Take a ride on the green side: How do CDM projects affect Indian manufacturing firms' environmental performance?

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Abstract

This study examines the causal impacts of the Clean Development Mechanism (CDM) on the environmental performance of Indian manufacturing firms, as measured by their energy use, carbon dioxide (CO_2) emissions and respective intensities. The impacts of the CDM projects are estimated by combining statistical matching with the difference-in-differences approach. We found that the CDM projects significantly reduced firm CO_2 intensity and energy intensity, but had no effect on total CO_2 emissions. Our results also reveal different channels through which firm CO_2 intensity was likely to be improved. We showed that firms hosting CDM projects increased the use of clean fuels and energy sources. These results suggest additionality of the CDM projects hosted by manufacturing firms in India had the firms' sales expanded in a similar fashion absent the CDM projects.

JEL: D22, Q53, Q54, Q58

Keywords: additionality, CDM projects, CO2 emissions, firm performance, India, micro level data, offsets

1. Introduction

To apply for carbon credits in the context of an offset program, one must prove additionality of the project. Additionality, however, is extremely difficult to prove.[1] In the context of the Clean Development Mechanism – the largest international offset programme linked to the Kyoto Protocol – a project is deemed additional if "anthropogenic GHG emissions are reduced below those that would have occurred in the absence of the registered CDM project activity." The difficulty lays in defining the right counterfactual to show that GHG emissions were reduced *because* of the implementation of the CDM project. However, researchers have the tools to empirically estimate *ex post* the causal impacts of participating into a program by comparing participating firms with non-participating "control'' firms, controlling for industry-wide trends in technology and demand. This paper argues that to prove additionality of CDM projects, we must rely on these standard policy evaluation techniques.

Existing studies that estimate the economic and environmental impacts of CDM projects *ex post* mostly fall into two groups.[2] First, some papers studied the impacts of CDM participation at a macro or regional level. For instance, Huang and Barker (2012) found that CO_2 emissions per capita decreased with CDM participation at the country level. By contrast, Zhang et al. (2018) showed that energy efficiency was not affected by the mechanism at the province level in China. Second, researchers have studied additionality by comparing the profitability of investing in wind or hydro energy production under a CDM project or without the CDM endorsement. They found that most of these investments were non-additional, in the sense that they were still profitable even without the participation into the offset program (Dechezlepretre et al., 2014; Haya and Parekh 2011).

In this paper, we use firm-level data in India for the manufacturing sector to assess *ex post* the impacts of CDM projects on firms' environmental performance. The names of companies that participate into at least one registered CDM project are available from the CDM Pipeline UNEP Database. We merge this information with the Prowess dataset that contains firm-level balance-sheet information along with the name of each firm.[3] Since we observe detailed energy-use data in Prowess, we can also compute CO_2 emissions associated with production, and thus assess the impacts of CDM projects on total emissions as well as on CO_2 emission intensity of firms. Because participation into a CDM project is voluntary, we may worry that some unobservable characteristics of firms may induce both the CDM participation and some reductions in CO_2 emissions for instance. Our empirical strategy relies on comparing the outcomes of participating firms with carefully identified control firms using a difference-in-differences approach. We first identify control firms using matching techniques that compare observables for the participating firm and its control firms two years before the CDM project starts. We then use several difference-in-differences (DID) models to estimate the effects of CDM projects on firm environmental performance. One of the DID models allows for different treatment dates, which is particularly convenient in our setting since CDM projects start at different times.

[1] The CDM has been heavily criticized for lacking additionality. Its design does not require specific data provision, does not use standardized baselines, and allows for claims of technologies being "not common practice" by developers without verifying these claims (Michaelova and Purohit, 2007; Schneider, 2007). Additionally, conflict of interests between developers and verifiers, as well as asymmetrical information between companies and the Executive Board of the CDM, undermine the efforts for securing additionality (Wara and Victor, 2008).

[2] For an overview of the literature on CDM projects, we refer to Spalding-Fecher et al. (2012).

[3] The other manufacturing database in India, the Annual Survey of Industries (ASI), run by the government each year does not contain the name of firms.

We find that firms hosting CDM projects significantly reduced their CO_2 intensity and energy intensity, while leaving their total CO_2 emissions unchanged or increased. Our results reveal different channels through which firm CO_2 intensity was likely to be improved. We show that firms hosting CDM projects increased the use of clean fuel and energy sources and generated more electricity on site instead of purchasing it from the grid. Additionally, we test the sensitivity of these results to unobserved selection into the treatment. To do so, we exploit the fact that not all firms that applied for hosting CDM projects were successful. These "unsuccessful firms" are especially eligible to be part of the control group as they were as likely to host CDM projects as the "successful firms". As suggested by earlier studies (see, e.g., Bernini and Pellegrini, 2011), the rejected application group is very similar to the treatment group in terms of its characteristics and allows to isolate the effects of policy intervention. We validate most of our results using the unsuccessful firms as a control group although some results lose their statistical significance.

Overall, our results tend to show additionality of the CDM projects hosted by manufacturing firms in India. However, the best evidence of additionality in our context is in the reduction of emission intensity, that is in a technique effect. A scale effect counteracts this technique effect so that total emissions are either constant or increasing after the CDM project has been implemented. We argue that the definition of additionality should be refined to consider both scale and technology effects. Indeed, these two effects matter for developing countries that continue to grow and where firms use technologies that are far from the frontier.

This paper is organized as follows. Section 2 provides a brief literature review of additionality issue. Section 3 describes the institutional setting of CDM project registration process and discusses the participation decision in the mechanism from the point of view of the firm hosting a CDM project. Next, we describe our data and empirical strategy in Sections 4 and 5, respectively. Estimation results and discussions are provided in Section 6. Finally, Section 7 presents our conclusions.

2. Literature review

Existing research on additionality can be grouped into three categories: (1) early studies that address additionality by analysing Project Design Documents (PDD), (2) studies that use aggregate macro level data to analyse whether participation in CDM projects in a broad sense alter aggregate CO_2 emissions, and (3) research that tries to estimate causal effects of CDM projects *ex post* by using micro level data.

Early additionality studies are rather qualitative and descriptive in nature and are based on analysis of PDDs submitted for CDM project registration purposes. They confirm the lack of additionality for over 40% of registered CDM projects and 20% of Certified Emission Reductions (CER) generated (Schneider, 2007; Michaelowa and Purohit, 2007). Sutter and Perreno (2007) provide indications of additionality through analysis of internal rate of return (IRR). If a CDM project substantially increases the IRR compared to the baseline IRR, the project is likely to be additional. They conclude that a majority of CERs (but a small number of projects) are likely to be additional, but their conclusions are highly influenced by low-hanging fruit projects (e.g., HFC-23 emission reduction projects).

Erickson et al. (2014) conclude that the efficiency of the CDM crucially hinges on the additionality of large-scale wind and hydropower projects. Sawhney and Rahul (2014) find that state fiscal incentives played an overwhelming role in determining renewable energy projects in India. Moreover, He and Morse (2010) show that host countries may be eager to change their national policies (feed-in tariffs, fiscal incentives) in order to trigger additionality from a financial perspective. Trotter et al. (2015) find that industrial emission reduction and wind power CDM projects were undertaken even when prices of CER were low, which indicates that those projects are not very CER price sensitive.

There are several empirical studies that analyze additionality of CDM projects *ex post* by using macro level data. For example, Huang and Barker (2012) perform their analysis by using the panel data of 80 countries and time span of 1993-2009. They find that CDM projects significantly reduced total CO_2 emissions per capita (by 1.31%) and those from the manufacturing and energy sectors (by 3-8%). Zhang et al. (2018) use the Data Envelopment Analysis and panel quantile regression model to study the relationship between the overall energy efficiency and carbon emission performance in sixteen countries hosting CDM projects during 1990–2015 period. They find that CDM projects do not improve the overall energy efficiency. However, CDM projects positively affect the environmental performance but only for lower carbon emission performance countries. The direction of the impact becomes negative with higher quantiles of carbon performance of CDM host countries. Zhang and Wang (2011) study the additionality of CDM renewable and energy efficiency projects in China through the prism of co-benefits. Since SO_2 emissions are co-generated along with CO_2 emissions in grid-level emission baseline, the CDM projects should lead to a decrease in SO_2 emissions as well. They find no reduction in SO_2 emissions, which suggests that CDM projects did not decrease CO_2 emissions neither. This casts doubt on additionality of CDM projects.

