Does Subsidizing Green Equipment Make Firms Greener?

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Abstract

We study the decision of manufacturing firms to invest in carbon-abating equipment. We do so by leveraging a one-billion-euro investment subsidy program aimed at fostering biomass-based energy adoption in the French manufacturing sector. Using rich data on eleven cohorts of subsidized projects, we show that subsidies cause green investment to increase, fossil fuel consumption to decrease and biomass consumption to increase. Conventional yearly plant-level CO_2 emissions decrease by 21%, while activity remains unchanged. Many selected projects are eventually abandoned, which can partly be explained by energy price shocks and financial fragility. We assess the implied cost per ton of CO_2 avoided, highlighting the role of interactions with emissions trading and alternative biomass carbon accounting assumptions.

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1 Introduction

Given the urgency of a decrease in greenhouse gas emissions and the weight of manufacturing in current emissions, designing successful policies to enhance carbon efficiency in this sector is of the utmost importance. While economists widely agree that carbon pricing is a powerful tool to achieve this goal (Sterner et al., 2019), its implementation faces strong political hindrances (Dechezleprêtre, Fabre, Kruse, Planterose, Sanchez Chico, and Stantcheva, 2025; Douenne and Fabre, 2022). Moreover, a growing body of evidence suggests that carbon pricing alone may be insufficient to meet reduction targets: theoretical contributions (Acemoglu, Aghion, Bursztyn, and Hemous, 2012; Acharya, Engle, and Wang, 2025) and empirical studies (Acemoglu, Akcigit, Hanley, and Kerr, 2016; Martinsson, Sajtos, Strömberg, and Thomann, 2024) alike point to the need for complementary direct interventions in the manufacturing sector. Although such interventions are diverse in nature and a relatively novel entry in the long list of industrial policies (Rodrik, 2007), they have recently become a central feature of major climate strategies (OECD, 2024)—most notably through the U.S. Inflation Reduction Act (IRA) and the EU Net-Zero Industry Act. Since they neither directly affect the price of carbon nor depend on actual reductions in carbon emissions, yet provide a stark impetus for change in manufacturing, such policies may also have unintended rebound effects on carbon emissions. It therefore remains unclear how firms react to these government interventions and under which conditions such alternative policy tools can complement carbon pricing.

In this paper, we study the investment decisions of manufacturing firms in green equipment, leveraging a large subsidy program aimed at shifting energy consumption away from fossil fuels towards innovative approaches using biomass, in the context of France. This policy, called the BCIAT program,[1] is a long-standing policy managed by the French environmental agency which awards subsidies for the purchase of large industrial boilers and furnaces that run on biomass rather than fossil fuels. Each year since 2009, subsidies worth between 30% and 45% of the equipment price have been awarded to firms based on project-level applications documenting the expected CO_2 abatement made possible by the project, and the planned investment costs and characteristics. Importantly, the policy was not meant to affect laureates' energy efficiency nor their output, and therefore aimed at reducing both their CO_2 intensity and overall CO_2 emissions.

A main empirical challenge to understand the causal effect of such policy concerns the potential selection of firms investing in this technology and adopting the subsidy. Biomass-based heating systems indeed involve large fixed investment costs and are only suitable for specific production processes. While the industry in which firms operate seems to be a very strong determinant of adoption, firms' decisions to apply for or adopt them are also likely correlated with unobserved characteristics—such as their energy intensity or expectations about future emis-

1. BCIAT stands for "Bas Carbone dans l'Industrie, l'Agriculture et le Tertiaire", or *Low-Carbon in the Manufacturing, Agriculture and Service industries*.

sions regulation. Furthermore, the agency operating the program makes a careful assessment of each project application and in particular its CO_2 abatement potential, so that selected firms may be more CO_2 intensive in the cross-section, and on a specific path of emissions over time. Empirical designs relying only on ever-treated firms will be more convincing in conditioning on selection effects, but will suffer from smaller samples and external validity concerns, and open up the possibility that any detected effects are just the reflect of a temporal reallocation of investment decisions. Designs leveraging a comparison of subsidized firms to "control" ones will present symmetric pros and cons. Out of precision concerns, we use a stacked difference-in-differences estimation as our baseline approach (Cengiz, Dube, Lindner, and Zipperer, 2019), disciplining the sample of non-beneficiary firms on observables. We test the robustness of our results through strategies either comparing laureates and rejected candidates or focusing on only those firms that have been awarded the public subsidy ("ever-treated" sample). To do so, we use a staggered event-study approach over the 10-year period of the program (de Chaisemartin and D'Haultfœuille, 2024; Borusyak, Jaravel, and Spiess, 2024): it yields less precise estimates but of similar magnitude, therefore alleviating concerns related to the nature of firms that select into the program. We also study the determinants of the timing of take-up, and find that it is uncorrelated with key variables indicative of the investment potential firms have. This is again reassuring regarding the importance of the timing in which firms self-select into the program on the investment effects we might find.

Once a credibly causal estimate of firms' investment responses to the subsidy is obtained, a second challenge arises: translating these reactions into gains in CO_2 emissions and computing the government cost per unit of CO_2 abated. This is first a measurement issue: regular and meaningful measures of carbon emissions are needed for manufacturing firms likely to apply for the program—both grant winners and losers as well as non-candidate firms—before and after each subsidy application. We mobilize micro-data from a yearly energy consumption survey, providing a detailed breakdown of energy use by source, allowing us to observe biomass consumption and to convert total energy use into conventional carbon emissions (similarly to Colmer, Martin, Muûls, and Wagner, 2024 and Martinsson, Sajtos, Strömberg, and Thomann, 2024). For the subset of plants covered by the EU-ETS, we also rely on verified emissions under this system. However, these conventional measures of CO_2 are not sufficient by themselves to evaluate the amount of subsidy needed per ton of CO_2 avoided in this program. The program's direct effect on CO_2 emissions of installations included in the EU-ETS interacts with the EU-ETS' own logic through the so-called *waterbed effect*: when beneficiary plants are covered by the EU-ETS, abatement frees up emission quotas for the rest of the market. We recompute the program's government cost of reducing CO_2 under a central scenario that accounts for this effect and also provide bounds to the implied cost. Finally, all these measures of CO_2 gains rely on the conventional emission factor associated with an energy unit of biomass which is close to 0, according to the French environmental agency and to EUETS guidelines. Yet, the raw CO_2 emissions per unit of energy associated to burning biomass are larger than the combustion of any fossil fuel. Whether biomass-fueled boilers are indeed green equipment, and whether the BCIAT effectively reduces CO_2 emissions, thus starkly depends on the validity of the assumptions underpinning this conventional carbon emission factor. We discuss these assumptions in detail and test the sensitivity of the program's estimated cost to alternative carbon accounting scenarios. We also discuss how this public cost of CO_2 emission reductions, i.e. the fiscal outlay required to induce a ton of CO_2 reductions under the existing capital stock, relates to the abatement cost, which would include the private costs of switching to biomass equipment.

Our results are as follows. First, the subsidy has a direct effect on both received subsidies and investment, in line with how much applicants indicate they would invest if they obtained the subsidy. Our stacked difference-in-differences results show that being awarded a subsidy causes investment in physical assets to increase by up to 14% of pre-subsidy total asset value, in the three years after a firm applies for a subsidy. The additional effect of the subsidy on the investment behaviour of beneficiary firms matches the value of subsidized equipment. We also measure a positive effect on green investment, confirming that the investment effect we measure is the same as the one targeted by the policy. This investment effect is important in itself as it means the policy does boost the demand for "clean" equipment with no crowding out. In line with these additional investments, we find that obtaining a subsidy for switching to biomass-sourced heat generates a very substantial reduction in conventional CO_2 emissions from the subsidized firm. Three to four years after a successful application to the subsidy, fossil fuel consumption decreases, and biomass consumption increases. The overall gains in GHG emissions are large; on average, subsidized plants each save 9,000 tCO_2 per year. Importantly, we find no significant effect on firms' economic activity or performance, which suggests the policy does not entail an unintended positive effect on emissions via a causal increase in output quantities. While these elements suggest that the policy was quite successful at triggering the desired investments, we also document a very high drop-out rate, by which 45% of laureate projects over the 2009-2019 period are later abandoned by their instigators before any equipment is installed. We provide a rationale to explain this drop-out behaviour, and show that it is largely due to firms getting hit by large variations in relative prices for energy in the phase-in period (two years) following the date at which the subsidy was awarded. Because the policy aimed at setting the private net present value (NPV) of green investment close to 0 for laureates at the time of application, price shocks may make a substantial share of private NPVs negative. In the timespan between when a firm is awarded the subsidy and when it actually sets up the equipment, said firm may thus change its private belief about the value of this investment. This highlights how decarbonization decisions depend on parameters—future energy prices—that are highly uncertain. Failure to provide insurance against this uncertainty can therefore harm the efficiency of active decarbonization policies such as the one we analyze.

Second, we calculate the fiscal cost of reducing CO_2 emissions associated with the subsidy program. In particular, we complement our estimates on total CO_2 emissions by accounting for the fact that 65% of subsidy recipients are part of the European Union Emissions Trading Scheme (EU-ETS). This generates a waterbed effect (Rosendahl, 2019), implying that the overall CO_2 impact of the subsidy program is smaller than it may appear *prima facie*, since some of the emissions abated by subsidy laureates subject to the EU-ETS may merely be transferred to other market participants. In our central scenario, we consider that each freed up quota by ETS plants thanks to the policy has to be bought back by governments, which yields a cost for the government of €100 by tCO_2. We also discuss the credibility of the conventional emission factor of biomass, which is close to zero, but is based on economic and policy-related assumptions, as opposed to other carbon emission factors that rely solely on physical properties. We remain agnostic to the true emission factor of biomass, which is beyond the scope of this paper, but calculate an emission factor at which gains from the policy would be neutralized.

We contribute to the literature in several ways. The economic literature on environmental performance-oriented industrial policies is scarce, partly because this type of industrial policies has until very recently been rare. An adjacent literature focuses on other types of industrial policies, whether these aim at fostering productivity (Criscuolo, Martin, Overman, and Van Reenen, 2019), local employment and economic development (Kline and Moretti, 2014), or R&D investment (Howell, 2017). For each of these types of industrial policies, the direct or indirect stated goal of the policy is economic development, with sales, value added, productivity or employment as indicative measures of the success of the policies, either at the firm or at the local level. The policy we study in this paper stands in sharp contrast, given that its objective is to leave the economic development of targeted firms largely unchanged, only to substitute an energy source with another. As a matter of fact, European regulation on state aid incentivizes the environmental agency to award subsidies that are enough to make the private net present value of decarbonizing investments positive, but not enough to be construed as economic support.

Our work also relates to the literature on technology adoption and the risks of technological lock-in. In the context of green industrial policy, the risk is not so much that technologies with poor economic development prospects are launched (Arthur, 1989) but rather that the government intervention targets a specific technology that is not the most efficient at reducing emissions and that it prevents manufacturing firms from identifying an appropriate technology for reducing emissions in a timely manner (Hawkins-Pierot and Wagner, 2023). In this paper, we show that such a risk is real for two reasons. First, we show that the carbon emissions factor of biomass appears to be uncertain enough to question the positive role of the subsidy in reducing emissions. Second, we find that a large number of manufacturing firms spend several years trying to implement the policy but eventually choose to abandon the adoption of biomass equipment altogether. The corresponding expenses in time and effort are not fully recoverable and might have been better spent on alternative, more appropriate carbon-reducing technologies.

