Decoding the Micro-Economic Impact of Carbon Reduction Policy: A Counterfactual Identification via Machine Learning.

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Extended Abstract -

<u>Introduction and background</u>

Do contemporary EU environmental and carbon reduction policies work? More specifically, is the recent direction taken by EU cohesion programs towards a technology-led initiative to support and encourage SMEs to invest in activities that optimize the use or reuse of water, energy, and materials a sustainable course leading the productive structures of EU countries to reduce emissions and pollution? While these questions may seem straightforward, they are, in fact, quite complex.

Indeed, while there is belief in the technologies and practices incentivized by EU policies, this type of policies implies that solving the public problem of carbon production leading to climate change depends on the active participation of economic actors for full implementation. A global, public problem is thus addressed through solutions mediated by local, private, economic actors. This mediation role, in which economic actors are called to play a pivotal role, force us to restructure our original question - or, at the very least, precede it - as follow: Do EU environmental and carbon reduction policies have an economic impact on adopters?

While economic actors may be concerned about the environment, managing climate change, and reducing pollution, their actions are primarily driven by profits and gains. Therefore, addressing the question of the micro-economic impact of EU policies is pivotal to understanding whether this major strategy, undertaken for the next decade, has a chance of success. Indeed, climate change is among the most pressing challenges of our time. In recent years, the ecological transition and the implementation of green technologies have become a priority on several policy agendas.

In the European Union, the *Green Deal*, introduced by the European Commission in December 2019, is a comprehensive set of actions with the aimed at reducing greenhouse gas (GHG) emissions in the EU by, at least, 55% by the year 2030 compared to 1990 levels. The ultimate goal is to achieve a climate-neutral society by the year 2050. The target of the European Green Deal is legally binding and is included in the European Climate Law (European Parliament and Council, 2021).

The industrial strategy should be grounded in growing competitiveness and energy efficiency, under the assumption that "innovative and climate-neutral re-industrialization will create local jobs and ensure the competitiveness of the European economy" (European Parliament, 2021).

Public interventions aimed at mitigating human impacts on the environment, in the next decade, align with this framework. For instance, one of the objectives of the Next Generation EU recovery plan is to promote investments in environmental protection, sustainable public transport and energy efficiency of buildings. The European cohesion policy plays a crucial role in encouraging the regional adaptation to the new overall vision of low-impact society.

With an expanding body of literature on the adoption of green transition technology and Circular Economy (CE) practice and policies (among others Clementi & Garofalo, 2023), there is no real consensus on the impact of these innovations when adopted by micro-economic actors. The environmental benefits of optimizing the use of water, energy, and materials are evident (Jaffe and Stavins, 1994; Miara et al., 2014); however, the economic benefits for micro-economic actors have only recently begun to be explored. Some studies suggest an overall increase of production costs associated with the implementations of CE transition innovations (Antonioli et al., 2022), while others individuate a causal link between public financial support and an improvement in material productivity and operating costs for certain industrial sectors (Flachenecker and Kornejew, 2019; García-Quevedo and Jové-Llopis, 2021) or with specific firm characteristics and managerial capacities (Leoncini et. al., 2019). Additionally, regional and territorial factors may play a role on the adoption and significantly influence these effects (Cainelli et. all., 2015), as well as the varying characteristics of micro-economic actors (Bassi and Dias, 2020; Leoncini et. al., 2019).

In summary, current literature does not provide a clear answer regarding the economic benefits of adopting these technologies.

Our contribution positions at the forefront of the discussion, aiming at shedding light on the microeconomic impact of receiving different levels of public support to firms implementing CE and green technologies for carbon reduction.

To achieve this and provide answer to the research question, we propose a novel design for counterfactual identification exploiting the potential of Machine Learning methods and algorithms. The policy impact over different levels of treatment (public financial support/total tangible assets of the firm) is measured via a Multiple Treatment Matching Difference in Difference, a common implementation of the Difference in Difference model, allowing to estimate the causal impact of a differentiated treatment by estimating for each level the difference in output with untreated units. The novelty of our design rests in the identification of counterfactuals, for which we exploit the potential of ML algorithms.

<u>Data and Methods</u>

For the analysis we focus on Italian Less Developed regions, in the southern part of the peninsula (Apulia, Calabria, Campania and Sicily), which are the larger beneficiary of cohesion funds for the programming periods 2014-2020. From Italian cohesion policy database managed (*Opencoesione)* we extracted all the firms participating in pilot programs and received an incentive, by the ERDF, to upgrade their production plants with sustainable technologies. Through the VAT number, this sample of treated firms is connected to the *Analisi informatizzata delle aziende italiane* (AIDA) database providing longitudinal balance sheet information for a large number of Italian firms between 2009 and 2019.

First, we identified the multiple treatment with the objective of assessing the impact of varying degrees of technologies implemented and implementation. 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 by 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 total tangible assets of the firms in the period prior to the treatment.