To the best of our knowledge, only one study addresses additionality *ex post* using project level data. Dechezleprêtre et al. (2014) study additionality of wind power CDM projects in India. They exploit the fact that CDM wind power projects co-exist with wind power projects that did not receive financial support from the CDM offset. The additionality of CDM wind power projects would be verified if non-CDM projects differ in characteristics that affect their investment profitability. The methodology used to test for additionality consists on matching of CDM project with non-CDM ones that have clearly lower profitability. Dechezleprêtre et al. (2014) find that 52% of wind power CDM projects were non-additional and only 1% is additional.

3. Institutional CDM settings

The participation in the CDM is voluntary. Several stages need to be validated in order to generate Certified Emission Reduction credits from CDM activity. First, projects participants must receive a letter of approval from a designated national authority (DNA) stating that the project assists the host country in achieving its sustainable development goals. Then, project participants submit the project activity to the Designated Operational Entity for evaluation. In this stage, a project design document is reviewed against the requirements of the CDM program and if these are met, the project is validated. Next, the project needs to be registered by the CDM Executive Board. A proposed activity may be withdrawn or rejected at any stage of the process. Revisions may be required in order to comply with the requirements of the CDM.[4]

The participation process in the CDM depends on the interests of many players, including hosting firms, consultants, host countries representatives (DOE and DNA) and the Executive Board. The preferences of the Executive Board and DOE have been studied by Xie et al. (2014) by comparing registered and rejected CDM projects. They find that higher reported price of CERs and internal rate of return without offsets increase the probability of rejection, whereas the bigger scale and higher generation capacity projects have a lower probability of rejection.

From the hosting firm's point of view, Lutken (2012) states that the prime drivers for CDM investments are not revenues from CERs but other considerations, mostly revenue stream gained from electricity generated. Several other factors motivate and encourage firms to engage in CDM projects. First, firms must be able to detect the opportunities that come from the CDM offset. The presence of R&D activities in a company stimulates innovation and allows firms to look for such opportunities. In particular, energy efficiency engineers help to identify project space suitable for CDM activities (Schneider et al.,2009; Phillips et al., 2013). In similar vein, large companies that are more prone to export and/or have multinational affiliation may also have more information about suitable CDM investments (Phillips et al., 2013; Dechezlepretre et al., 2009 and 2008). Firms belonging to the same group of companies should be equally more inclined to participate in CDM projects, if a positive experience already took place within their group. Second, identified opportunities should be followed by real capacity to undertake the project. Schneider et al. (2008) notice that "most barriers tend to be more striking for SMEs, especially lack of information and access to capital." Production size, human capital capacity and financial capacity have a preponderant role in stimulating participation (Pulver et al., 2010; Arimura et al., 2012; Schneider et al. 2009).

Carbon market consultants are often primary agents to push for CDM projects. Trusted information from business networks and pre-existing relationships with carbon industry provide a positive incentive to participate in CDM (e.g., see Pulver et al. (2010) for the sugar industry). This raises the question of what attracts the interest of carbon market consultants. Large companies with obsolete technologies provide large opportunities for emissions reduction and attract the attention of consultants in the first place (UN CDM website; Koo, 2017; Zhang et al., 2018). Other factors that are important for consulting companies are raw material base, financial stability of partner, sustainable business, capacity to maintain the change and improvement on the level and shared views and values (UN CDM website- media podcasts). Consultants are therefore important factors in determining participation through the payment structure for their services (e.g., upfront or as a share in CER).

Finally, state regulations are of equal importance in triggering participation decision since firms have little incentives to engage in emission reductions if regulation is weak or if there are no subsidies for alternative sources/taxes on conventional sources of energy.

[4] Source: UN website: cdm.unfccc.int.

4. Data

Data sources

First, the information about CDM projects comes from the CDM Pipeline UNEP Database.[5] Among the 12,474 CDM projects reported in the database, 3,337 are hosted in India. Among these projects, 1,669 of them obtained registered status, 247 were in the process of registration (requested validation status) whereas the rest obtained unsuccessful status under various reasons (i.e., projects were withdrawn, rejected, negatively evaluated or replaced). Table 1 shows the number of the main types of projects for the three different statuses.

Table 1. Different types of CDM projects under registered, under evaluation or rejected status

Type of project	Number of Registered Projects	Number of Projects under Evaluation	Number of Unsuccessful Projects
Wind energy	717	68	273
Biomass energy	263	37	282
Hydro energy	167	26	123
Solar energy	133	35	25
Energy efficiency through own generation	75	19	133
Energy efficiency in industrial process	59	12	133

Sources: CDM Pipeline UNEP Database and authors' compilation.

According to Phillips et al. (2013), Indian CDM projects are mostly unilateral activities undertaken by Indian firms solely with no investing country or buyer on hand. This would suggest that these projects have the potential to generate enough revenues (for instance, from electricity generation) that firms do not need to secure CERs' buyers upfront. Indeed, Table 1 indicates that most Indian projects (both registered or unsuccessful) aim at producing energy with renewable resources or at improving energy efficiency through self-generation of electricity or through investments in the manufacturing production process.

Second, we utilize the data on Indian manufacturing firms compiled by the Center for Monitoring the Indian Economy (CMIE) in a dataset called Prowess. The data is based on annual reports filed publicly by large Indian manufacturers. We compile a firm-level panel data that spans the period from 1988 to 2016. The Prowess dataset contains information primarily from the income statements and balance sheets for 109,579 firm-year observations. Variables include revenues, value of total assets, value of fixed capital stock, total costs of labor, materials and energy used in production. Industries are grouped using India's National Industrial Classification (NIC) codes. Additionally, the dataset contains detailed description of the energy inputs used for production for 46,326 firm-year observations. In particular, firms report annual expenditures and consumption (with units) of different energy sources – including coal, electricity from the grid, natural gas and biomass. Using these detailed energy use reports, we compute CO_2 emissions related to production at the firm level.

To compute CO_2 emissions from manufacturing production, we follow previous work in multiplying energy consumption by fuel-specific CO_2 emissions factors (Marin & Vona,

[5] The authors obtained the version of the CDM Pipeline UNEP DTU CDM/JI Pipeline Analysis and Database from May 2019 (http://www.cdmpipeline.org/).

2017; Forslid et al., 2018; Barrows & Ollivier, 2018). This strategy rests on the assumptions that a given source of energy has a fixed carbon content and that burning the energy inputs releases that carbon content, which forms CO_2 in combination with oxygen, regardless of the technology used. These assumptions seem reasonable in the context of CO_2 in India where carbon capture technologies are not often used, and for primary energy sources (e.g., coal, gas, petroleum). In the context of electricity production, however, technologies play a role in determining the amount of CO_2 emissions associated with a kWh of electricity. When firms independently produce electricity, they report the energy inputs used for that self-generation, hence we can compute CO_2 emissions from self-generated electricity using the quantities of energy sources and multiplying them by our CO_2 emissions factors. When firms purchase electricity from the grid, we use a CO_2 emissions factor that reflects the average energy mix of electricity in India. In fact, the location of production is not reported in Prowess, hence we cannot attribute regional CO_2 emissions factors for electricity to firms. We provide details on the construction of these variables in Appendix A.