Our work also speaks to a literature highlighting the difficulties in designing efficient environmental policies interacting with carbon pricing systems such as the EU-ETS. We study a setting that is particularly exposed to the risk of a waterbed effect (Rosendahl, 2019; Akey, Appel, Bellon, and Klausmann, 2024), whereby the effect of other instruments aimed at reducing carbon emissions is partly neutralized by the existence of the carbon market, given a target trajectory of quotas (Perino, Ritz, and van Benthem, 2025). This does not disqualify such a policy altogether, even without reference to other potential policy objectives. First, many of the recipients are not subject to the EU-ETS, either because of their size or because of their sector. For these actors the estimated impact of the policy is straightforwardly positive, as its point estimate matches the *ex ante* stated objective of carbon reduction. Second, in the presence of financially constrained actors within the carbon market, a decrease in the number of quotas in circulation can push the price of CO_2 artificially high, which will distort decarbonization efforts towards non-constrained actors rather than towards the ones with the lowest carbon abatement costs. Alleviating these financial constraints can thus help restore a more efficient distribution of decarbonization efforts (Inderst and Heider, 2023; Döttling and Rola-Janicka, 2023). Third, we find suggestive and anecdotal evidence that the BCIAT program helped overcome barriers to adoption that have been shown in the theoretical literature to limit the efficiency of carbon pricing (Acharya, Engle, and Wang, 2025). Agency engineers mention learning effects and knowledge diffusion over the course of the different waves of the program. Fourth, in the presence of uncertainty over whether the EU-ETS will be binding early enough, a direct subsidy may still hasten the reduction in carbon emissions (Lecuyer and Quirion, 2013). This is likely to be relevant for the context we study, where most subsidies were awarded prior to the Market Stability Reserve being introduced in 2019.

Finally, a distinctive aspect of the environmental policy we investigate is its dependence on energy price vectors, which had already been shown for other carbon policy designs. In particular, the negative impact of coal prices on the price of carbon in the EU-ETS system is well-documented (Batten, Maddox, and Young, 2021). In the context of a direct subsidy subject to repeated contracting between the government and subsidized firms, together with limited access to a long-term derivatives market for fossil fuels, contracts for differences embedded in the subsidy may help sustain the commitment of manufacturing firms to engaging in clean technology adoption (Richstein and Neuhoff, 2022).

The paper is organized as follows. Section 2 describes the subsidy program and the data sources we use in the analysis, while section 3 presents our empirical strategy. We then present our main estimation results in section 4, test their robustness in section 5, and discuss the abatement cost of the policy and the assumptions related to the biomass emission factor in section 6. Section 7 concludes.

2 Institutional Context and Data

2.1 The BCIAT program

The subsidy program analyzed in this paper is the French BCIAT program, a regular call for projects managed by the French environmental agency (*Agence de l'environnement et de la maîtrise de l'énergie*, hereafter Ademe). It aims at helping firms in manufacturing, agricultural or services industry finance their investments to switch from fossil fuels (mainly natural gas, but also heavy fuel oil, or coal) to biomass for their heat production. This annual call for projects was first launched in 2009 following the creation of the Fonds Chaleur, a government fund for heat production projects using renewable energies, to target specifically large installations with a minimum energy production from biomass of 1000 toe per year, i.e. roughly the size of smaller renewable power plants. It was then extended in 2020 with an increased budget as part of France's Recovery Plan from the Covid crisis.

Each year, firms apply for subsidies with a project, that details its technical and financial aspects. Eligible projects must involve an investment of at least €3 million. Candidate firms specify how many tons of CO_2 will be saved by the project with regards to a counterfactual scenario where they would purchase a gas boiler instead of the biomass boiler they have in mind, using a reference lifespan of equipment of 15 years. The CO_2 saved by the project is a function of the size of the equipment (the installed capacity) and the annual number of hours for which it is used, which yields the yearly heat power generation target. This target is divided by a benchmark energy efficiency of 90% for gas boilers, which yields the counterfactual energy consumption. This consumption is then multiplied by the emission factor of the substituted energy to yield the tCO_2 avoided by the project. This assumes that the CO_2 emissions associated with running the biomass equipment are nil, that is, the conventional carbon emission factor of biomass is zero. This is in line with European regulation, but is also a strong economic assumption, which we discuss in Section 6. We note here that it is in theory supported by restrictions that the Ademe sets for the procurement of biomass that is consumed by eligible equipment, which must be locally sourced and originate mostly from secondary sources. Firms also declare the total costs of the project and elicit the amount of subsidy they would like to be awarded, knowing that this will be the criterion on which they will be evaluated, with credible cheaper abatement costs being prioritized.

The subsidy is awarded after a back-and-forth between the Ademe and the applicants, whereby the Ademe's own engineers challenge the technical and economic aspects of each project. The Ademe also provides technical guidance in the setting up of applications. It awards subsidies to the most efficient projects in terms of public euros per expected avoided tons of CO_2. Essentially, the projects are selected by the environmental agency based on the amount of subsidy per ton of carbon emissions avoided over 15 years, if the project is deemed credible, with the projects displaying the lowest ratio selected first, and until exhaustion of the funds.

Between 2009 and 2021, the BCIAT program received 353 unique applications and awarded almost €1 billion in subsidies to 275 projects, totalling €2.5 billion in biomass equipment investment. The average success rate over the years is 78%. A typical project involves a €9 million investment, for a €3.5 million subsidy (or 38% support rate). The subsidized equipment is typically an industrial boiler generating heat or hot air, with an average installed power capacity of 13 MW. The cumulative expected annual reduction in CO_2 emissions totalled 4.2 $MtCO_2$ in 2021, which represents 5% of total industrial emissions in France at the launch of the program in 2009.

We further highlight two aspects of the program that impact our empirical exercise.

First, firms applying to the BCIAT program are also required to satisfy two other eligibility criteria, for which they must submit proof: financial stability and energy efficiency.[2] An important point to note is that we do not observe the precise reason for why projects are rejected. They may be projects of firms comparable to laureate firms but slightly more expensive per tCO_2 abated than the last subsidized project, as per the selection rule, but also those of firms that are deemed unviable financially.

Second, an important feature of the BCIAT program is its high dropout rate, at 35% overall, and 45% for pre-2020 application waves. "Abandoning" a project typically takes place prior to the subsidized equipment actually being purchased. In this case, the subsidy never appears on the balance sheet of firms, since the funds are transferred upon the purchase of the equipment. The precise date at which firms drop the project is not recorded, nor the reason why the project was abandoned. A project is typically classified as abandoned after the beneficiary firm declares it will not go through with the project after all, or after it has stayed silent for a few years. In most of our analysis, we focus on all treated plants, meaning that we aim for ITT estimates. We analyse the drivers of dropout and discuss the policy implications in Section 4.4.

2.2 Data sources

This paper relies on several databases to get information on the decarbonization projects submitted, the allocated subsidy amounts, and the energy consumption, direct CO_2 emissions, and economic characteristics of industrial plants and firms. The databases used are described below as well as the construction of the final samples.

2. A singularity of the BCIAT program resides in the fact that it explicitly does not aim to improve the energy efficiency of the subsidized installations, but simply to replace the use of fossil fuels as a primary source of energy by that of biomass. Energy efficiency is an *ex ante* requirement. This distinguishes it from other programs in which the decarbonization objective rather relies on a decrease in energy use. Another peculiarity of the program is that it has no economic objective; rather, it aims at being neutral with regards to the beneficiary's economic performance, as it is bound by EU regulations on State aids.

Data on the subsidy program. We use records of all the applications to the BCIAT program since its inception in 2009. Each record is at the application level[3] and contains information on the round to which the application belongs, and details about the project. Records also include some identifying information on the industrial plant concerned by the project,[4] the firm the plant belongs to, and if any, the project holder. We use this information to gather firm and plant identifiers for each record, and for both the industrial firm, and if any, the project holder, so as to match record data to tax and survey data. Data on rejected projects, and to some extent, abandoned ones, are unfortunately more incomplete than for completed projects, in particular with regards to the characteristics of projects. This unfortunately prevents us from leveraging the theoretically discontinuous nature of the subsidy's award decision in a regression discontinuity framework using the government's marginal abatement cost as the relevant running variable. Instead, in our main specifications, we exclude rejected projects and focus either on "ever-treated" plants and "pure controls", or only on "ever-treated" plants and firms; and we look at rejected projects and firms in a robustness check.

Project data include: the power capacity of the equipment concerned by the project ; the projected heat production level (i.e. the number of hours the equipment will be used for in a year) ; an estimation of the CO_2 emissions avoided by the project ; the total investment cost of the project ; the subsidy asked for, and obtained by the project if any.

Corporate tax returns. Every fiscal year, firms subject to the corporate income tax must fill in their detailed accounts. This data source is at the level of each firm (legal unit), and includes all elements of assets and liabilities, as well as details on the financial results to compute the corporate income tax. The data source is produced by the French tax administration, and accessible for the universe of French firms since 2005. In particular, it allows us to compute investment at the firm level as the yearly change in physical assets, as well as standard measures of activity such as turnover, value-added and profits.

Energy consumption survey. The annual survey on the energy consumptions of manufacturing firms (*Enquête annuelle sur les consommations d'énergie dans l'industrie*, hereafter EACEI) is a survey of industrial plants in France, active in the manufacturing sectors (excluding energy production and refineries) ; it is produced by the national statistical office. It is exhaustive for plants above 250 workers and a random sample for plants above 20 workers, and covers an average of 8,500 plants yearly over the period 2005-2022. A key feature of the policy is that it targets plants that

3. A given project may lead to several applications; a plant may apply to the program via several projects, either at the same or at different times; and a firm may have several plants involved in different projects. We identify 6 instances where the same project has been submitted in two different applications waves: in these cases, we keep the latest application.

4. In extremely rare cases, a project concerns two plants, which we collapse in a single unit.

are typically large enough to be sampled regularly, regardless of whether the surveyed units benefited from a subsidy.

The EACEI data contain information on annual volumes and values of energy purchases, energy production and energy final consumption, for 15 categories of energy. This allows us to observe consumption of biomass and heat. Additionally, using data from the Ademe emission factor database, this allows us to reconstruct a measure of direct emissions from energy combustion for all plants in the data, and in particular for plants not covered by the EUETS data (see below). The program we study targets the reduction of carbon emissions only through a decline in fossil fuel consumption, making energy consumption data particularly appropriate.

All EACEI data is self-declared by firms; however, for some types of energy, the ministry of environment leverages administrative sources to check on extreme values, namely meter data for electricity and natural gas from public network operators.

Green investment survey. To analyse green investments specifically, we use the annual survey on investments to protect the environment, called ANTIPOL, also produced by the French statistical office. Plants are asked to report about the environmental investments they made during the year, detailing the environmental area targeted by the investment ant the type of investment made. The possible areas are waste, sewage, air protection, reduction of greenhouse gas emissions, noise and vibrations, land and water, and landscape and biodiversity. Prior to 2015, air protection and reduction of greenhouse gas emissions were grouped together in a single category so we group them in the years after 2015 as well for consistency. The type of investment refers to the primary purpose of the investment, that is whether it is specifically made to improve some environmental outcome or it also serves some other purpose, such as production. The former type of investments are called ”specific” and the latter ”integrated”. An important difference between the two types of investment is that the amount reported for specific investments corresponds to the total amount invested while for integrated investments, the amount reported is the difference between the green investment made and an alternative investment with no environmental benefit.

Similarly to EACEI, the survey is exhaustive for plants above 250 workers and covers a random sample of plants above 20 workers every year from the mining and quarrying, manufacturing and energy production sectors. On average, about 11,000 plants are surveyed yearly over the period 2005-2022.