<u>Counterfactual Identification</u>

Second, we leveraged a Machine Learning supported counterfactual identification. The main novelty of this paper lies in the attention posed in the identification of suitable counterfactuals for the design of the quasi-experimental setting. The issue of significant heterogeneity between treated and untreated units, where treated units exhibit specific characteristics - also linked to varying levels of public support requested - cannot be effectively addressed through conventional matching techniques (Fantechi and Cusimano, 2024).

To address the specificities of treated units and compare the performance of firms implementing CE and green transition technologies with similar untreated firms, we design a strategy based on Machine Learning algorithms to identify the most appropriate counterfactuals. The application of Machine Learning algorithms for counterfactual identification is, per se, not novel and is currently recognized as a best practice in several fields (i.e., pharma, medical, informatics) and, recently, it is being picked-up also in economics (Fantechi and Cusimano, 2024). However, while these studies show the ability of ML classification algorithms in identifying counterfactuals for binary treatments, they do not address the whole problem of varying intensity (dose). To advance in this direction, this paper proposes the implementation of a non-parametric Machine Learning regressor to synthetize/simulate a potential dose for untreated units, based of pre-treatment characteristics. We train a model on a random sample of treated and untreated units to identify based on a given set of pre-treatment firms' characteristics, the level of funds they would have required - if any - they had decided to participate in the policy programs.

This methodology is rooted on the idea that i) in the programming period 2014-2020 the implementation of firms' oriented policies for CE and green transition are still in its infancy and very few programs are enacted in this direction; ii) in this period (compared to 5-6 years later) very few firms, especially in the still developing southern part of Italy, have their attention focused on these types of implementations. For the design of a quasi-experimental setting, we exploit the fact that not all firms that could or should have participated in these policies have done so. As a matter of fact, most of them did not. The machine Learning regressor is trained to identify these firms and assign them, based on their characteristics, a specific level of the potential dose. This potential dose is exploited to identify different counterfactual for different treatment levels. This identification strategy, encompassed within the whole empirical strategy, is detailed in the flowchart below.

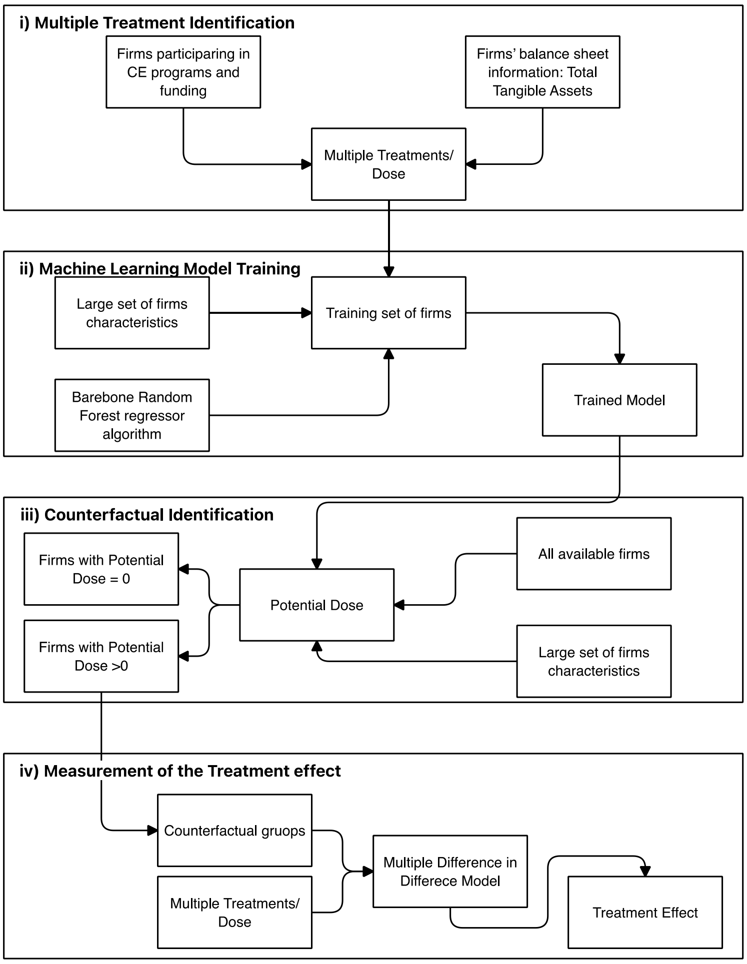

Figure 1. Flowchart of the empirical strategy.

The same dose that will be used to identify different levels of treatment will also be used in the training of a Random Forest regressor algorithms (Fig.1, panel ii). The regressor, a non-parametric ensemble of decision trees, is chosen from a range of possible algorithms as the literature indicates it is most suitable for handling a large set of covariates. Formally, a Random Forest Regressor is recursively trained to estimate the amount of funds received. This is accomplished by feeding the algorithms with firm-level information regarding multiple pre-treatment characteristics, whether a specific firm has received any funding, and the specific amount. Through multiple iterations, the algorithm estimates and checks its accuracy, adjusting the weights of the regressor accordingly.