Merging the two datasets

Both the CDM Pipeline UNEP dataset and the Prowess dataset identifies firms by their name. Most CDM projects have more than one firm participating in the project. We thus create lists of firms participating in each CDM project. And we merge the two datasets by hand based on name recognition. Since the Prowess database focuses on the manufacturing sector, CDM projects hosted by the power sector are by construction excluded from our analysis. From our list of 734 firms that were successful in implementing at least one CDM project, we found 388 of them in Prowess; and from our list of 521 firms that were unsuccessful in implementing a CDM project, we found 328 of them in Prowess.

Main outcomes variables

Since firms' economic and environmental performance can be measured in many ways, we use different outcome variables in our analysis. First, firms' economic performance is reflected by total sales, total assets, the amount of fixed capital, and compensation for employees (wages). These variables will reflect the size of firms and also their financial capacity to invest in CDM projects. Second, firms' environmental performance is reflected by the level of total CO_2 emissions (in kilotonne – kt) used in production and by their CO_2 emissions intensity (in kt of CO_2 per rupees of sales). We also consider total energy expenditures and energy intensity as the ratio of total energy expenditures over total sales. The larger this ratio, the more firms should pay attention to their energy bill and be willing to pay for energy efficiency investments. Finally, we will look at particular energy expenditures to understand potential impacts of CDM projects on the energy mix of firms. We therefore compute coal expenditures and expenditures for clean fuels and other energy sources (e.g., wind power). Last but not the least we consider expenditures for electricity bought from the grid and expenditures of self-generated electricity as well as changes in the total fixed capital stock.

Descriptive statistics

Table 2 provides the descriptive statistics measured separately for CDM firms and non-CDM firms for the period 1988-2016. In the sample of CDM firms we include only whose CDM firms that are observed in Prowess database during CDM project registration year and at least two years before and two years after CDM project registration date. This leaves us with 266 unique CDM firms. CDM firms are, on average, more CO_2 intensive, consume a higher share of energy and fuel inputs, including the amount of coal. This is in line with our expectations, as more energy intensive firms have more incentives to reduce their energy use and improve their emission intensity. It is also evident that CDM firms, on average, generate more electricity on site and purchase less electricity from the grid when compared to non-CDM firms. CDM firms are also, on average, bigger in terms of total sales, total assets, fixed capital and compensation for employees.

The sectoral allocation reveals (see Table 3) that CDM firms, which are observed in our sample, are operating in various manufacturing sectors. Most CDM firms belong to the sectors producing food products, beverages and tobacco and to the sectors of manufacturing of basic and fabricated metals products. Textiles and chemicals are the other two manufacturing sectors where we observe a rather high number of CDM projects.

5. Empirical strategy

5.1 Identification of causal effects

In order to estimate causal effects of CDM projects on firm environmental performance, we base our analysis on the potential outcome framework that is now standard in the program evaluation literature. The two potential outcomes are Y^1 (firm's CDM project is granted meaning the firm received the treatment, $D = 1$) and Y^0 (firm does not receive the treatment, i.e., the firm did not apply for a CDM project or the firm's application for CDM project was unsuccessful, $D = 0$). The observed outcome for any firm i can be written as: $Y_i = Y_i^1 \cdot D_i + (1 - D_i) \cdot Y_i^0$. The treatment effect for each firm i is then defined as the difference between its potential outcomes: $\tau_i = Y_i^1 - Y_i^0$. However, the fundamental problem with causal inference is that we cannot observe both potential outcomes for the same firm at the same time. That is, in our case, we do not know what would have happened for CDM firms if they had not hosted CDM projects.

In our analysis, we will focus on the most known evaluation parameter, which is the average treatment effect on the treated (ATT), and is given by:

$$\tau_{ATT} = E\left(Y^1 \middle| \mathrm{D} = 1\right) - E\left(Y^0 \middle| \mathrm{D} = 1\right). \qquad \text{Eq. 1}$$

The last term on the right-hand side of Eq. (1) describes the hypothetical unobserved outcome without treatment for those firms that receive the treatment. Since the condition $E\left(Y^0 \middle| \mathrm{D} = 1\right) = E\left(Y^0 \middle| \mathrm{D} = 0\right)$ is usually not satisfied with non-experimental data, estimating ATT by the difference in sub-population means of participants $E\left(Y^1 \middle| \mathrm{D} = 1\right)$ and non-participants $E\left(Y^0 \middle| \mathrm{D} = 0\right)$ will lead to a selection bias. This bias arises because participants and non-participants are selected groups that would have different outcomes, even in the absence of CDM investments due to observable or unobservable factors. In this study we will apply matching and thus we will rely on the conditional independence assumption (CIA), which states that conditional on observable characteristics (X) the counterfactual outcome is independent of treatment: $Y^0 \perp D \mid X$, where $\perp$ denotes independence. In addition to the CIA, we will also assume a common support or overlap condition. This ensures that any combination of characteristics observed in the treatment groups can also be observed among the control group, in other words, that there are no perfect predictors which determine participation into treatment. These assumptions are sufficient for identification of the ATT (Heckman et al., 1997).

$$\tau_{ATT}^{MATCHED} = E\left[E(Y^1|X, D = 1) - E(Y^0|X, D = 0)\,\middle|\, D = 1\right], \qquad \text{Eq. 2}$$

where the outer expectation is taken over the distribution of X in the treated group.

The CIA is clearly a very strong assumption and the applicability of the matching estimator depends crucially on its plausibility. Blundell et al. (2005) argue that the plausibility of such assumption should always be discussed on a case-by-case basis. Only variables which simultaneously influence the participation decision and the outcome variables should be included in the matching procedure. Hence, economic theory, a sound knowledge of previous research and information about the institutional setting should guide the researcher in selecting matching variables. We studied the literature on firm decision to host CDM projects and we use firm economic indicators, which enables us to control for numerous firm characteristics and market conditions. Additionally, we test the sensitivity of the results with respect to unobserved selection into the treatment (see Section 4.3). That is, in the estimation of the counterfactual, we exploit the fact that not all firms that applied for hosting CDM projects were successful. This means that these "unsuccessful firms" are especially eligible to be part of the control group, as they show a propensity for hosting CDM projects and a need to invest in environmental measures which is very similar to that of "successful firms." As suggested by earlier studies (see, e.g., Bernini and Pellegrini, 2011), the rejected application group is very similar to the treatment group in terms of its characteristics and allows to isolate the effects of policy intervention.

Furthermore, we apply conditional difference-in-differences estimator, which enables us to control for time-invariant unobserved differences between participants and non-participants and which further relaxes the CIA. Conditional DID was initially suggested by Heckman et al. (1998). It combines a conventional DID estimation and matching. As CDM projects start (i.e., are registered) in different years, that is we have heterogeneous treatment start dates, we will rely on the flexible conditional DID approach suggested by Dettmann et al. (2019), which allows for the flexibility in the definition of treatment start and treatment duration and the possibility to consider time information in the matching process.

The first step of flexible conditional DID is an extensive data reorganization to incorporate the observation date of all matching variables and outcomes. The flexible conditional DID algorithm limits the set of potential control firms for every treated firm to those observed just at the individual matching date, e.g., the pre-treatment start. Then the matching algorithm selects one or more statistical twins among these pre-selected firms.

The second step is matching. In this study, we will implement nearest neighbour matching based on a combined statistical distance function (for more details see Dettmann et al., 2019). In the third step, based on the matched and balanced sample, we will estimate the average treatment effect for the treated as follows:

$$\tau_{ATT}^{MATCHED-DID} = \frac{1}{J}\sum_{j=1}^{J}(Y_{j,t_{1j}+\beta_j} - Y_{j,t_{0j}}) - \frac{1}{J}\sum_{k=1}^{K} w_{jk}\left(Y_{k,t_{1j}+\beta_j} - Y_{k,t_{0j}}\right), \qquad \text{Eq. 3}$$

where J denotes the number of firms in the treatment group in the matched sample. The treated CDM firms are indexed by j; the non-CDM firms are indicated by k. The weight placed on firm k when constructing the counterfactual estimate for treated facility j is w_{jk}. In our case, as we will implement nearest neighbour matching with replacement, the weight w_{jk} shows how many times the matched control firm is used to construct the ATT. Note that the flexible conditional DID compares the mean of the individual differences in outcome development between the treated firms j and their respective controls k. As can be observed from equation 3, we include individual pre-treatment start dates, denoted by index t_{0j}, and a flexible number of time units, e.g. years, $t_{1j} + \beta_j$, reflecting the individual duration of the treatment. Due to heterogeneous treatment start dates and treatment durations, the observed periods can be heterogeneous among the treated individuals.