EUETS data. We use data from euets.info, at the plant and firm level, for the period 2005-2023. This provides us with an alternative measure of CO_2 emissions for the subsample of plants that are subject to the EUETS[5]. The coverage of the data is better than that of EACEI, as EUETS data is

5. Contrary to our reconstructed measure based on energy consumption data, EUETS verified emissions include all CO_2 emissions, including non-combustion emissions, such as industrial processes emisssions.

administrative and thus exhaustive on its specific population. Finally, the EUETS data provides information on the amount of free quotas that each plant is allocated each year.[6]

A typical difficulty with working with EUETS data is that the register data do not contain information on official plant identifiers, and only incomplete data on official firm identifiers. We make these data more robust and complete by a series of manual checks using the official register of plants and firms, and various sources (newspaper articles, firms' websites, web mapping platforms). Another difficulty is that plants change identifiers over time. We use the administrative registry of plants and firms (*Registre des Etablissements et Entreprises*) to identify such moves.

3 Empirical Strategy

Our preferred identification strategy is a stacked difference-in-difference analysis (as in Cengiz, Dube, Lindner, and Zipperer, 2019). It consists in constructing a control group for each cohort (subsidy wave) of treated plants/firms, drawn from all the never-treated plants/firms present in the year of treatment. This section details our main difference-in-difference analysis, and covers the threats we face for identification and the robustness checks we design to address them.

3.1 Estimation samples and specification

Subsidies are granted to projects, that are defined by the plant in which the project is implemented, and the year in which the subsidy is applied for and granted. Plants can apply for several projects over the period so we define treatment status relative to the date of the first accepted project. Because some outcomes are available in the data at the plant level and others at the firm level, we construct two estimation samples: one at the plant level, and the other at the firm level. Indeed, a substantial share of firms have at least one plant not covered by the plant-level survey, so that we cannot aggregate plant-level data at the firm level. The same treatment definition applies to firms and to plants in each sample.

At the plant level, we match the administrative data on the BCIAT program with the energy consumption and carbon emissions data as well as the EU ETS data using the plants' unique identification number (SIRET). In the baseline specification, we keep in the "treated" group only those plants that are observed for at least two years before the year they were awarded a subsidy for the first time. The resulting panel contains 96 plants in total that were awarded a subsidy for at least one project over the period 2009-2021. For each cohort of treated plants, we define a control group of plants based on the sector and age bin of the treated plants at the time of treatment. This means that a control plant may appear several times in the sample, as a control

6. The ratio of freely allocated quotas to verified emissions has been used in the literature (Dechezleprêtre, Nachtigall, and Venmans, 2023) in order to test that marginal carbon prices are a meaningful metric of the incentives delivered by a quota market with free quotas. We use it as a measure of the financial "bite" of the quota market.

for different cohorts (see, for a seminal example, Cengiz, Dube, Lindner, and Zipperer, 2019). Not-yet-treated plants are not included in the controls.

At the firm level, the BCIAT program data are matched with the corporate tax returns of the firms for which at least one plant has been awarded or has applied for a subsidy, thanks to the firms' unique identifiers (SIREN). The baseline sample contains only the firms for which we have observations for at least the two years preceding the first subsidy award. 171 firms with at least one accepted decarbonization project are included in the final firm-level panel. Similarly to the plant-level case, we include as control for each treated cohort never-treated firms in the same sector and age bin. Because our preferred measures of investment and subsidy rate at the firm level are normalized by the size of physical assets prior to the treatment, we also restrict control firms to have some positive physical net assets above a size threshold (€ 50,000).

Specification. The equation for the stacked difference-in-difference is as follows:

$$Y_{ict} = \alpha_{ic} + \delta_{ct} + \sum_{k \neq -1} \beta_k \left(\text{Treated}_{ic} \times D_{ct}^k \right) + \varepsilon_{ict} \tag{1}$$

where Y_{ict} is the outcome for unit i belonging to cohort c in period t, α_{ic} are unit-cohort fixed effects, and δ_{ct} are cohort-by-year fixed effects; Treated_{ic} is a dummy variable indicating whether unit i from cohort c is a laureate; and D_{ct}^k a dummy variable indicating relative time to treatment (or to cohort year for controls). The coefficient of interest is β_k, the effect of the subsidy in relative year k, with $k = -1$ as the reference period. Standard errors are clustered at the unit level (firm or plant identifier) to account for the potential repetition of control units across cohorts.

3.2 Identification threats

Our empirical exercise leverages differences across calendar time and across treatment status to identify the treatment effects associated with time relative to the relevant event. As for any difference-in-differences analysis, this relies on the assumption that the counterfactual trajectory of outcomes after $k = 0$ in the absence of the treatment for the treated group would have been parallel to the observed trajectory for the control group. The main threat to causal identification in our context is selection into the treatment, which can be decomposed along three dimensions: selection into applying for a subsidy, selection into being awarded a subsidy conditional on applying, and timing of the application which is chosen by candidates.

Selection of subsidized firms. As stated above, the main threat to causal identification that we face is due to selection into "ever-treated" status, which combines a self-selection step of firms into applying to the subsidy program, and a selection step achieved by the environmental agency which attributes the subsidy to some firms within the pool of candidates, and denies it to others. It may imply that candidate firms are fundamentally different from non-candidates, for instance because they have different equipment needs, such that their trajectories cannot credibly be compared. Similarly, accepted firms may be different from rejected firms, typically because they are economically more viable and therefore more likely to invest, such that any differences in investment behaviour would be stemming from firm characteristics rather than from obtaining the subsidy.

We test for the importance of these selection phenomena by implementing event studies on candidates versus laureates as well as on laureates-only, that are detailed in Section 5. To alleviate the concerns related to systematic differences between candidates and the firms in our control group, we propose a version of the estimation where we consider only candidates in our sample, switching to staggered design event-study estimates proposed by Borusyak, Jaravel, and Spiess (2024). Similarly, to further ensure that our effects are not driven by systematic differences due to the selection of laureates within the pool of candidates by the environmental agency, we also provide similar estimations focusing only on the group of "ever-treated" firms. Moreover, we also design a test to make sure that the subset of firms whose private value of adopting the green equipment was particularly high is not driving the effects. Indeed, this subset of firms may be the most likely to adopt the green equipment even absent the subsidy program, implying that the effects we measure should not be driven by these firms if one is to claim that the subsidy is causing them.

Timing of the applications. These tests, however, do not alleviate concerns with regards to the endogeneity of the *timing* of treatment status, conditional on being ever-treated, which is a second threat to causal identification in our setting. Projects may occur in a given cohort due to time-varying firm characteristics or changes in the environment in which firms operate. If that is the case, idiosyncratic firm dynamics linked, for instance, to investment decisions, may confound the effect we attribute to the policy. Figure 1 documents the size of the cohorts of accepted projects over time. This series exhibits a clear temporal pattern, with cohorts in the mid-2010s being much smaller on average than cohorts in the early or late 2010s. This raises some concern as to the comparability of beneficiaries of different cohorts, as well as on the underlying factors explaining the timing of BCIAT application. Indeed, if the selection of firms that apply to the BCIAT program in a given year reflects heightened incentives to decarbonize their activity in that specific year (as compared to other candidates) absent the subsidy program, then the parallel trend assumption might not be verified.

We perform several checks to address the potential endogeneity of application timing. First, the specification on candidates versus laureates mentioned above alleviates the concern that treated firms are those that need to replace their boiler at the time of application, since it compares only firms that, through their application, have signaled that they are ready to invest in this specific period. Second, to further back our causal interpretation, we make sure that, conditional on ever applying to the BCIAT program, the timing of the application of a given plant or firm cannot be explained by time-varying observables that may reflect decarbonization incentives (see Table 4). Notably, the timing is not explained by the financial state of the firm at the time of application (panel a), nor by the growth in energy prices (panel b). Second, we test for the heterogeneity by restricting the sample to larger cohorts (see Section 5). Third, we examine the evolution of *ex ante* declared costs of projects, normalized by projected tons of CO_2 avoided - using only project data. This speaks to how program selectivity has evolved over time, and to how different the projects of different cohorts are. Figure A1 displays this ratio, using both total investment costs and total subsidies awarded. The invested euros to projected tCO_2 avoided remain very stable in the bottom half of the distribution, while they moderately and steadily increase over time for the top half. This seems however reassuringly unrelated to the size of cohorts (Figure 1). Finally, we rule out anticipation and procrastination effects by examining pre-trends in the investment behaviour and the dynamics of the investment trajectory post-treatment.

4 Results

4.1 Impact on received subsidies and investment

A natural first step to assess the impact of the program on beneficiary firms is to check that, at the firm level, we do observe an increase in the amount of investment subsidies received after the firm is laureate of the BCIAT program for one of its projects. Investment subsidies are a balance-sheet variable in the firms' accounting data, and therefore reflect a stock of received subsidies. Because subsidies are paid out by instalment, we show the estimated effect on the stock, which we normalize by the total value of assets in the reference year ($T = -1$).

Figure 2 shows insignificant differences prior to the treatment, supporting our identifying assumption. Starting in the year when firms are officially awarded the subsidy, we observe a clear increase in the stock of investment subsidies received by laureate firms as compared to control firms, significant at the 1% level over the whole period of study. Two years after the subsidy award, at their highest, the investment subsidies of laureate firms amount on average to around 4.8% of their assets in the reference year. The gradual increase in the subsidy's value on beneficiaries' balance sheets is in line with the fact that the subsidy is received in four tranches. The first 40% is received upon the equipment being purchased, the next three 20% tranches are received in year 1, 3 and 5, the last two of them being awarded conditional on the equipment being in use.

The second outcome variable of interest at the firm-level, aiming to check the implementation of the program, is the investments undertaken by firms shortly after their projects are awarded a subsidy. Figure 3a shows result on investment in physical assets, as a fraction of the reference value of total net assets. There is no significant pre-treatment estimates, again lending credibility to our identifying assumption. We then detect a significant impact of the program on laureate firms' investment at the 1% level from year $T = 1$ to $T = 3$, suggesting most firms trigger their investments in the three years following the acceptance of the project. In later years, as expected, we observe no significant differences in investment. The sum of coefficients for year 0 to 3 is equal to +13.9% of total net assets in year -1. Compared to the 4.8% increase in the subsidy, this yields a 34.5% "subsidy rate" for the investment's response, or an investment response equal to 2.9 times the subsidy received. In application data, and restricting to the estimation sample, projects are subsidized at 39%, meaning that the projected investment's value is equal to 2.6 times that of the subsidy, which is remarkably close to our estimates. This suggests that the subsidy neither crowds in or out unrelated investments at the level of the firm, which is in line with its objective of being economically neutral. While one might have expected the sum of coefficients on investment to be equal to those on the subsidy if firms truly had a null private NPV (meaning that the subsidy just covers the difference in capital expenditures between a green and a conventional piece of equipment), it is important to keep in mind that operating costs also differ, with biomass being, on expectation, cheaper. Therefore, it is reassuring to find an effect on investment larger than the coefficient on subsidies.

We use the ANTIPOL survey to qualify the nature of these investments. Investments in this survey are reported at the plant level and classified into two categories: specific and integrated investments. Specific investments refer to investments specifically, and only, made to improve some environmental outcomes. One example is ozone generators, which have no other purpose than sanitizing air or water. Integrated investments, on the other hand, refer to investments the primary objective of which is not environmental, such as production equipment, but which have a higher environmental performance than standard equipment. Biomass-fueled boilers therefore fall into this second category. The investment amount reported corresponds to the differential cost between the environmentally efficient equipment and the standard one. The ANTIPOL survey also details the type of environmental outcomes the investments seek to improve. We therefore look at the effect of the subsidy on integrated investments to protect the air and limit greenhouse gases emissions. The results, presented in Figure 3b, show a sharp and significant increase in green investments for laureate plants two years after being awarded the subsidy, and a smaller increase in year T=3, which is consistent with the timing of investments observed previously.