The trained model outputs a potential dose (Fig.1 panel iii). From this point, we first exclude those untreated observation with a potential dose of 0. Then, we apply the same boundaries used to identify the multiple treatments to the potential dose. In this way, for each treatment level, we identify a subset of untreated units which are very similar in characteristics to the treated units.

Results and Conclusions

The Machine Learning supported counterfactual identification informs and provides a solid ground to implement a Multiple Treatment Difference in Difference model and study the short time microeconomic impact of firms implementing different levels of CE and green technologies with public support.

The homogeneity of the territorial and regional context (all firms locate in developing regions in the southern part of Italy) and the robustness/similarity of the counterfactual allows to establish a credible link between different levels of implementation and a micro-economic output.

The micro-economic output is measured as the change in Operating Margins at the firm level. A statistically significant positive difference in Operating Margins after the treatment for treated units, indicates increase efficiency of production processes which - in our quasi-experimental design - is the causal result of the implementation of publicly funded CE and green technologies. Results are summarized in Fig.2 below.

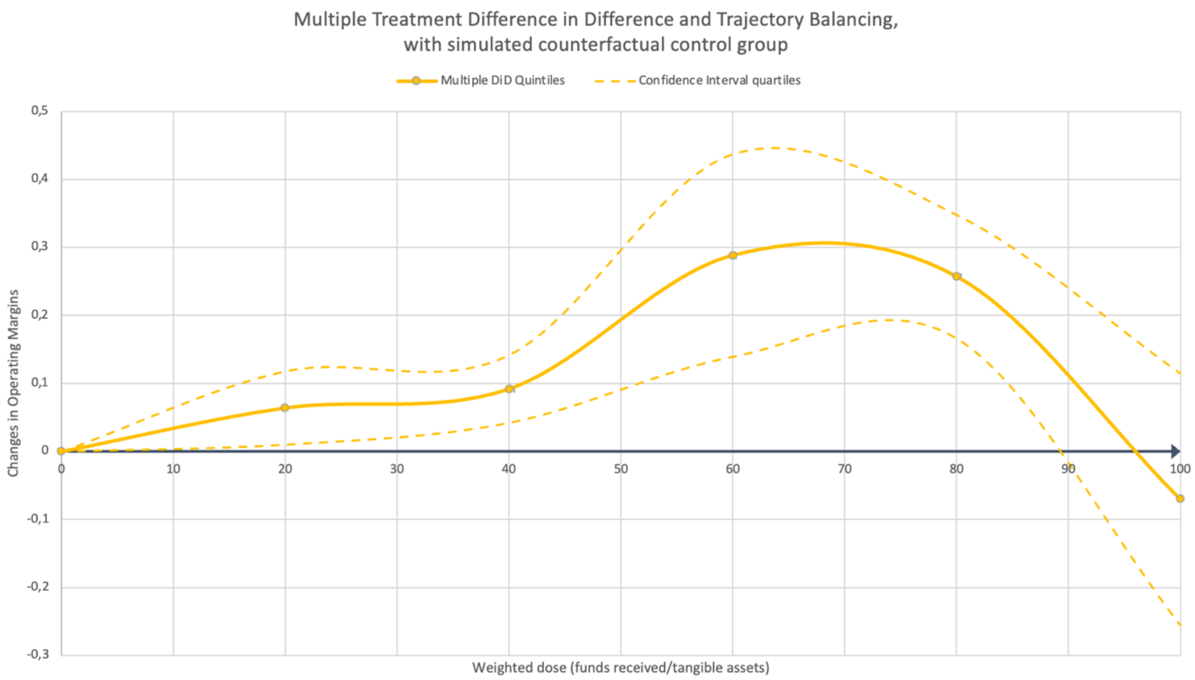

Figure 2.

Results show that different levels of treatment have different, in intensity, impacts on beneficiary firms. While most of the treatment levels (except for the fifth quintile, 80-100% of the dose) show positive and significative differentials, the coefficients are quite different in intensity. Coefficients of treatment levels from 1 to 3 increase in intensity almost linearly, declining for higher treatment levels (4 and 5). Overall, the dose shows an inverted 'U' shape, suggesting that the implementation of more basic technologies, especially on a large scale, has a higher marginal effect compared to the implementation of very high-end and costly technologies.

The overall figure shown by our results is quite relevant in a context composed of developing regions both in terms of environmental and economic impact. Indeed, the increase in efficiency of the productive system plays within the aims of European policymakers suggesting a potential for reduction in carbon production in developing regions. Moreover, in microeconomics terms, the same increase in operating margins indicates that treated firms are able to produce with more efficiency, thus freeing the opportunity to increase production without substantially increasing cost of production thanks to the implementation of novel technologies.

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