In addition to the flexible conditional DID estimator, we also provide the mean treatment effect estimators and yearly mean treatment estimators from the fixed-effects DID models. For this purpose, we use a panel dataset for the matched firms.These parametric DID models control for year effects and industry-year effects.

For identification of causal effects, any general equilibrium effects need to be excluded, that is treatment participation of one firm cannot have an impact on outcomes of other firms. This corresponds to the stable unit treatment value assumption (SUTVA). Imbens and Wooldridge (2009) argue that the validity of such an assumption depends on the scope of the program as well as on resulting effects. We argue that in the case of CDM projects in India, the SUTVA is potentially fulfilled because these projects are of small scope and of scattered geographical coverage. One of the possible and most evident "spillover channels" could be, if a CDM firm is related to another CDM or non-CDM firm via the same firm ownership. In this case we might suspect that some CDM-induced technological solutions may be passed on to related firms. To the best of our knowledge, in our sample we do not have such firms.

5.2 Estimation procedure

After having discussed identification issues, we proceed with the estimation of causal effects. We apply nearest neighbour matching based on a combined statistical distance function. Let's us briefly discuss the main components that influence the selection into the treatment. After our discussion in Section 2 it is clear that many variables might be important for selection into CDM projects since participation in a CDM project activity is voluntary.

As a rough guide, to facilitate the selection of matching variables that will be used in the flexible conditional DID approach described above, we estimate the propensity scores for CDM firms versus non-CDM firms for the year 1999 – one year before the first CDM projects appear in our sample. We test different specifications following economic theory and previous empirical findings as discussed above. We also check econometric indicators such as significance of parameters or pseudo-R2 to find the final list of matching variables. The results of the probit-estimation can be found in Table B1 in Appendix B. In the case of the Indian manufacturing sector, we observe that variables describing firm production (total sales) and main inputs (total fixed capital assets and compensation for employees) are important. We may argue that larger firms have the capital and capabilities to undertake CDM-related investments. Many other variables, such as age, exporter status, sectoral activity, location among many others, appeared to be insignificant or only slightly significant, hence, these variables were dropped from the estimation of propensity scores. Also, to avoid confounding, we dropped the share of fuel expenditure from the matching, even though it was evident that firms with higher shares of fuel expenditures in total material expenditures are more likely to host CDM projects. In addition, we provide the distribution of the estimated propensity scores in Figure B1 in Appendix B. As we can see, the distributions of propensity scores are biased towards the tails, that is only a small fraction of CDM firms have a higher probability, on average, of investing into CDM projects than other firms. Nevertheless, non-CDM firms' propensity score distribution overlaps the region of the propensity scores of CDM firms almost completely; therefore, the overlap assumption is fulfilled.

In sum, the matching variables which are used in the flexible conditional DID approach are firm-level total sales (log), total assets (log), total fixed capital assets (log) and compensation for employees (log). Additionally, we include a two-digit industrial classification variable as an exact matching variable. We also define the matching time in relation to the treatment start. In our case, the matching time for each individual treated firm is two years before the individual treatment starts. The individual pre-treatment year is the first year before the individual treatment start year. To assess the quality of nearest neighbour matching based on a combined statistical distance function, that is, whether the matching procedure balances the distribution of observable variables between participants and non-participants, Appendix C summarises different quality measures. In sum, we can conclude that the matching quality is good.

In the next step, we estimate the average treatment effects on the treated as described in Equation 3. We also provide the mean treatment effect estimators and yearly mean treatment estimators from the fixed-effects DID models by using the panel dataset for the matched firms.

6. Results

In Section 6.1, we discuss the causal effects of the CDM projects with respect to the outcome variables described in Section 3. In Section 6.2, we verify the validity of our results with respect to unobserved selection into the treatment.

6.1 Main results

Table 4 summarises the average treatment effects on the treated as defined in Eq. (3). As the CDM projects were registered at different years, for each treated firm we use the individual pre-treatment year. The individual pre-treatment year is the first year before the individual treatment start year. The outcome variables in the pre-treatment years are then compared with their counterparts in the subsequent five treatment years. Additionally, we report the mean treatment effects estimators from the fixed-effects DID models in Table 5 and the yearly mean treatment estimators from the fixed-effects DID models in Table 6. In the fixed-effects DID models the pre-treatment period consists of all pre-treatment years available in the sample.

Total CO_2 Emissions and CO_2 Intensity

Table 4 shows that, when using the flexible conditional DID models, the CDM projects increased absolute CO_2 emissions four and five years after the treatment. However, these ATT estimates compare the developments of CO_2 emissions for the period from the first pre-treatment year until one to five years afterwards. The ATT estimates and yearly ATT from the fixed-effects DID models (see Table 5 and Table 6), which consider the overall pre-treatment period, show that the CDM projects did not significantly affect total CO_2 emissions.

These absolute CO_2 emission measures, while interesting from the point of view of the environmental integrity of the policy, do not allow us to discriminate between changes in production levels and other adjustments the firms might have made, for example, in terms of their fuel mix or their production technologies. To gain some insight into this second group of factors, we next look at changes in CO_2 intensity, measured as the ratio of firm total CO_2 emissions over firm total sales.

The ATT from the fixed-effects DID models show that the average CO_2 intensity decreased once considering five treatment years (see Table 5). The annual ATT reveal dynamics of CO_2 intensity: these estimates show that CO_2 intensity significantly decreased during the second, third and the fifth years of the treatment (see Table 6). Thus, CDM projects seem to improve CO_2 intensity immediately after the official registration date of CDM projects. Also, it seems that the CDM projects caused not a one-off decrease in firm CO_2 intensity, but rather a long-lasting improvement. This suggests that CDM firms possibly opted to reduce their use of the most CO_2 intensive fuels and invested in cleaner technologies. This implication is further strengthen by the CDM-caused increase in the total fixed capital.

Total Energy Purchase and Energy Intensity

To investigate which of these strategies have been followed by CDM firms, first, we start by looking at purchases of energy and fuels and overall energy intensity. Subsequently, we will look at the changes in fuel mix – purchases of coal, purchases of clean fuels and other energy sources, and purchases of electricity from the grid as well as self-generated electricity.

We now ask the questions whether CDM firms increased or decreased their overall energy and fuel purchases and overall energy and fuel intensity as the result of the hosted CDM projects. As one can see in our result tables, the average treatment effects on the treated estimated by using all of our considered DID models show that CDM-induced dynamics of overall energy and fuel purchases and overall energy and fuel intensity reflect CDM-induced dynamics of CO_2 emissions and CO_2 intensity. Hence, we can conclude that because of the CDM projects CDM firms became less energy and CO_2 intensive. Although it seems this result is expected, but it is not straightforward: it is not guaranteed that lower CO_2 intensity is achieved by lower energy intensity. On the opposite, it is often postulated that reductions in firm CO_2 intensity are achieved by the use of more expensive fuels and energy sources, which in the end increase the energy bill. At least in the case of CDM projects hosted by manufacturing firms in India this is not true.

Fuel Mix and Electricity Purchase

The results for CO_2 intensity may suggest that CDM projects encouraged substitution from dirty fossil fuel sources to cleaner fuel and energy sources. To investigate the CDM-induced changes in fuel mix of CDM firms, we look at the changes in purchases of coal and purchases of clean fuels and energy sources.