4.2 Impact on energy consumption and conventional carbon emissions

We next turn to the effect of these investments on the energy mix of beneficiary plants. We carry out a similar analysis as before, using as the relevant time of treatment the first date at which any project of a plant is subsidised. Control plants are plants from the same sectors as the laureates who either did not apply for or did not receive the subsidy.

Figure 4a represents the causal effect of the subsidy on the energy consumption behaviour of plants.[7] We represent this behaviour by the share of heat and biomass in the total energy consumption of plants. Indeed, for some industrial beneficiaries of the subsidy, a large energy supplier acts as an intermediary, by applying and receiving the subsidy, purchasing and running the equipment, and providing heat to the end beneficiary[8]. In these cases, the effect on the end beneficiary's energy consumption would not show up as direct biomass consumption but as heat purchased as such. This total share of biomass-related energy increases starting year $T = 2$, and plateaus starting year $T = 4$, which corresponds to the expected gradual setup of the subsidized equipment. After four years, the share of heat and biomass in the total volume of energy consumption has increased by 14 percentage points, up from a 6% baseline. Symmetrically, the carbon intensity of energy consumption decreases over time, as shown by Figure 4b. In relative year $T = 5$, the conventional carbon intensity of energy consumption of beneficiary firms has decreased by 0.2 tCO_2 per ton of oil equivalent (t.o.e), or 14% from a 1.42 baseline.[9]

Figure 5 represents the effect of the subsidy on total direct, combustion-related CO_2 conventional emissions at the plant level. Our preferred measure of CO_2 emissions uses administrative data from the EU-ETS when available, and survey-based based measures when not, so as to maximize sample size. Figure A4a presents the results for each source separately. The total effect on CO_2 aggregates the positive effect of biomass consumption (which is attributed a zero emission factor, as per Ademe's official database), and the negative effects on various fossil fuels. The standard errors are quite large but the CO_2 emissions of treated plants clearly decline after receiving the subsidy compared to control plants. Five years after receiving the subsidy, total emissions of beneficiary plants decrease by -21.3% or -5,736 tCO_2.

At the plant level and within our estimation sample, 63.5% of treated plants actually complete an investment, with the remaining 36.5% dropping their project. Taking this as a measure of "take up" of the awarded subsidy, we rescale the effect on subsidy beneficiaries to obtain a local average treatment effect of -9,033 tCO_2.

Based on these estimates, we can compute the average cost of abating CO_2 induced by the

7. We measure energy consumption in volume rather than value terms. This allows us to measure pure technical change within the firm rather than a combination of technical change and energy price volatility (see Martinsson, Sajtos, Strömberg, and Thomann, 2024 and Iovino, Martin, and Sauvagnat, 2021 for a discussion of this measurement issue).

8. The project application is still specific to the end beneficiary's characteristics, and the commitments in terms of CO_2 avoided are specific to the energy needs of the industrial process of the end beneficiary, and they are assessed as such. Additionally, only a handful of these energy suppliers are present in the data. They run several laureate projects of several cohorts, and their activities are very diversified beyond their biomass-related one, so that studying their own trajectories is not feasible.

9. While we use 0 as the carbon emission factor for biomass consumption, we use 0.112kg of CO_2 as the emission factor of all heat consumed by firms in the sample. This corresponds to the French average and originates from the Ademe emission factor database, but is conservative since heat consumed by beneficiary firms *after* the treatment date is likely produced with the newly acquired green equipment, and should therefore have a 0 emission factor.

program. This calls for several assumptions. We take as given the LATE effect of -9,033 tCO_2 per year, which we project on the expected lifespan of equipment which is used by the Ademe in its calibration of the subsidy level, ie 15 years. We attribute this 135.5 $ktCO_2$ reduction over 15 years to all 61 beneficiaries in the estimation sample that do not drop their project, to estimate that the subsidy has induced a reduction of 8.3 $MtCO_2$ emissions over the lifetime of the subsidized equipment. Said 61 beneficiaries received a total of €296.15 million in subsidies. This yields a cost of about €36 of investment subsidy per ton avoided by the beneficiaries.

4.3 Impact on economic outcomes

Finally, we look into the economic effects of being awarded a BCIAT subsidy, and assess whether the program succeeded in generating no positive effects on economic activity and performance. We look at the effects of the subsidy on total sales, value added, markup rate and profit rate of beneficiary firms (Table 3). Our results indicate that there might have been a positive effect of the subsidy on sales and value added, yet temporary and significant only at the 10% level. The markup and profit rates, however, have not been impacted. These effects are both in line with the overall goal of the BCIAT program, which is to merely substitute an energy source for another; and with its selection process, which aims at screening out financially fragile candidates.

4.4 Project completion and energy prices

A key point to understand how successful the project was is to assess the compliance within the treated group, which is the share of subsidy laureates which actually end up buying the subsidized equipment. In the context of the program studied in this paper, the dropout rate of projects over the 2009-2019 cohorts[10] is as high as 46%, representing 42% of the *ex ante* expected CO_2 gains. Abandoned projects are present in all sectors where laureate projects are present, are slightly smaller than completed projects by all measures of size (investment, installed power capacity, planned production and CO_2 avoided), and are mechanically more prevalent within earlier cohorts. Importantly, we do not observe either the date at which or the precise reason for which a project is abandoned. However, we can check in fiscal data that no investment subsidies appear on the balance sheet of firms that are classified as having abandoned their projects.

Given this very high abandonment rate, understanding the drivers of abandonment is key to provide insights into a more efficient policy design. Anecdotally, agency engineers have stressed the role of natural gas prices, and more generally, fossil fuel prices, in motivating the decision of industrial companies to both apply to the BCIAT program, and go through with their investment after the subsidy has been awarded.

10. Obviously, some recent projects from later waves might not yet have had the time to be abandoned, so that focusing on earlier cohorts for this part of the analysis is less prone to bias.

Following this intuition, we give ourselves the following linear model :

$$\text{Abandon}_{psft} = \delta_t + \sigma_s + \beta * \text{Price growth differential}_{t+1} + \gamma * \mathbf{X}_{sft} + \epsilon_{psft} \quad (2)$$

where Abandon_{psft} is a dummy variable taking value 1 if project p, subsidized in year t, and obtained by firm f active in sector s, has been later on abandoned. δ_t and σ_s are vectors of fixed effects for the year in which the subsidy was obtained and the sector in which the plant is active in. Price growth $\text{differential}_{t+1}$ is the difference between the growth rate of prices of the initial energy, the one that is being substituted, and the growth rate of biomass prices in the year after the subsidy was awarded.

Since we include application wave fixed-effects (δ_t), common trends between the dropout rate and the overall trend in international energy prices are controlled for. The remaining exploitable variation in the data comes from the fact that some projects are substituting away from natural gas, some away from heavy fuel oil, and some away from coal. In other words, we are capturing the partial correlation between the evolution of the fossil energy price that matters for the plant and its dropout behaviour, given a certain time period.

The results are reported in Table 5. The probability that a project is completed is positively correlated with the growth rate of the substituted energy. This effect is significant both statistically and in magnitude, as a 1 percentage point increase in the difference between the growth rate of the initial energy price and that of biomass is associated with a 0.44 percentage point increase in the probability of completion. Symmetrically, this means that firms are more likely to abandon their project when fossil fuel prices fall. This correlation is robust to controlling for sector and application year fixed effects, overall NPV rank,[11] and various time-varying firm characteristics such as stock of net assets, capital intensity, investment rate or leverage.

This result is consistent with the initial intention of the policymakers to make the private NPVs of subsidized firms close to 0, and with our results on economic outcomes, which confirm that the subsidy did not act as a windfall gain that could have stimulated activity. We interpret our results in the following way: private NPVs of laureate firms were *ex ante* positive and distributed close to 0, so that price shocks on the main sources of energy used by laureate firms may have made some of these expected NPVs negative, which triggered these firms to give up on the planned investment.

5 Robustness

In this section we consider a set of additional results on our main outcomes, addressing in particular the threats to causal identification detailed in section 3. These are, in particular, meant to

11. It is also robust when using inital project NPVs or within-cohort NPV rank as a measure of the project's financial viability

alleviate concerns regarding the selection into the "ever-treated" status of laureate firms relative to control firms in our baseline estimation sample.

5.1 Alternative specifications

Accepted versus rejected candidates. Our main estimation strategy compares firms or plants that have applied for and have been awarded the subsidy to firms or plants that, in their majority, have not even applied for the subsidy. If laureate firms or plants differ significantly from other plants or firms in a way that explains both their decision to apply to the subsidy and their decarbonization behaviour, then our estimates could suffer from selection bias. To address this concern, we perform an event-study analysis comparing accepted and rejected candidates. We choose as our baseline estimator the one proposed by Borusyak, Jaravel, and Spiess (2024), which presents two main advantages in our context. First, it is specifically designed to handle setups with both staggered treatment and heterogeneous treatment effects. Second, it is efficient in the statistical sense, meaning that it maximises power, which is valuable in our context.[12] The estimates referred to as BJS are obtained using the results of estimating the following Equation (3) by ordinary least squares:

$$Y_{it} = \alpha_i + \delta_t + \sum_{e \notin C} \sum_{k \geq 0} \beta_{e,k} \mathbb{1}\{E_i = e\} \times D_{i,t}^k + \epsilon_{it} \tag{3}$$

where $Y_{i,t}$ is the outcome for unit i in period t, α_i and δ_t are, respectively, unit and calendar year fixed effects ; $\mathbb{1}\{E_i = e\}$ is a dummy variable indicating whether unit i belongs to cohort e ; and $D_{i,t}^k$ a dummy variable indicating relative time ; and $\beta_{e,k}$ is the fixed effect for year relative to treatment k and cohort e. For each relative period k, the causal estimator we display is then the weighted average of the $\beta_{e,k}$, where the weights correspond to the share of each cohort e for which $\beta_{e,k}$ is defined in the observations available for relative time period k (following the representation of the BJS procedure given by de Chaisemartin and D'Haultfœuille, 2024).

Accepted candidates only. While the previous specification addresses the selection into applying for the subsidy, there remains a potential bias from selection into getting the subsidy conditional on applying. In theory, the environmental agency follows a rule for the attribution, awarding the subsidy to the projects with the lowest ratio of CO_2 emissions avoided over the subsidy amount until funds are exhausted. In that case, comparing just accepted and just rejected candidates would yield a credible causal estimate of the effect of the subsidy. However, in practice, candidates can be rejected for other reasons that are not observable in our data. As such, the

12. This comes at the cost of estimating treatment effects in the post period relative to the average of pre-treatment observations, and therefore does not allow to show pre-treatment coefficients jointly with post-treatment ones. For a useful explainer, see Roth (2024).

previous specification could suffer from selection bias as well. In this alternative specification, we restrict our attention to the sample of "ever-treated" plants and firms; this means that we use the last cohort, namely 2021, as the implicit control group.

We report pre and post-treatment coefficients for both alternative specifications in Appendix Figures A2 and A3. While the standard errors are larger than in our baseline specification, the results similarly show a significant increase in investment the year after receiving the subsidy and a decrease in CO_2 emissions, statistically significant, or close to be, from year t+3.

