. https://doi.org/10.1080/02692170903426146.

Caragliu, A. 2021. "Energy Efficiency-Enhancing Policies and Firm Performance: Evidence from the Paper and Glass Industries in Italy." *Energy Policy* 156. https://doi.org/10.1016/j.enpol.2021.112415.

Cerulli, G. 2021. "Improving Econometric Prediction by Machine Learning." *Applied Economics Letters* 28 (16): 1419–1425. https://doi.org/10.1080/13504851.2020.1820939.

De Chaisemartin, C., and X. d'Haultfoeuille. 2023. "Two-Way Fixed Effects and Differences-In-Differences with Heterogeneous Treatment Effects: A Survey." *The Econometrics Journal* 26 (3): C1–C30. https://doi.org/10.1093/ectj/utac017.

DeCanio, S. J. 1998. "The Efficiency Paradox: Bureaucratic and Organizational Barriers to Profitable energy-Saving Investments." *Energy Policy* 26 (5): 441–454. https://doi.org/10.1016/S0301-4215(97)00152-3.

Donati, C. 2016. "Firm Growth and Liquidity Constraints: Evidence from the Manufacturing and Service Sectors in Italy." *Applied Economics* 48 (20): 1881–1892. https://doi.org/10.1080/00036846.2015.1109044.

Du, W., and M. Li. 2019. "Government Su Pport and Innovation for New Energy Firms in China." *Applied Economics* 51 (25): 2754–2763. https://doi.org/10.1080/00036846.2018.1558356.

European Parliament. 2021. "Resolution on the European Green Deal (2019/2956(RSP))." Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020IP0005.

Fricke, H. 2017. "Identification Based on Difference-In-Differences Approaches with Multiple Treatments." *Oxford Bulletin of Economics and Statistics* 79 (3): 426–433. https://doi.org/10.1111/obes.12178.

Ganau, R., and A. Rodríguez-Pose. 2023. "Firm-Level Productivity Growth Returns of Social Capital: Evidence from Western Europe." *Journal of Regional Science* 63 (3): 529–551. https://doi.org/10.1111/jors.12636.

Greening, L. A., D. Greene, and C. Difiglio. 2000. "Energy Efficiency and Consumption - the Rebound Effect - a Survey." *Energy Policy* 28 (6–7): 389–401. https://doi.org/10.1016/S0301-4215(00)00021-5.

Hazlett, C., and Y. Xu. 2018. "Trajectory Balancing: A General Reweighting Approach to Causal Inference with time-Series cross-Sectional Data." *Working paper, UCLA and Stanford*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3214231.

Holland, P. 1986. "Statistics and Causal Inference." *Journal of the American Statistical Association* 81 (396): 945–960. https://doi.org/10.1080/01621459.1986.10478354.

Jaffe, A. B., and R. N. Stavins. 1994. "The energy-Efficiency Gap What Does it Mean?" *Energy Policy* 22 (10): 804–810. https://doi.org/10.1016/0301-4215(94)90138-4.

Jevons, W. S. 1866. *The Coal Question*. London: Macmillan and Co.

King, G., and R. Nielsen. 2019. "Why Propensity Scores Should Not Be Used for Matching." *Political Analysis* 27 (4): 435–454. https://doi.org/10.1017/pan.2019.11.

Kohavi, R. 1995. "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection." *Ijcai* 14 (2): 1137–1145.

Lee, B. K., J. Lessler, and E. A. Stuart. 2010. "Improving Propensity Score Weighting Using Machine Learning." *Statistics in Medicine* 29 (3): 337–346. https://doi.org/10.1002/sim.3782.

Lian, Y.-J. 2014. "WINSOR2: Stata Module to Winsorize Data." *Statistical Software Components*, Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s457765.html.

Liu, L., and X. Xu. 2025. "The Effect of Government Subsidies on firms' Innovation Performance: Does Subsidy Continuity Matter?" *Applied Economics* 57 (5): 471–487. https://doi.org/10.1080/00036846.2024.2305160.

Lu, M., and K. Wang. 2024. "The Direct Energy Rebound Effects for Manufacturing and Service Sectors in China: Evidence from Firm-Level Estimations." *Journal of Cleaner Production* 474. https://doi.org/10.1016/j.jclepro.2024.143617.

Newman, J., and M. Mintrom. 2023. "Mapping the Discourse on Evidence-Based Policy, Artificial Intelligence, and the Ethical Practice of Policy Analysis." *Journal of European Public Policy* 30 (9): 1839–1859. https://doi.org/10.1080/13501763.2023.2193223.

Nunn, N., and N. Qian. 2011. "The Potato's Contribution to Population and Urbanization: Evidence from a Historical Experiment." *Quarterly Journal of Economics* 126 (2): 593–650. https://doi.org/10.1093/qje/qjr009.

Santos, A., J. Barbero, S. Salotti, O. Diukanova, and D. Pontikakis. 2023. "On the Road to Regional "Competitive Environmental Sustainability": The Role of the European Structural Funds." *Industry and Innovation* 30 (7): 801–823. https://doi.org/10.1080/13662716.2023.2236048.

Shao, Y., and Z. Chen. 2022. "Can Government Subsidies Promote the Green Technology Innovation Transformation? Evidence from Chinese Listed Companies." *Economic Analysis and Policy* 74:716–727. https://doi.org/10.1016/j.eap.2022.03.020.

Slonim, R., C. Wang, E. Garbarino, and D. Merrett. 2013. "Opting-In: Participation Bias in Economic Experiments." *Journal of Economic Behavior & Organization* 90:43–70. https://doi.org/10.1016/j.jebo.2013.03.013.

Thiesen, J., T. S. Christensen, T. G. Kristensen, R. D. Andersen, B. Brunoe, T. K. Gregersen, M. Thrane, and B. P. Weidema. 2008. "Rebound Effects of Price Differences." *The International Journal of Life Cycle Assessment* 13 (2): 104–114. https://doi.org/10.1065/lca2006.12.297.