First, we consider the impacts of the CDM projects on purchases of biofuels and clean energy sources. Our estimates as reported in Table 4, Table 5 and Table 6 reveal that, the CDM projects had a positive and significant effect on purchases of clean fuels and energy sources. This effect is persistent – it starts immediately at the start of the treatment and continues during the five-year treatment period. We argue that the increase in the use of clean energy sources might be one of the channels through which CO_2 intensity of CDM firms was improved. This implies additionality (as we defined it) of CDM projects in the case of our sample of manufacturing CDM firms in India.

Manufacturing firms in India are well-known for relying on large shares of coal and its products in their production. Our data sample reveals that some industrial firms entirely rely on coal and coal products. It is also evident from Table 2 that, on average, CDM firms use more coal than non-CDM firms. Hence, from an environmental policy perspective, it is desirable to reduce coal consumption among the largest coal users. As one can see in Table 4, Table 5 and Table 6, the average treatment effects estimated by using all our considered DID models show that the CDM projects had no effect on coal purchases of CDM firms. This result is expected in the context of the main objectives of CDM regulation.

The final part of our analysis focuses on assessing the effects of the CDM projects on CDM firms' use of electricity. In principle, industrial firms can either purchase electricity from the grid or generate it on the site (i.e., self-generation). Knowing that many CDM projects were investing into renewable electricity technologies such as wind and solar power, it is likely that the CDM projects increased self-generation and reduced purchases of electricity from the grid. These expectations are to some extent confirmed by our results. As one can see in Table 6, the CDM projects had a negative and significant effect on electricity purchased from the grid (three years after treatment) and positive significant effect on electricity generated on site (four and five years after treatment).

6.2 Robustness test

We further test the sensitivity of the main results with respect to unobserved selection into the treatment (see our discussion in Section 5). That is, in the estimation of the counterfactual, we exploit the fact that not all firms that applied for hosting CDM projects were successful. This means that these "unsuccessful firms" are especially eligible to be part of the control group, as they show a propensity for hosting CDM projects and a need to invest in environmental measures which is very similar to that of "successful firms." We argue that the unsuccessful-application group is very similar to the treatment group in terms of its characteristics and allows us to isolate the effects of policy intervention. This argument is supported by a very good overlap of our estimated propensity scores for the "unsuccessful firms" and "successful firms" (see Appendix D).

In this robustness exercise, we consider the same outcome variables and we estimate the ATT by using the same DID models as in Section 4. The estimated results are reported in Table D1, Table D2 and Table D3 in Appendix D. The results support our main findings albeit at lower significance levels. To sum up, we conclude that for "successful" CDM firms, CDM projects made a difference when compared to "unsuccessful" CDM firms. In particular, we find that for this sample of CDM firms the CDM projects reduced CO_2 intensity, energy intensity and increased self-generation. The fact that the main results are supported by the results of this robustness test suggests that unobserved selection into treatment is not such a big issue in the case of our sample of CDM projects in India.

7. Conclusions

In this paper, we used firm-level data in India for the manufacturing sector to assess ex post the impacts of CDM projects on firms' environmental performance. Because participation into a CDM project is voluntary, we may worry that some unobservable characteristics of firms may induce both the CDM participation and some reductions in CO_2 emissions for instance. Our empirical strategy relied on comparing the outcomes of participating firms with carefully identified control firms using the difference-in-differences approach. We first identified control firms using matching techniques that compared observables for the participating firm and its control firms two years before the CDM project starts. We then used several difference-in-differences (DID) models to estimate the effects of CDM projects on firm environmental performance.

We found that the CDM projects significantly reduced firm CO_2 intensity and energy intensity, but had no effect on total CO_2 emissions. Our results also reveal different channels through which firm CO_2 intensity was likely to be improved. We showed that firms hosting CDM projects increased the use of clean fuels and energy sources. These results suggest additionality of the CDM projects hosted by manufacturing firms in India had the firms' sales expanded in a similar fashion absent the CDM projects.

Table 2: Descriptive statistics, 1988-2016

		CDM firms			non-CDM firms		
Variable	Measurement Unit	No. of obs.	Mean	Std. Dev	No. of obs.	Mean	Std. Dev
Sales	Millions R.	5,616	762	4381	103,963	46	386
Total assets	Millions R.	5,616	761	3303	103,950	46	256
Capital	Millions R.	5,612	422	1998	103,406	23	111
Compensation for empl.	Millions R.	5,616	25.4	103.6	103,963	2.7	14.4
Share of energy and fuel expenditure	%	5,616	9.98	10.34	103,954	6.0	7.9
CO2 emissions	kt	3,728	1.76E+06	6.20E+06	43,555	3.01E+06	2.47E+08
CO2 emission intensity	kt per R.	3,728	3.57E+05	2.08E+07	43,555	1.84E+05	1.43E+07
Energy purchase incl. electricity	Millions R.	3,900	88.93	391.82	45,426	50.83	5962.28
Energy intensity incl. electricity	ratio	3,900	0.18	1.71	45,426	1.61	85.05
Electricity purchased on the grid	Millions R.	3,900	8.87	34.13	45,426	36.53	6167.67
Electricity generated on the site	Millions R.	3,900	38.75	1327.15	45,426	6.56	376.08
Coal purchase	Millions R.	3,900	25.27	164.07	45,426	0.67	7.30
Biofuel purchase	Millions R.	3,900	0.54	11.71	45,426	0.04	0.34

Notes: Sales are reported in millions of current year rupees.

Table 3: Sectoral distributions of CDM and non-CDM firms

Sector name	Non-CDM firms	CDM firms	Total
Food products, beverages & tobacco	1,399	50	1,449
Textiles	1,282	41	1,323
Leather	129	1	130
Wood & Furniture	75	3	78
Paper & paper products	324	14	338
Coke & refined petroleum products	108	8	116
Chemicals	1,187	30	1,217
Pharmaceuticals	651	6	657
Plastics & Rubbers	606	11	617
Non metallic mineral products	390	24	414
Basic & Fabricated Metals	1,522	50	1,572
Computers & Electronics	892	9	901
Machinery & Transport equipment	1,134	15	1,149
Other manufacturing	205	4	209

Table 4: ATT from the flexible conditional DID models

Outcome variable	1st treatment year	2nd treatment year	3rd treatment year	4th treatment year	5th treatment year
CO_2 emissions (log)	0.0391	0.0457	0.1234	0.2309**	0.2387*
CO_2 emission intensity (log)	0.0061	-0.0844	-0.0588	-0.1012	0.0079
Energy purchase incl. electricity (log)	-0.0243	0.0281	-0.0179	0.2845**	0.1015
Energy intensity incl. electricity (log)	-0.0442	-0.0921	-0.1852	-0.0631	-0.1108
Electricity purchased on the grid (log)	0.0826	-0.0042	-0.0527	-0.0129	-0.1384
Electricity generated on the site (log)	-0.1	-0.0316	0.0162	0.3069	0.2619
Coal purchase (log)	0.0132	0.0215*	0.0066	0.0016	0.0102
Clean fuel and energy purchase (log)	0.0103	0.0558	-0.0138	0.1527	0.1821
Fixed capital (log)	0.0453**	0.0886**	0.1325***	0.1207*	0.2075***

Notes:
1. ***p <= 0.01, **p <= 0.05, *p <= 0.1.
2. In total, the sample consists of 266 treated firms and 9904 control firms.
3. The numbers of the treated and control firms in the matched sample depend for which outcome variable and at which point of time the average treatment effects were calculated.
4. In the matched sample, the number of the treated firms range from 123 to 257; The number of the control firms range from 94 to 217.

Table 5: The mean treatment effects from the fixed-effects DID models for the defined 5-years treatment period starting at individual treatment start.