5.2 Alternative samples

Keeping only high take-up cohorts. As the size of the cohorts varies greatly over the period (see figure 1), one concern could be that our results are driven by very specific plants or firms applying when very few others do. To verify that is not the case, we perform our main analysis on a restricted sample with only the cohorts from the years 2009, 2010, 2011, 2019, 2020 and 2021. The results for our main outcomes, presented in table A1, are similar in magnitude and significance to those of our baseline specification.

Removing high NPV projects. Similarly, we also check that our results are not driven by projects with unusually high ex-ante, that is without the subsidy, net present value. This is meant to ensure that our effects are not driven by a set of firms with very large private NPVs, that would have adopted the green equipment even absent the subsidy program. To do so, we trim the samples by excluding the 10% of projects with the highest *ex ante* NPV[13]. Our results are robust, as shown in table A1, suggesting that high NPV projects are not driving the effect.

Balanced panel. Finally, we restrict the samples to plants and firms always observed in the two years prior to and the two years following the year of treatment, that is the year of application to the subsidy program. This is to ensure that our results are not an artefact of the imbalance of our samples. Again, as reported in table A1, the results for our main outcomes hold.

6 Government Cost of Abating CO_2

In this section, we examine the assumptions behind the program's budgetary cost per ton of emitted CO_2 it allows to avoid. We show that interactions with other schemes to reduce CO_2 emissions or with alternative uses of renewable resources can lead to a higher government cost per ton of CO_2 than the €36 we estimate at baseline.

13. We calculate the NPV of each project as follows: $NPV = -$ initial investment + counterfactual investment + $\sum_{t=1}^{15} \frac{\text{avoided yearly costs (counterfactual)}}{1+\delta_t} - \sum_{t=1}^{15} \frac{\text{new yearly costs}}{1+\delta_t} + \sum_{t=1}^{15} \frac{\text{avoided energy consumption} \times \text{energy price}_t}{1+\delta_t} - \sum_{t=1}^{15} \frac{\text{new energy consumption} \times \text{energy price}_t}{1+\delta_t} + \sum_{t=1}^{15} \frac{\text{avoided } CO_2 \text{ emissions} \times \text{t}CO_2 \text{ price}_t}{1+\delta_t}$

6.1 Waterbed effect of subsidizing EUETS plants

The subsidy per tCO_2 avoided under an ETS framework is affected by the waterbed effect, whereby emissions reductions in ETS-covered sectors may simply free up quotas for use elsewhere, yielding no net reduction unless quotas are withdrawn. This is an important caveat to the government's abatement cost initially calculated, as 64% of the BCIAT beneficiaries that went through with their project are subject to the EUETS. For them, a trajectory of carbon emissions is already set through allocated quotas, with a price given to any upward or downward deviation from this trajectory. Therefore, the extent to which the emissions avoided by these industrial plants are actually transferred to other market actors via the carbon market, either through the sale of freely allocated quotas, or through the non-purchase of auctioned quotas, is not entirely straightforward to compute, as the literature on the waterbed effect shows. This is especially true since the Market Stability Reserve was introduced in 2018, that is, well into the lifetime of subsidized equipment.

One way of approaching the government cost of abatement and setting up such subsidies is to withdraw one quota for each expected ton of CO_2 abated by ETS plants. This would be a meaningful strategy for a government desiring to unilaterally curb the EU GHG trajectory faster than agreed (consistent with the buy-bank-burn strategy highlighted by Gerlagh and Heijmans, 2019). We make the additional assumption that the subsidy's impact on EUETS beneficiaries is the same as its impact on non-EUETS beneficiaries. Figure 5 is compatible with this assumption, even though because of statistical power issues, we take the statistical meaningfulness of such a comparison with great caution. In this setting, the government's abatement cost would effectively be 36 euros per ton for non-ETS plants (as calculated), while for ETS plants it would be the sum of the 36 euros and the market cost of a quota. For instance, using the January 2023 quota price of 83 euros, the total cost for ETS plants would be 119 euros per ton abated. Consequently, the government's overall abatement cost of the program averages 100 euros per ton of CO_2, fully accounting for quota withdrawal to ensure net reductions.

Alternatively, supposing the government cannot or does not wish to influence the number of quotas in the EUETS, we can trivially bound this waterbed effect between 0% and 100% of the emissions avoided by beneficiaries that are subject to the EUETS. A non-existing waterbed effect corresponds to the €36 per ton benchmark; this corresponds to all emissions avoided by EUETS-submitted beneficiaries being net global reductions in CO_2 at the European level. This could only occur if all EUETS-submitted beneficiaries decided to cancel their unused quotas. Conversely, a full waterbed effect corresponds to all emission gains by EUETS-submitted subsidy beneficiaries, ie 77.7% of all gains in the estimation sample, being essentially neutralized. This drives up the government cost of CO_2 abatement induced by the BCIAT program in our estimation sample to €160 per ton. Overall, this means that the government's abatement cost associated to the program, accounting for the waterbed effect induced by the EUETS, is 100 euros per tCO_2 in our central scenario, and can be bounded between 36 and 160 euros per tCO_2.

6.2 Are biomass burners green equipment?

A key assumption underlying the estimated magnitude of CO_2 abatement through the BCIAT program is that biomass combustion is carbon-neutral. This is aligned with the emissions accounting framework used in the French "Base Carbone" database developed by Ademe, which assigns a zero emission factor to biomass as an energy source (Ademe, 2024), and with European regulations[14].

Yet, unlike most other carbon emission factors, biomass carbon-neutrality is primarily an economic assumption rather than a physical measurement. Woody biomass has a physical carbon emission factor of 112 $kgCO_2/GJ$ (IPCC, 2006), which is higher than that of coal (98 $kgCO_2/GJ$), and is twice as large as that of natural gas, the predominant energy source from which many program beneficiaries are transitioning. However, woody biomass is renewable: over their life cycle, trees and plants capture carbon and release some or all of it into the atmosphere when decaying or being burned as fuel. This implies the possibility that a production-consumption cycle of biomass may yield zero net emissions over a certain time period.

The literature in forestry highlights two key issues with assuming biomass energy is carbon neutral (Searchinger et al., 2009; Camia et al., 2021). First, the time needed to offset the emissions associated with harvesting biomass varies widely depending on biomass type, forest age and composition, harvesting methods, regrowth rates, climate factors, and emissions from transport and processing, meaning net carbon benefits – if any – may take decades or centuries to materialize (Mitchell, Harmon, and O'Connell, 2012). These variations have been widely acknowledged, including by French environmental bodies (Axelos and Geoffron, 2023). Second, much biomass used for energy is not sourced from forests grown specifically for this purpose, so that carbon sequestration occurs after harvest. This delays achieving carbon neutrality beyond critical climate target dates like 2035 or 2050; and, for a given carbon budget, it increases net emissions in the short-term before any potential longer-term benefits emerge (Winkler, Myneni, Reimers, Reichstein, and Brovkin, 2024). In this respect, determining whether the biomass whose consumption is triggered by the program is responsible for the marginal demand matters for determining its CO_2 footprint.

In our empirical analysis so far, we have adopted the convention of a zero emission factor, which aligns with the requirements imposed by Ademe regarding the sourcing of biomass to be burned in the equipment subsidized by BCIAT. Carbon neutrality is more credible for sec-

14. See for instance: Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC, Official Journal of the European Union 25/10/2003, Annex IV, page L 275/44; and Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources, Official Journal of the European Union 21/12/2018, Annex VI, page L 328/185

ondary sources such as wood offcuts and deadwood or residues, which are the biomass sources on which the program is focused. Ademe indeed imposes restrictions on the forestry management practices that must be certified in forests where biomass is sourced. It also has gradually introduced restrictions on biomass imports, which decrease the processing emissions associated with using biomass. This discussion is however critical in understanding the external validity of our results; both for the extent to which our analysis would transfer to a different context, but also with regards to the scalability of the program in France. This analysis should also be guided by which uses of biomass are given priority. In particular, if there is only a fixed quantity of biomass that can reasonably be deemed to be produced at zero net emissions, and if abatement costs are heterogeneous across sectors, it is reasonable to associate the lowest emissions to sectors with the highest counterfactual abatement cost. In the context of this study, the bulk of biomass is used by households, which may be able to transition toward alternative green technologies at a lower cost than the manufacturing sector.

We investigate how sensitive our results are to this carbon-neutrality assumption. We do this by computing alternative values of CO_2 emissions at the plant-level modifying two emission factors, namely those of wood and heat. For wood, we use an emission factor comprised between 0 – our baseline assumption – and 112 $kgCO_2/GJ$ – the raw value associated to burning biomass; for heat, we assume that all heat provided to treated units after treatment is produced with biomass, with an efficiency of 90% (following Ademe's assumption), and with the same emission factor as for wood.We make this emission factor vary until finding the value for which the coefficient in year $t + 3$ is equal to 0; this value is 54 $kgCO_2/GJ$. This corresponds to the carbon emission factor for which the estimated net carbon benefits from the program are null.

6.3 Relation to the abatement cost

Our estimated government cost measures the fiscal cost per ton of CO_2 avoided needed to induce adoption under the existing capital stock, but cannot be interpreted as the abatement cost associated to the policy without further assumptions. An important point to assess the potential wedge between the two measures is that firms were intended to apply only when the private net present value of switching to biomass, taking the subsidy into account, was close to zero. This means that the subsidy approximately offsets the incremental private cost of conversion, including any residual value of incumbent boilers and integration, logistical burdens, expected operating costs, etc. Consequently, forces that would normally push the abatement cost above the government cost (such as uncompensated scrapping or premature capital replacement) are partly internalized by design: the program selects firms precisely when the subsidy is sufficient to neutralize most net private losses. The resulting wedge between the government cost and the actual resource cost is therefore smaller than it would be absent screening. It is, however, not eliminated entirely, given heterogeneity in equipment life, operational conditions, as well as uninsured price changes, which as we have shown trigger substantial abandonment of the subsidy.

Overall, we take our results as indicative that some of the key building blocks in the agency's computations of the expected abatement cost of the program turn out to be aligned with our *ex post* point estimates. These building blocks are the additional effect on investment, and the reduction in CO_2 intensity of energy consumption and total CO_2. There are of course standard errors associated with these estimates, and there are other assumptions entering these carbon abatement computations, for which we cannot present a validation exercise. Taking these building blocks at face value, however, suggests that the *ex ante* calibration of the subsidy is close to the abatement cost associated with switching each of the laureate industrial boilers to biomass.

7 Conclusion

In this paper, we investigate the impact on carbon emissions of manufacturing firms of subsidizing a specific kind of green technical change.

We find that the program is effective at spurring investment in clean technology by firms receiving the subsidy, thereby reducing their conventional CO_2 intensity and emissions. Indeed, we find that the subsidy allows laureate firms to decrease their annual CO_2 emissions by 21% on average. This alleviates the concern that such a policy could have an adverse rebound effect on the environment by increasing firms' energy consumption, and as a consequence their CO_2 emissions as well. Similarly, activity remains unchanged for treated firms relative to control ones. An important feature of the program is that many laureate projects are eventually abandoned, and particularly so when the price of fossil fuel energy is attractive. This is consistent with the wish of policymakers to set private NPVs for participants close to 0, such that they can easily turn negative because of energy price shocks, but points to the need for a better policy design including insurance against energy price variations for better compliance.

The government's abatement cost associated to the program is not aligned with the CO_2 reduction observed in treated plants, notably because a large share of subsidy recipients are already covered by the EU-ETS, meaning that quotas freed up thanks to the policy can be used by other actors. As a result, the real cost for the government of abating one ton of CO_2 is € 100 in our central scenario. Furthermore, we discuss how the uncertainty about the emission factor of biomass when used at scale affects the CO_2 gains allowed by the program.