Outcome variable	One treatment year	Two treatment years	Three treatment years	Four treatment years	Five treatment years	Year effects	Industry-year effects
CO_2 emissions (log)	0.1056	0.0989	0.0212	0.0519	0.0034	Yes	Yes
CO_2 emission intensity (log)	-0.0129	-0.0637	-0.1141	-0.1255	-0.1779*	Yes	Yes
No. of observations	3863	4061	3956	3789	3388		
Energy purchase incl. electricity (log)	0.1319*	0.1566**	-0.0499	0.0155	-0.0549	Yes	Yes
Energy intensity incl. electricity (log)	-0.0555	-0.1195	-0.1691*	-0.1441*	-0.2208**	Yes	Yes
Electricity purchased on the grid (log)	-0.1299	-0.1763	-0.2212	-0.2297	-0.2372	Yes	Yes
Electricity generated on the site (log)	0.4109*	0.3656	0.1564	0.4016	0.3070	Yes	Yes
Coal purchase (log)	-0.0373	0.0764	0.1436	0.2063	0.0081	Yes	Yes
Clean fuel and energy purchase (log)	0.2438**	0.3205***	0.2922***	0.2923**	0.2568*	Yes	Yes
No. of observations	4065	4245	4196	4021	3615		
Fixed capital (log)	0.1860***	0.2227***	0.2495***	0.2520***	0.2074***	Yes	Yes
No. of observations	6675	7155	7193	7091	6336		

Notes:

1. ***p <= 0.01, **p <= 0.05, *p <= 0.1.
2. In total, the sample consists of 266 treated firms and 9904 control firms.
3. The numbers of the treated and control firms in the matched sample depend for which outcome variable and at which point of time the average treatment effects were calculated.
4. In the matched sample, the number of the treated firms range from 123 to 257; The number of the control firms range from 94 to 217.

Table 6: The mean annual treatment effects from the fixed-effects DID models.

Outcome variable	1st treatment year	2nd treatment year	3rd treatment year	4th treatment year	5th treatment year	Year effects	Industry-year effects	No. of control firms	No. of treated firms	No. of observations
CO_2 emissions (log)	-0.0756	-0.0649	-0.0879	0.1181	0.0933	Yes	Yes	94	123	3388
CO_2 emission intensity (log)	-0.1439	-0.1948*	-0.2624**	-0.1138	-0.1817*	Yes	Yes	94	123	3388
Energy purchase incl. electricity (log)	-0.1457	-0.1204	-0.2286	0.1135	0.0527	Yes	Yes	101	130	3615
Energy intensity incl. electricity (log)	-0.1737	-0.2355*	-0.4037***	-0.1032	-0.2033*	Yes	Yes	101	130	3615
Electricity purchased on the grid (log)	-0.0823	-0.2177	-0.3844**	-0.2821	-0.3114	Yes	Yes	101	130	3615
Electricity generated on the site (log)	-0.0853	-0.0141	0.2683	0.6934**	0.6378**	Yes	Yes	101	130	3615
Coal purchase (log)	-0.2157	0.0939	-0.0700	0.0520	0.1753	Yes	Yes	101	130	3615
Clean fuel and energy purchase (log)	0.1619	0.2621*	0.2639‡	0.3020	0.3186*	Yes	Yes	101	130	3615
Fixed capital (log)	0.1174‡	0.1588**	0.2235**	0.2488***	0.2846***	Yes	Yes	214	254	6336

Notes:

1. ***p <= 0.01, **p <= 0.05, *p <= 0.1, ‡p <= 0.15.
2. Before matching the sample consisted of 266 treated firms and 9904 control firms.
4. In the matched sample, the number of the treated firms range from 123 to 257; The number of the control firms range from 94 to 217.

Appendix A: Data Appendix

We compile a firm-level panel data set that spans the period from 1988 to 2016 based on the Prowess database, collected by the Centre for Monitoring the Indian Economy (CMIE). Like most firm surveys, the Prowess database contains information primarily from the income statements and balance sheets of large publicly listed companies.

Unlike the Annual Survey of Industries (ASI), the Prowess data is a panel of firms that have not been anonymized. As a result, we use the name of companies to merge the information on sales, production and inputs from their annual reports to the lists of participating Indian firms in the CDM Pipeline UNEP Database. From our list of 734 firms that were successful in implementing at least one CDM project, we were able to find 388 of them in the Prowess dataset. Additionally, from our list of 521 firms that were unsuccessful in implementing a CDM project, we were able to find 328 of them in Prowess.

We only exploit firm-level information from the Prowess database, even though many studies have focused on the product-level information contained also in Prowess (Barrows & Ollivier, 2018; De Loecker et al, 2016; Goldberg et al 2010). In their annual reports, firms give detailed accounts of both inputs – especially energy – and outputs. In particular, firms report the total values of their sales, of their assets, and of their fixed assets (capital). On the input side, firms report total compensation to their workers (wages), the value of materials, and total fuel and energy expenditures. They also report in detail the value and quantity (with units) of each energy source – coal, electricity from the grid, natural gas, etc. – used in the production process. From this detailed information, we compute the share of each energy source in total energy expenditures.

We compute CO2 emissions from the detailed energy-use reports contained in Prowess. We follow previous work in multiplying energy consumption by energy-specific CO2 emissions factors. In particular, we follow the same methodology as in Barrows and Ollivier (2018). We translate physical quantities of energy consumed into physical quantities of CO2 emissions and sum over energy sources to compute firm-level emissions. Source specific emissions factors come from the US EPA 2012 Climate Registry Default Emissions Factors (http://theclimateregistry.org/wp-content/uploads/2015/01/2012-Climate-Registry-Default-Emissions-Factors.pdf). For electricity generation, we use the Indian average CO2 emission intensity of grid electricity that equals 951 g CO2 per kWh. Once units have been standardized, if we cannot match units of energy from Prowess with the EPA report, we drop these observations. Overall, we are able to assign an emission factor to 83% of energy source unit pairs (e.g., kWh of electricity). Of the 17% of such pairs that we cannot assign an emission factor, in many cases it appears that units have been misspecified: for instance, we cannot assign an emission factor to observations denominated in “liters” of electricity.

We also address an issue relating to self-generated electricity. When firms produce their own electricity, they report the energy inputs used for that production. Hence, to avoid double counting, we compute the CO2 emissions for self-generated electricity based on the energy inputs reported, and we do not use the national average CO2 emission factor for grid electricity.

Finally, we treat outlier observations in the input dataset in two ways. First, we identify firm emission intensities which look like entry errors and assign to those values instead the average emission intensity of the firm over the period. This procedure affects less than 1% of the data. Next, we drop entire firm profile if the emission intensity of the dirtiest year of the firm is at least 600 times greater than the cleanest year of the firm. We also drop a few outlier observations with implausibly large implied CO2 emissions (1% of the data).