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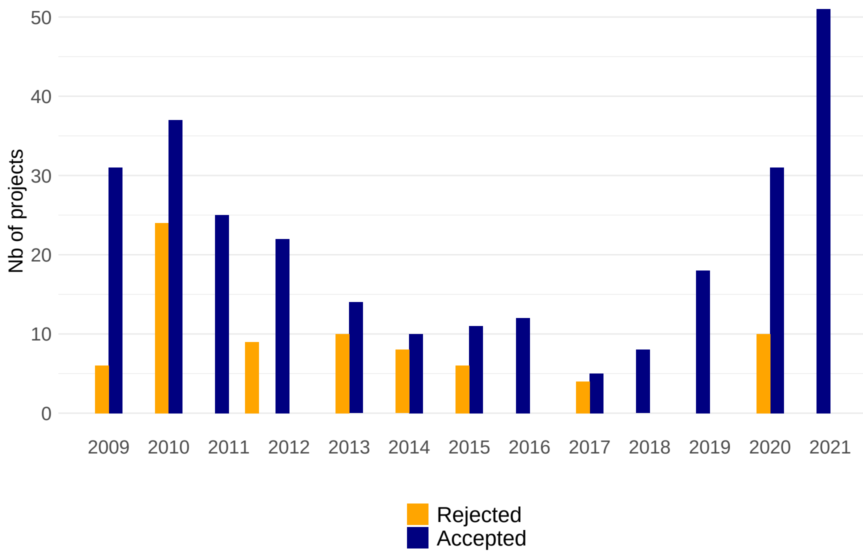
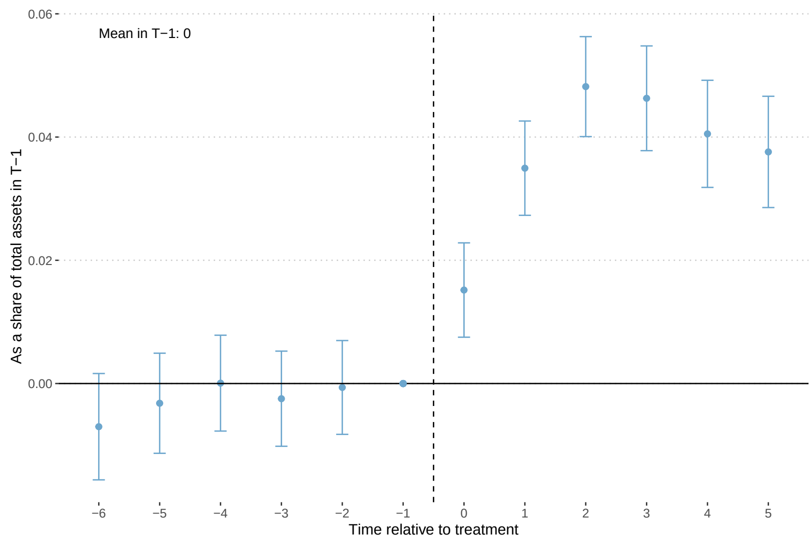
Figures

Figure 1: Number of accepted and rejected BCIAT projects, by application year



NOTES: The figure displays the number of accepted and rejected BCIAT projects by application year over the period 2009-2021.

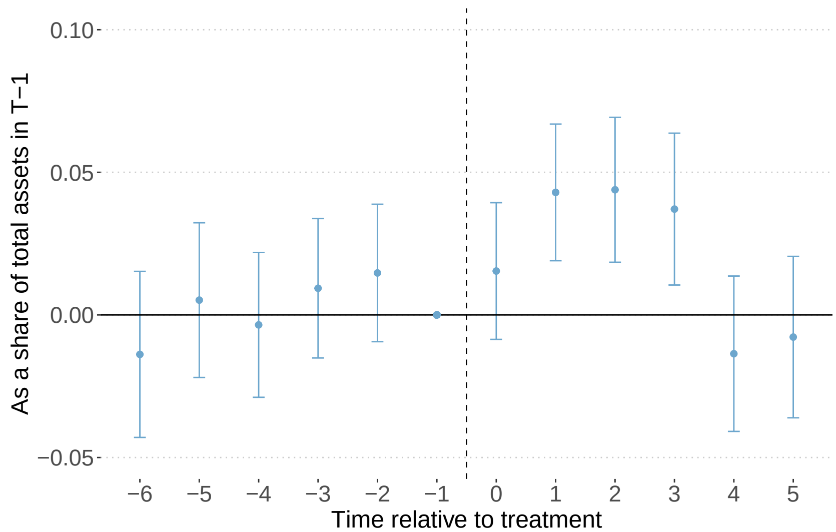
Figure 2: Estimated effects on total subsidies received



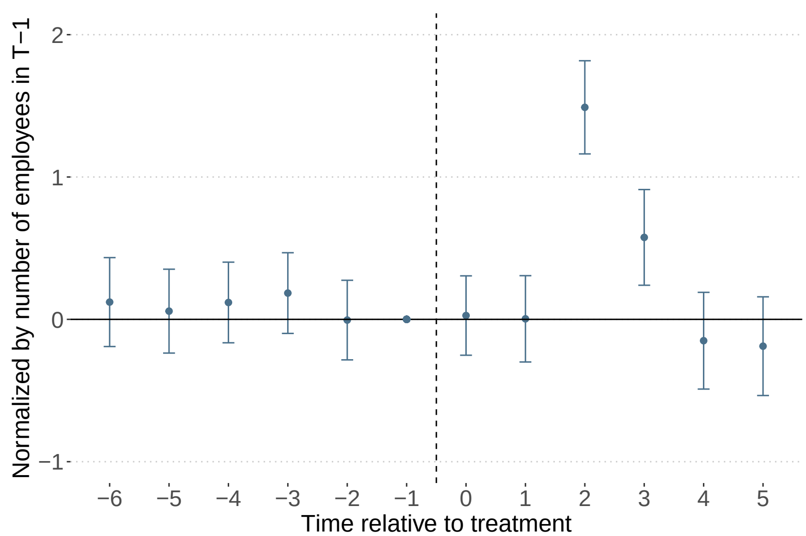
NOTES: The figure displays stacked difference-in-differences estimates and the corresponding 95% confidence intervals, estimated using Equation 1. The outcome variable is the stock of investment subsidies each year, normalized by the value of assets in the reference year (year to treatment = -1). The definition of the treatment and the estimation are at the firm level.

Figure 3: Estimated effects on investment

(a) Increase in tangible assets (corporate tax data)



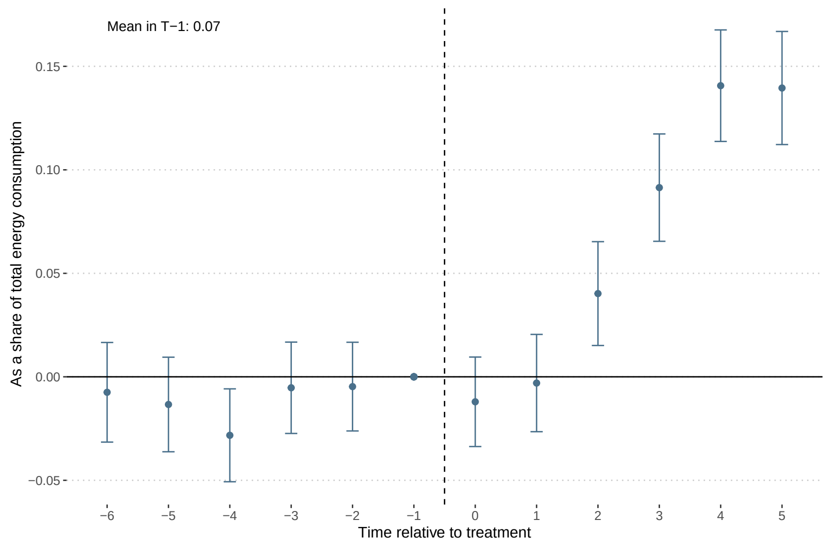
(b) Green investment (survey data)



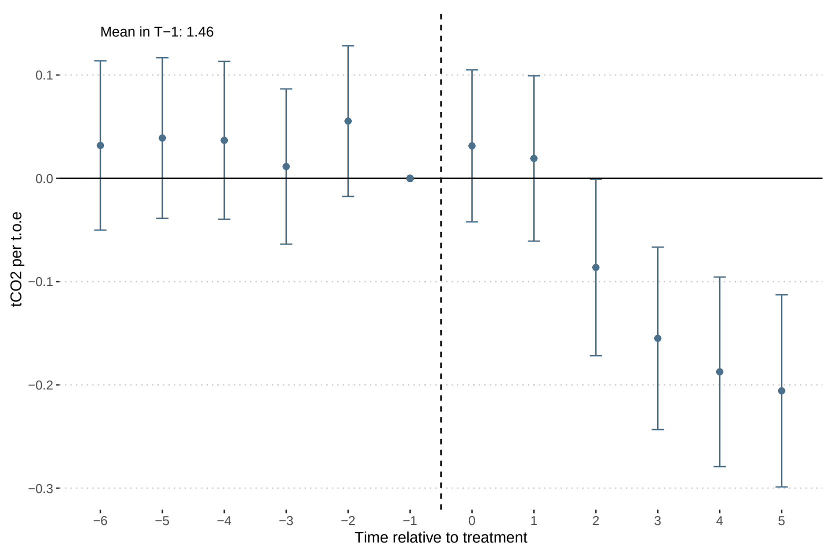
NOTES: Panels (a) and (b) display stacked difference-in-differences estimates and the corresponding 95% confidence intervals, estimated using Equation 1. In Panel (a), the outcome variable is investment each year, defined as the change in tangible assets, normalized by the value of assets in the reference year (year to treatment = -1); the variable is winsorized at the 1% level. The sample is all firms in the corporate tax data. The definition of the treatment and the estimation are at the firm level. In Panel (b), the outcome variable is the amount (in thousand euros) of integrated investment in air protection and GHG emissions reduction each year, normalized by the number of employees in the reference year (year to treatment = -1). The definition of the treatment and the estimation are at the plant level.

Figure 4: Impact on the composition and carbon intensity of energy consumption

(a) Share of heat and biomass in energy consumption

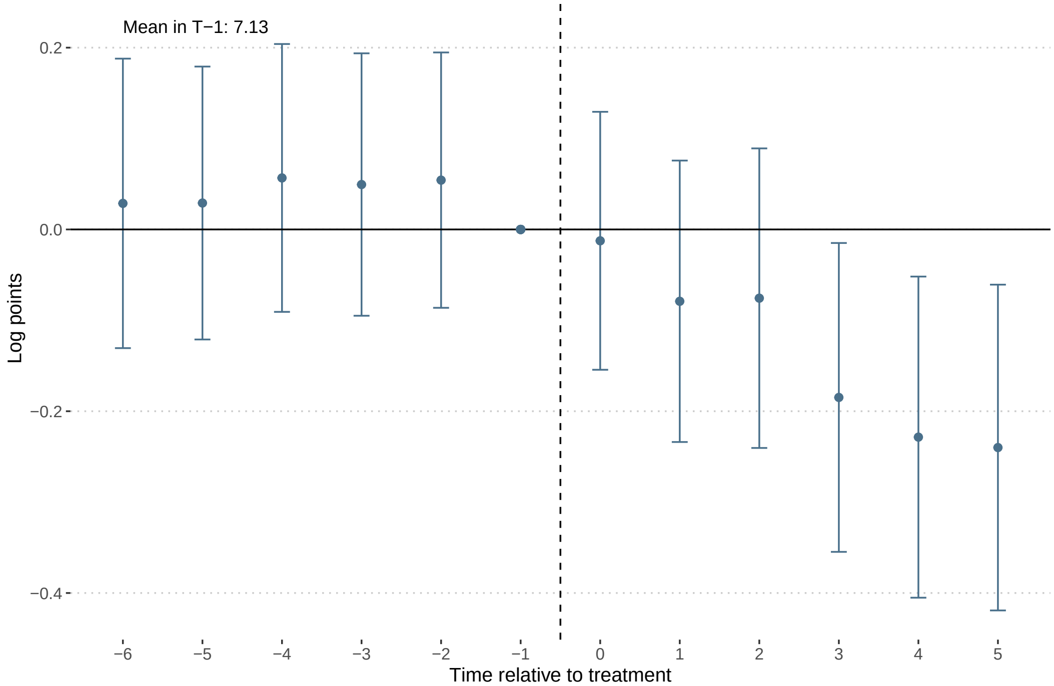


(b) Carbon intensity of energy consumption



NOTES: Panels (a) and (b) display stacked difference-in-differences estimates and the corresponding 95% confidence intervals, estimated using Equation 1. In Panel (a), outcome variable is the share of heat and biomass in total energy consumption. The definition of the treatment and the estimation are at the plant level. The definition of the treatment and the estimation are at the firm level. In Panel (b), outcome variable is the carbon intensity of energy consumption, measured in tCO_2 per ton of oil equivalent. The definition of the treatment and the estimation are at the plant level.