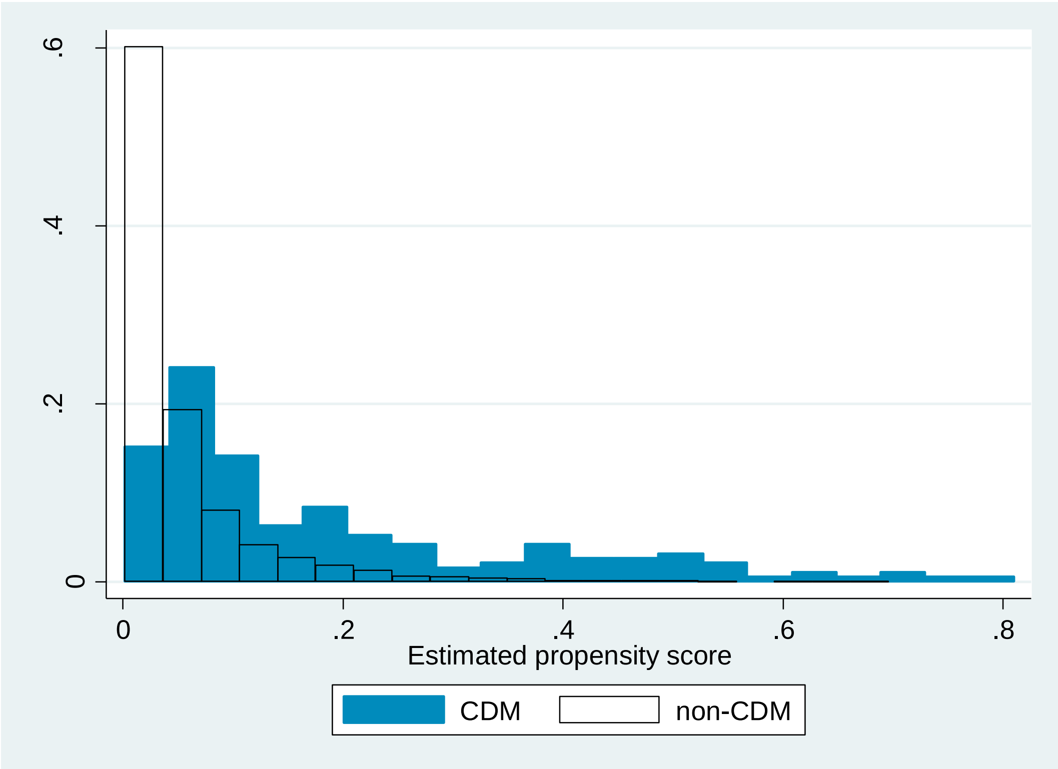
Appendix B: Measurement of propensity scores

Table B1: Estimation of propensity scores

Variables	Coef.		Stad err.
Sales (log)	0.3048	***	0.0577
Total assets (log)	-0.0099		0.0914
Total capital (log)	0.2723	***	0.0751
Compensation for empl. (log)	-0.2182	***	0.0519
Constant	-2.9957	***	0.1487
No. of observations			
LR $Chi^2(4)$			
Prob > Chi^2			
Pseudo R^2			

Note: 1. ****p* <= 0.01, ***p* <= 0.05, **p* <= 0.1.

Figure B1: Distributions of the estimated propensity scores for CDM and non-CDM firms in the panel satysfying the common support



Appendix C: Quality of matching

To assess the quality of matching and comparability of the matched groups, the results of different tests are presented next. For every matching procedure, we get the results from the tests as provided in the *Stata* command *pstest* by Leuven and Sianesi (2003) and a graphical proxy of the balance of the variable distributions in the treated and control groups. The tests are performed at matching time, in our case, two years before the treatment starts. Below we summarise the tests applied for the largest matched sample. The results for the smaller matched samples are available from the authors upon request.

For each of the matching variables, we find the means in the treated and in the control groups, a measure for the standardized percentage difference – or bias – between the means in both groups, and a test if the means in the control group equal the ones in the treated group. Additionally, we get an information on the similarity of the variances in the treated and the control group. From the summary of these tests presented in Table C1 we conclude that the means and variances of all the matching variables are balanced.

Table C1: Ps-test

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
logsales_pre1	4.3783	4.2913	4.9	0.56	0.578	1.11
logtotassets_pre1	4.4595	4.3003	9.1	1.04	0.301	1.20
logcapital_pre1	3.8292	3.7708	3.2	0.36	0.718	1.14
logcompensation_pre1	1.1855	1.1463	2.3	0.26	0.793	1.11

* if variance ratio outside [0.78; 1.28]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.008	5.73	0.221	4.9	4.1	20.9	1.99	0

* if B>25%, R outside [0.5; 2]

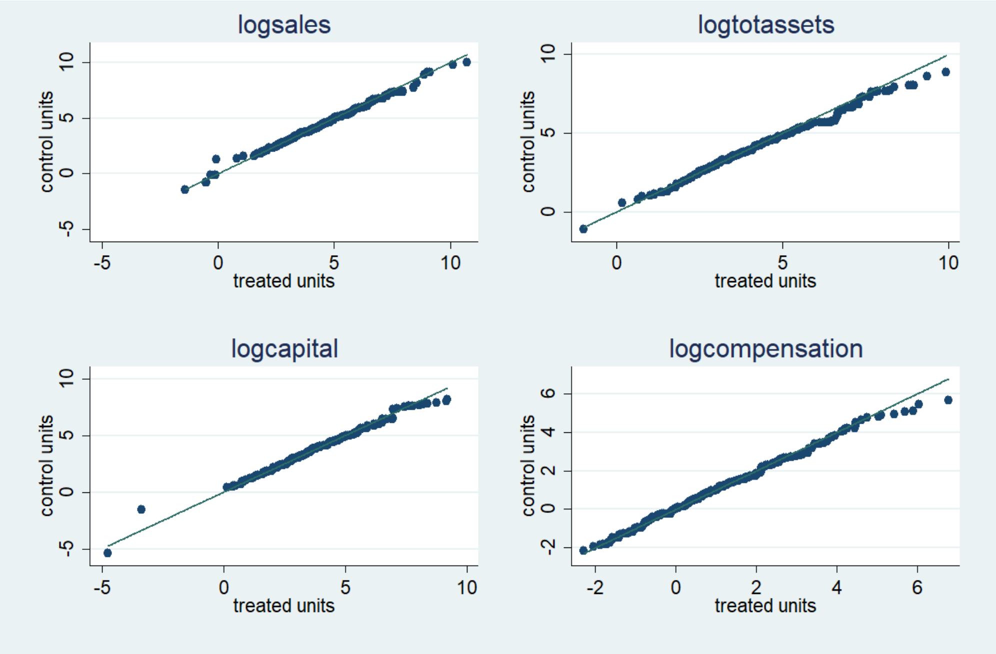
Additionally, Table C2 presents the results of a Kolmogorov-Smirnov (KS) test. The corrected *p*-values indicate that there are no statistically significant differences in the matching variable distributions between the treated and control groups.

Table C2: Two-sample Kolmogorov-Smirnov test for equality of distribution functions for matching variables

```
ksmirnov logsales_pre1 , by(treated)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 0:                 0.0467    0.571
 1:                -0.0195    0.907
 Combined K-S:      0.0467    0.942      0.929

Note: Ties exist in combined dataset;
      there are 504 unique values out of 514 observations.
ksmirnov logtotassets_pre1 , by(treated)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 0:                 0.0623    0.369
 1:                -0.0350    0.730
 Combined K-S:      0.0623    0.702      0.664

Note: Ties exist in combined dataset;
      there are 504 unique values out of 514 observations.
ksmirnov logcapital_pre1 , by(treated)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 0:                 0.0467    0.571
 1:                -0.0233    0.869
 Combined K-S:      0.0467    0.942      0.929

Note: Ties exist in combined dataset;
      there are 502 unique values out of 514 observations.
ksmirnov logcompensation_pre1 , by(treated)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 0:                 0.0506    0.518
 1:                -0.0311    0.780
 Combined K-S:      0.0506    0.897      0.877

Note: Ties exist in combined dataset;
      there are 498 unique values out of 514 observations.
```

The quantile-quantile (QQ) plots of the matching variables compare the distributions in both groups by means of the plotted quantiles. The 45º-line represents identical distributions. From Figure Figure C1 we see very small deviations from the 45º-line for all matching variables. This ensures even further that the quality of matching is very good.