Figure 5: Effect on total carbon emissions



Notes: The figure displays stacked difference-in-differences estimates and the corresponding 95% confidence intervals, estimated using equation 1. The outcome variable is annual carbon emissions in tonnes, sourced from EUETS data for EUETS plants or estimated from energy use survey for other plants. The definition of the treatment and the estimation are at the plant level.

Tables

Table 1: Descriptive statistics on applications to the BCIAT program (2009–2021)

	Laureate projects						Rejected projects	
	All		Completed		Abandoned			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Planned investment (M€)	9.03	11.28	9.72	12.14	7.73	9.37	9.40	11.17
Awarded subsidy (M€)	3.36	3.74	3.61	3.83	2.87	3.53	3.85	4.19
Installed power (MW)	12.44	11.94	12.76	12.23	11.84	11.40	14.42	15.97
Expected annual heat production (GWh)	70.78	76.72	71.22	76.98	69.96	76.62	75.20	84.62
Expected annual CO2 avoided (ktCO2)	15.69	16.89	15.81	16.89	15.47	16.97	15.97	17.50
Invest. cost/avoided CO2 over 15y (€/tCO2)	16.06	9.91	16.72	9.65	14.82	10.31	19.23	18.54
Share by broad industry:								
Food industry	0.32		0.38		0.21		0.23	
Paper/Cardboard	0.14		0.13		0.15		0.10	
Chemistry/Pharmaceuticals	0.11		0.09		0.15		0.13	
Construction materials	0.09		0.07		0.14		0.09	
Wood industry	0.19		0.24		0.11		0.13	
Other	0.13		0.08		0.21		0.18	
Nb. of projects	275		180		95		78	

NOTES: Table 1 provides the mean value and the standard deviation for key variables associated to each project submitted to the BCIAT subsidy program.

Table 2: Descriptive statistics of the estimation samples

Panel A: Firm-level sample	Treated firms				Control firms			
	Mean	p25	Median	p75	Mean	p25	Median	p75
Total wage bill (M€)	55.98	2.66	8.98	27.37	1.11	0.00	0.10	0.44
Net assets (M€)	623.90	18.67	66.14	278.80	30.12	0.39	1.17	4.48
Share of investment subsidies (as a % Net assets)	0.85	0.00	0.02	0.66	0.44	0.00	0.00	0.00
Sales (M€)	762.90	21.74	90.57	345.00	14.32	0.06	0.52	3.28
Value-added (M€)	127.90	4.42	21.27	75.21	2.63	0.02	0.20	0.92
Investment in physical assets (M€)	2.99	0.35	1.46	6.47	0.13	0.00	0.00	0.05
Investment in physical assets (as a % of Net assets)	4.88	0.96	3.25	6.38	0.70	0.00	0.02	2.56
N	171				74609			
Panel B: Plant-level sample	Treated plants				Control plants			
	Mean	p25	Median	p75	Mean	p25	Median	p75
Workforce (FTE)	435.40	102.00	185.10	442.10	250.50	45.46	100.00	218.10
Has biomass/wood consumption	0.18				0.06			
Annual biomass/wood consumption (tep)	887.00	0.00	0.00	0.00	326.90	0.00	0.00	0.00
Has natural gas consumption	0.89				0.69			
Annual natural gas consumption (tep)	7997.00	1884.00	4725.00	10167.00	2601.00	0.00	131.30	1115.00
Has fossil consumption	0.98				0.90			
Annual fossil consumption (tep)	8779.00	2949.00	5685.00	11087.00	5348.00	45.80	260.50	1386.00
CO_2 emissions (t)	27961.00	9068.00	17563.00	37963.00	17736.00	275.30	1105.00	4823.00
Is part of EU ETS	0.65				0.15			
N	96				5322			
Green investment outcomes								
Green specific investment (k€ per worker)	0.74	0.00	0.06	0.35	0.76	0.00	0.01	0.32
Green integrated investment (k€ per worker)	0.33	0.00	0.00	0.02	0.18	0.00	0.00	0.00
Integrated investment for air and climate (k€ per worker)	0.11	0.00	0.00	0.00	0.09	0.00	0.00	0.00
N	83				3951			

NOTES: Table 2 provides the descriptive statistics for the plant-level and firm-level estimation samples for the date t0-1, where t0 is defined as the first year in which any of the plant's (or firm's) projects is laureate; or the year of the cohort for controls.

Table 3: Results for economic outcomes

Outcome	Static Coefficients		Obs.	Pretrends
	t+0 to t+2	t+3 to t+5		
Sales	0.089*	0.088	683861 obs (68664 units)	-0.036
	(0.048)	(0.081)		(0.038)
Value Added	0.077*	0.100	653571 obs (67665 units)	-0.022
	(0.046)	(0.063)		(0.042)
Profit rate	0.036	0.038	684326 obs (68684 units)	-0.004
	(0.036)	(0.051)		(0.021)
Markup rate	0.015	0.012	684326 obs (68684 units)	-0.020*
	(0.018)	(0.031)		(0.011)

NOTES: Table 3 presents the results for economic outcomes of the static version of the model presented in Equation 1. Columns 2 and 3 correspond to the static coefficients for the periods from t+0 to t+2 and from t+3 to t+5 respectively, relative to the year of the cohort. Column 4 reports the number of observations used in the regression and the number of units, that is the number of unique siren-cohort, in parentheses. The average of the pre-trend coefficients from the dynamic model corresponding to Equation 1 is presented in the last column as a test for the parallel trends assumption. Standard errors are reported in parentheses below their corresponding coefficient. * indicates a 10% significance level, ** a 5% level and *** a 1% level.

Table 4: Timing of application

Panel A: Sensitivity to firm characteristics

Unit of observation: firm

	Prob. of applying in T_0	
Net assets	0.001	0.001
	(0.004)	(0.004)
Value added per worker	-0.008	-0.026
	(0.086)	(0.090)
Capital intensity	-0.011	-0.011
	(0.052)	(0.052)
Investment rate	0.003	0.002
	(0.003)	(0.003)
Subsidy (to net assets)	0.199	0.230
	(0.405)	(0.422)
Cash (to net assets)		0.047
		(0.100)
Leverage		-0.014
		(0.016)
Pays dividends (==T)		0.001
		(0.012)
Firm FE	Y	Y
Year FE	Y	Y
Num.Obs.	2936	2936

Panel B: Sensitivity to changes in energy prices

Unit of observation: plant

	Prob. of applying in T_0		
Growth of energy prices in T_0	0.336	-0.060	-0.159
	(0.055)	(0.211)	(0.242)
Growth * energy intensity (Q==1)			.
			(.)
Growth * energy intensity (Q==2)			0.190
			(0.149)
Growth * energy intensity (Q==3)			0.068
			(0.152)
Growth * energy intensity (Q==4)			0.168
			(0.152)
Plant FE	Y	Y	Y
Year FE	N	Y	Y
Num.Obs.	1960	1960	1960

NOTES: Table 4 studies the timing of applications to the subsidy. Panel A displays results at the firm level, regressing the probability of applying in a year T_0 on accounting variables, and including both firm and year fixed-effects. Panel B displays results at the plant level, and studies specifically the probability of applying in a year T_0 on the yearly price change of the plants' energy vector. * indicates a 10% significance level, ** a 5% level and *** a 1% level.

Table 5: Determinants of dropout

	Probability of completing a project (LPM, OLS)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Price growth differential	0.481**	0.533**	0.478**	0.480**	0.444**	0.283	0.530**	1.058**	0.909**
	(0.162)	(0.169)	(0.160)	(0.247)	(0.174)	(0.296)	(0.230)	(0.414)	(0.421)
Rank of project NPV		0.059	0.046	0.047	0.026	0.047	0.003	0.002	0.000
		(0.053)	(0.050)	(0.052)	(0.075)	(0.083)	(0.087)	(0.059)	(0.058)
Net assets								0.013	0.012
								(0.022)	(0.022)
Value added per worker								0.944	0.88
								(0.54)	(0.51)
Capital intensity								-0.418	-0.396
								(1.318)	(1.395)
Investment rate								-0.196	-0.173
								(0.229)	(0.253)
Investment subsidy rate								10.374	10.339
								(4.167)	(4.157)
Cash (to assets)									0.334
									(0.438)
Leverage									0.089
									(0.163)
Pays dividends (== 1)									0.152**
									(0.085)
Sector FE	N	N	Y	Y	Y	Y	Y	Y	Y
Application year FE	N	N	N	Y	N	Y	Y	Y	Y
Energy FE	N	N	N	N	Y	Y	N	N	N
N	193	193	193	193	193	193	164	164	164
R^2	0.044	0.05	0.194	0.296	0.213	0.333	0.156	0.364	0.383

NOTES: Table 5 presents the results of a linear probability model regression of the probability of completing a projet conditional for the sample of projects which are awarded a subsidy, on a number of explanatory variables and fixed-effects. * indicates a 10% significance level, ** a 5% level and *** a 1% level.