Figures C1: QQ plots of the matching variables at matching time



Appendix D: The sample of “successful firms” vs. “unsuccessful firms”

Figure D1: Distribution of propensity scores of “successful firms” (CDM firms) vs. “unsuccessful firms” (non-CDM firms)

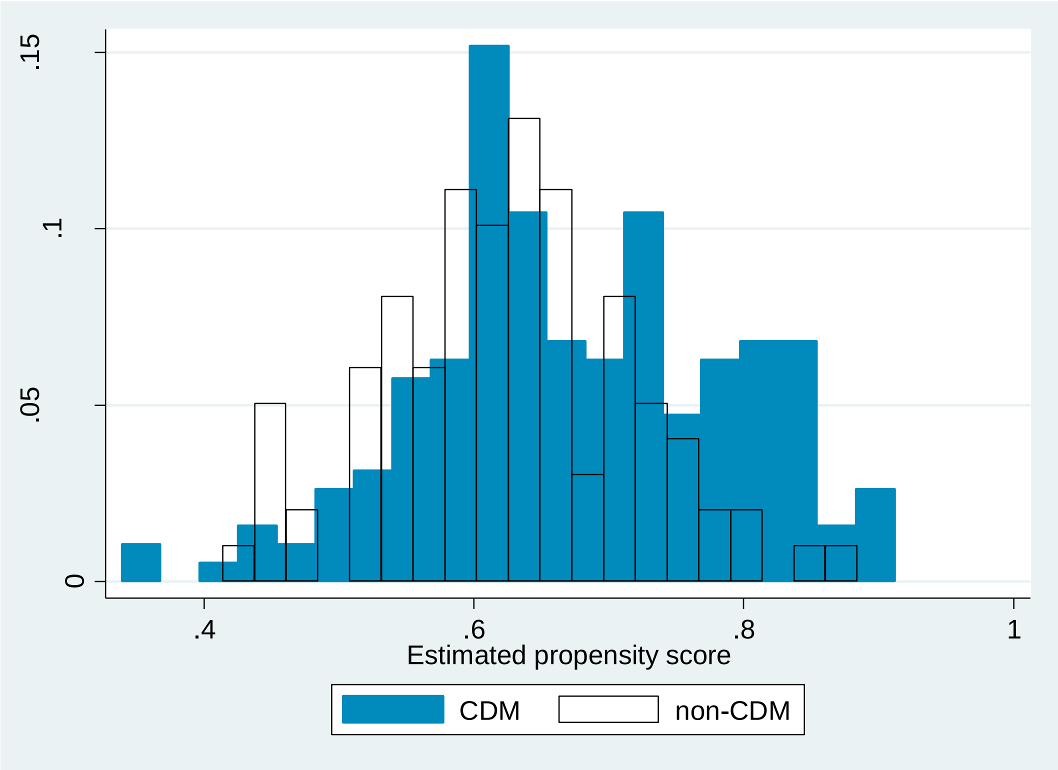


Table D1 ATT from the flexible conditional DID models, the sample of "successful firms" vs. "unsuccessful firms"

Outcome variable	1st treatment year	2nd treatment year	3rd treatment year	4th treatment year	5th treatment year
CO_2 emissions (log)	-0.0555	0.074	0.0773	0.1276	0.011
CO_2 emission intensity (log)	-0.059	-0.0058	-0.0455	-0.0117	-0.0725
Energy purchase incl. electricity (log)	-0.0387	-0.0335	-0.1185	-0.0187	-0.1966
Energy intensity incl. electricity (log)	-0.0211	-0.0855	-0.2447**	-0.1343	-0.2396*
Electricity purchased on the grid (log)	0.0054	-0.0345	-0.0925	-0.1374	-0.3515*
Electricity generated on the site (log)	-0.0248	-0.1065	0.0026	0.193	0.062
Coal purchase (log)	0.0806	0.3815**	0.2407	0.1588	0.2777
Clean fuel and energy purchase (log)	-0.0411	0.0785	0.1014	0.1361	0.1767
Fixed capital (log)	-0.0091	0.0056	-0.0136	-0.0337	-0.0095

Notes:

1. ***p <= 0.01, **p <= 0.05, *p <= 0.1.
2. In total, the sample consists of 266 treated firms and 201 control firms.
3. The numbers of the treated and control firms in the matched sample depend at which point of time the average treatment effects were calculated.
4. In the matched sample, the number of the treated firms range from 122 to 187; The number of the control firms range from 53 to 87.

Table D2: The mean treatment effects from the fixed-effects DID models for the defined 5-years treatment period starting at individual treatment start, the sample "successful firms" vs. "unsuccessful firms"

Outcome variable	One treatment year	Two treatment years	Three treatment years	Four treatment years	Five treatment years	Year effects	Industry-year effects
CO_2 emissions (log)	-0.0856	-0.0227	0.0343	-0.0589	-0.1017	Yes	Yes
CO_2 emission intensity (log)	-0.0494	0.0228	0.0395	-0.0708	-0.0411	Yes	Yes
No. of observations	2956	3068	3120	2833	2660		
Energy purchase incl. electricity (log)	-0.0212	-0.0598	-0.0083	-0.1241	-0.1563	Yes	Yes
Energy intensity incl. electricity (log)	0.0190	-0.0073	-0.0386	-0.1656	-0.1360	Yes	Yes
Electricity purchased on the grid (log)	-0.0927	-0.1559	-0.1124	-0.3059**	-0.4327***	Yes	Yes
Electricity generated on the site (log)	0.4779*	0.4362*	0.4081‡	0.3863	0.4637‡	Yes	Yes
Coal purchase (log)	0.0208	0.1352	0.1413	0.1007	-0.1548	Yes	Yes
Clean fuel and energy purchase (log)	-0.1472	-0.0761	0.1018	0.1687	0.1200	Yes	Yes
No. of observations	3121	3233	3332	3006	2851		
Fixed capital (log)	-0.0022	-0.0081	0.0061	-0.0179	0.0230	Yes	Yes
No. of observations	4922	5186	5334	5176	4848		

Notes:

1. ***p <= 0.01, **p <= 0.05, *p <= 0.1, ‡p <= 0.15.
2. In total, the sample consists of 266 treated firms and 201 control firms.
3. The numbers of the treated and control firms in the matched sample depend at which point of time the average treatment effects were calculated.
4. In the matched sample, the number of the treated firms range from 122 to 187; The number of the control firms range from 53 to 87.

Table D3: The mean annual treatment effects from the fixed-effects DID models, the sample of "successful firms" vs. "unsuccessful firms"

Outcome variable	1st treatment year	2nd treatment year	3rd treatment year	4th treatment year	5th treatment year	Year effects	Industry-year effects	No. of control firms	No. of treated firms	No. of observations
CO_2 emissions (log)	-0.1821	-0.2159	0.0019	-0.0750	-0.2567‡	Yes	Yes	53	122	2660
CO_2 emission intensity (log)	-0.0765	0.0515	0.0590	-0.0117	-0.2211‡	Yes	Yes	53	122	2660
Energy purchase incl. electricity (log)	-0.1547	-0.0900	-0.2179	-0.0407	-0.2993*	Yes	Yes	55	129	2851
Energy intensity incl. electricity (log)	-0.0864	-0.0729	-0.2225	-0.0249	-0.2755*	Yes	Yes	55	129	2851
Electricity purchased on the grid (log)	-0.2883**	-0.4463***	-0.4451 **	-0.4402**	-0.6736**	Yes	Yes	55	129	2851
Electricity generated on the site (log)	0.4178	0.2724	0.2724	0.8273**	0.6279	Yes	Yes	55	129	2851
Coal purchase (log)	-0.2594	0.1636	-0.1790	-0.1789	-0.1664	Yes	Yes	55	129	2851
Clean fuel and energy purchase (log)	-0.0096	0.1996	0.2611	0.1071	0.0742	Yes	Yes	55	129	2851
Fixed capital (log)	-0.0171	-0.0193	-0.0163	0.0114	0.0230	Yes	Yes	87	187	4848

Notes:

1. ***p <= 0.01, **p <= 0.05, *p <= 0.1, ‡p <= 0.15.
2. In total, the sample consists of 266 treated firms and 201 control firms.
3. The numbers of the treated and control firms in the matched sample depend at which point of time the average treatment effects were calculated.
4. In the matched sample, the number of the treated firms range from 122 to 181; The number of the control firms range from 53 to 74.

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