Online Appendix

A Additional Tables

Table A1: Aggregated event-study results for alternative samples

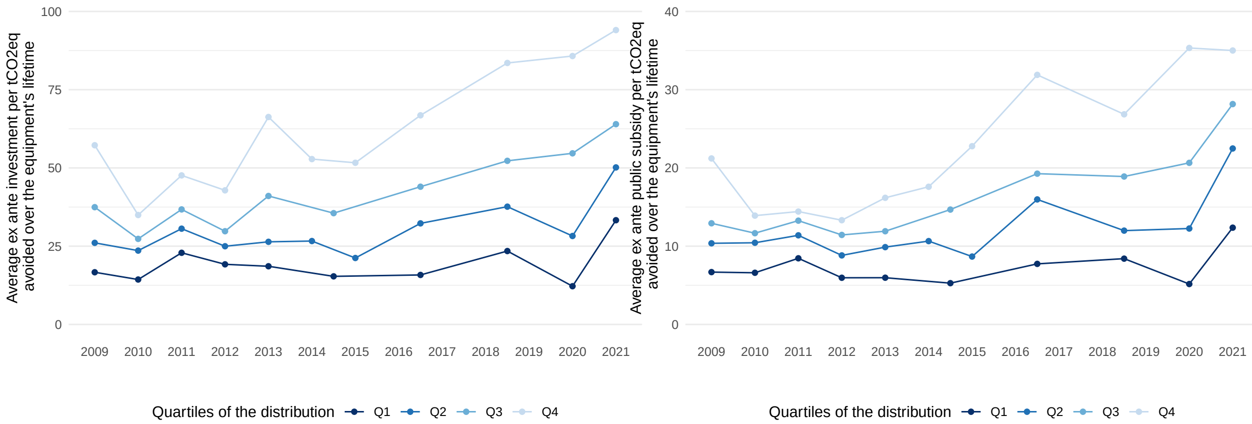
	Static Coefficients		Obs.	Pretrends
	t+0 to t+2	t+3 to t+5		
Baseline				
Tangible investment	0.034***	0.005	753430 obs (74780 units)	0.002
	(0.012)	(0.012)		(0.010)
Log of CO2 emissions	-0.056	-0.218***	48151 obs (5428 units)	0.044
	(0.059)	(0.085)		(0.042)
Only high takeup cohorts				
Tangible investment	0.035***	0.009	492038 obs (53265 units)	0.016
	(0.013)	(0.015)		(0.010)
Log of CO2 emissions	-0.021	-0.280**	33349 obs (3980 units)	0.069
	(0.086)	(0.122)		(0.053)
Removing high NPV projects				
Tangible investment	0.042***	0.015	753108 obs (74753 units)	0.008
	(0.013)	(0.013)		(0.011)
Log of CO2 emissions	-0.073	-0.258**	47962 obs (5412 units)	0.056
	(0.073)	(0.101)		(0.049)
Balanced t-2 to t+2				
Tangible investment	0.030**	0.004	466683 obs (40270 units)	0.002
	(0.013)	(0.013)		(0.012)
Log of CO2 emissions	-0.089	-0.213**	31276 obs (2799 units)	0.084
	(0.076)	(0.093)		(0.065)

NOTES: Table A1 presents the results of the static version of the model presented in equation 1 on different samples as robustness tests. The panel "Baseline" corresponds to our baseline results. The panel "Only high takeup cohorts" presents the results for the plant and firm-level samples including only the cohorts 2009, 2010, 2011, 2019, 2020 and 2021. The panel "Removing high NPV projects" presents the results for the samples excluding high NPV projects. The panel "Balanced t-2 to t+2" presents the results for the samples containing only plants or firms observed each year from t-2 to t+2, where t+0 is the year of the cohort. Columns 2 and 3 correspond to the static coefficients for the periods from t+0 to t+2 and from t+3 to t+5 respectively, relative to the year of the cohort. Column 4 reports the number of observations used in the regression and the number of units, that is the number of unique siren-cohort, in parentheses. The average of the pre-trend coefficients from the dynamic model corresponding to equation 1 is presented in the last column as a test for the parallel trends assumption. Standard errors are reported in parentheses below their corresponding coefficient. * indicates a 10% significance level, ** a 5% level and *** a 1% level.

B Additional Figures

Figure A1: Distribution of *ex ante*, declared € per projected ton of CO_2 avoided

(a) Investment / avoided CO_2 (b) Subsidy / avoided CO_2



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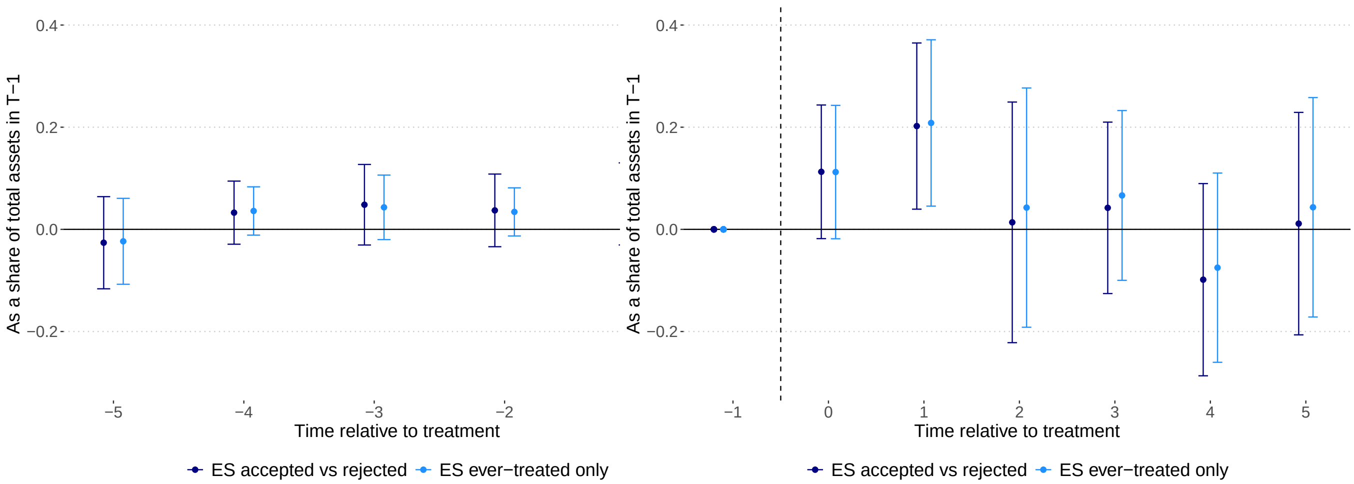
NOTES: The figure displays, for each cohort of subsidized projects, the distribution of the ratio between *ex ante*, declared, total costs (in €) and the total CO_2 avoided over 15 years, as per the project data. Panel (a) uses the total investment costs declared by project applicants, and panel (b) uses the total subsidy awarded to projects. The first quartile represents, for a given cohort, the average ratio of total investment costs to projected total CO_2 avoided over 15 years for the 25% of projects for which this ratio is the smallest. The top quartile thus corresponds to the 25% of projects that are "most costly" in terms of invested € per projected ton of CO_2 avoided.

Figure A2: Effect on investment in tangible assets, alternative specification

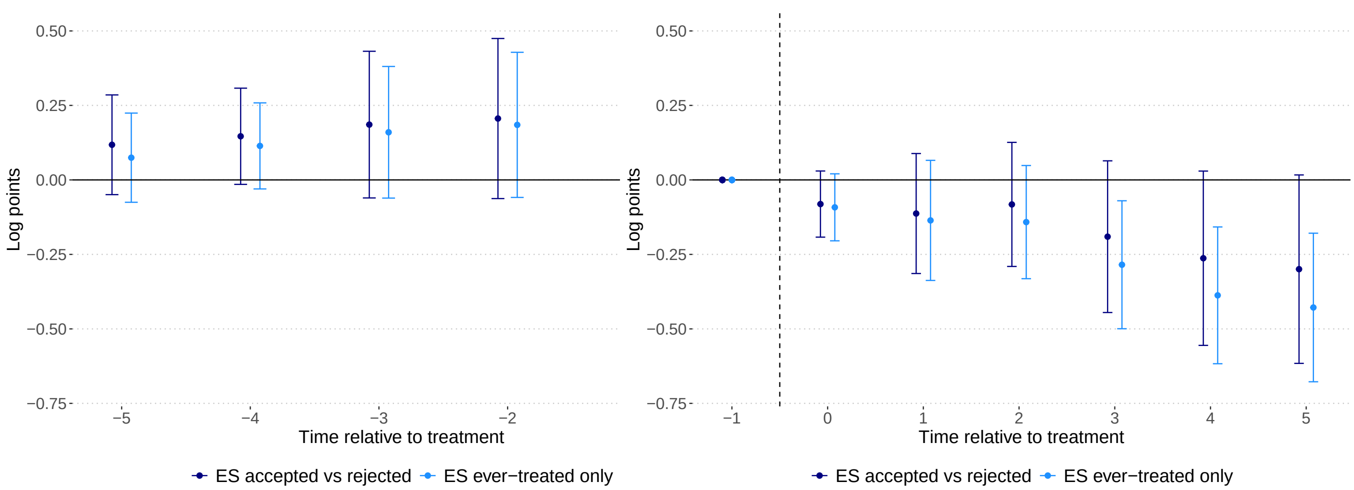
(a) Pre-trends (b) Post trends



Notes: Panels (a) and (b) display event-study estimates and the corresponding 95% confidence intervals, estimated using Equation 3. The outcome variable is investment each year, defined as the change in tangible assets, normalized by the value of assets in the reference year (year to treatment = -1); the variable is winsorized at the 1% level. The sample is all firms in the corporate tax data. The definition of the treatment and the estimation are at the firm level. Panel (a) shows pre-trend coefficients, calculated relative to the last pre-treatment year. Panel (b) shows treatment effects in the post period relative to the average of pre-treatment observations.

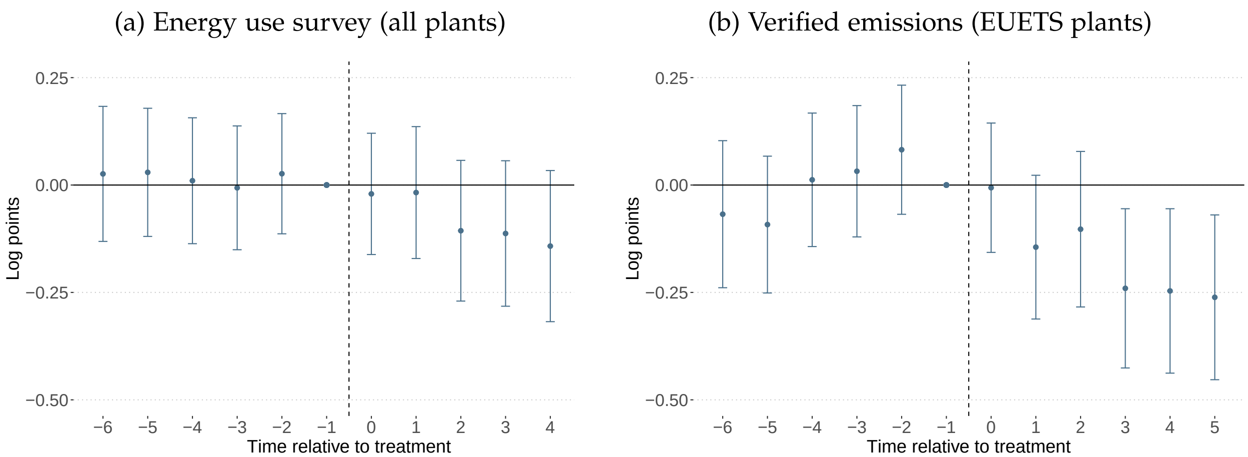
Figure A3: Effect on total CO_2 emissions, alternative specification

(a) Pre-trends (b) Post trends



Notes: Panels (a) and (b) display event-study estimates and the corresponding 95% confidence intervals, estimated using Equation 3. The outcome variable is annual carbon emissions in tonnes, sourced from EUETS data for EUETS plants or estimated from energy use survey for other plants. The definition of the treatment and the estimation are at the plant level. Panel (a) shows pre-trend coefficients, calculated relative to the last pre-treatment year. Panel (b) shows treatment effects in the post period relative to the average of pre-treatment observations.

Figure A4: Effects on CO_2 emissions by data source



Notes: The figure displays stacked difference-in-differences estimates and the corresponding 95% confidence intervals, estimated using Equation (1). The definition of the treatment and the estimation are at the plant level. In Panel (a), the outcome variable is the total direct combustion emissions of plants, as reconstructed from the detail of their yearly energy consumptions ; thus the sample is all treated plants within the EACEI survey sample, and all control plants, ie plants in the EACEI survey sample in the same years and in the same sectors as the treated plants. In Panel (b), the outcome is the total yearly verified emissions of a plant as registered in the official EUETS register.