I'm Sitting This One Out: What non-participants reveal about counterfactual emissions*

Kim Liu Leslie A. Martin[†]

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Abstract

In a voluntary emissions-reductions system, regulators must evaluate and sign off on firms' claims of what they would do absent credits. This paper uses the behavior of non-participants to ex-post evaluate these claims. We focus on carbon offset projects in industrial energy efficiency, co-generation, input substitution, and fuel switching that are supplied by firms in India to the international emissions trading market through the Clean Development Mechanism (CDM). We identify the firms involved in over 600 CDM projects in a comprehensive dataset of Indian manufacturing firms. We first look for signs of strategic selection into program participation. After controlling for firm size and industry, there is no evidence that applicants are more likely to have decreasing emissions trends pre-application. We then evaluate behavior ex-post. We find that participants indeed reduce emissions intensity relative to similar non-participant firms, but in a way that is moderated by a greater expansion of output. Looking across project types, the largest emission reductions come from projects that improve energy efficiency and export excess energy to the grid. Fuel switching and input blending projects are more questionable recipients of credits because non-participants engage in these activities at similar rates.

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[†]Corresponding author: leslie.martin@unimelb.edu.au, Department of Economics, University of Melbourne. JEL codes: Q56, Q52, O14

1 Introduction

There is an increasing trend in the use of opt-in regulation to encourage environmental protection at a minimal cost to economic growth, particularly in developing and industrializing countries.[1] These policies reward abatement efforts rather than punish emitters. One important example of opt-in regulation is emissions offsets. With offsets, one party voluntarily agrees to reduce emissions in exchange for a payment from another party. Offsets can be linked to a cap-and-trade system, in which case regulated firms or countries can use low-cost emission reductions in regions outside of a regulator's scope to comply at lower cost. However, the success of such programs has proven difficult to quantify and justify.

There is a real concern that current offset programs provide credits that don't truly reduce emissions. To allocate the right number of credits to an offset project, regulators need to estimate counter-factual emissions trajectories. They need to first determine whether each project is *additional*, i.e. that it would not have taken place were it not for the credits. Firms have incentive to propose projects that they would want to undertake even absent offset credits.

If the project is deemed additional, the regulators furthermore need to determine exactly how many credits to award. Offset projects typically improve environmental outcomes by displacing dirtier processes, so the number of credits awarded depends critically on what is displaced, which can be difficult to determine. In some cases, projected emissions in the absence of the project also include assumptions about expected firm growth, which can also be difficult to access or evaluate. Finally, firms may self-select strategically into providing offsets based on systematic errors in establishing counterfactuals. Specifically, firms that expect to benefit from over-generous baselines may be particularly keen to apply.

In this paper we evaluate a subset of projects in the largest project-based crediting system to date, the Clean Development Mechanism (CDM). The CDM is one of three "flexibility mechanisms" in the Kyoto Protocol. Countries and firms can meet part of their Kyoto Protocol commitments in the EU Emissions Trading Scheme using Certified Emission Reductions (CERs) generated by CDM projects. Launched in 2005, the CDM has directed funding to over 7000 projects in 80 poor or industrializing countries. In the first phase between 2006 and 2012, it credited 1.5 billion tons of carbon reductions.

We focus on carbon offset projects in industrial energy efficiency, co-generation, fuel switching, and input substitution in India. India is the second largest source of CERs and the host of over 1400 projects. It is also an ideal candidate for analysis because extensive firm-level financial data is available with firm-name identifiers. The emergence of India as a major industrial economy makes it an

[1] The policy goals of voluntary regulation are different for countries at varying stages of development. Blackman et al. (2010) suggest that for developed countries, voluntary regulation is designed to complement mandatory regulation and encourage over-compliance. In developing countries on the other hand, voluntary programs are often preferred in order to remedy non-compliance with mandatory regulation, as a result of limited public support, weak institutions, or insufficient resources.

important player in the global climate challenge, with possible implications for other developing nations. We focus on the manufacturing sector because it is an essential and emissions-intensive component of India's economy. Also, in manufacturing – unlike in most renewable generation projects – firms exist and can be observed pre-treatment.

The main innovation of our research is that, unlike previous studies, we don't just look at the behavior of participants after the program was launched. We identify the firms involved in CDM projects in a comprehensive dataset of Indian manufacturing firms, the CMIE Prowess dataset. By focusing on firms instead of projects, we are able to observe both participants and non-participants, both during the program and in the years before the program was announced. We use pre-program data to match applicants to similar firms that did not apply, and participants to similar firms that did not participate. We can thereby study both who offers to reduce emissions and how much participants reduce emissions relative to their similar peers. Specifically, we ask: To what extent does a distorted selection of firms enter the market to supply offsets? and then: To what extent do firms that receive credits fundamentally alter their emissions profiles relative to similar non-participant firms?

In the first stage we model this selection equation: specifically, we model the firm's decision to offer to supply carbon offsets to the CDM. We use pre-program data from 2001 through 2003. We document that firms applying to the CDM are indeed on average larger, i.e. better able to afford the high fixed costs associated with project participation. Once we control for firm size and industry, applicants are no more likely to be less productive, more capital-intensive, heavily indebted, exporters, or members of conglomerates. These results are in line with a model where fixed costs of preparing projects for approval deter smaller, less well-connected firms from applying. Human capital intangibles, like managerial expertise, which have been shown to play a strong role in the decision to export, do not appear to directly drive participation above and beyond a correlation with firm size. We also find that CDM applicants and participants are more likely to be on ex-ante trajectories of expanding capacity, which is consistent with the view that abatement is cheaper at the investment stage than as a retrofit.

We also check for signs of selection with respect to emissions profiles. We impute fuel-based emissions using firm-level input data on physical quantities and expenditures disaggregated by fuel type, and we impute additional process-based emissions for cement firms based on limestone inputs. Because credits are allocated based on historical emissions or emissions intensity, depending on the methodology, firms on a trend of decreasing emissions or emissions intensity may be over-compensated with credits. Yet we find no evidence that firms on trends of decreasing emissions or emissions intensity are more likely to apply to supply carbon offsets.[2] Heavy emitters are also no more likely to apply once we control for firm size.

[2]Pre-CDM emissions trends are unlikely to reflect strategic inflation of baselines because the program was largely unanticipated.

We then examine the impact of CDM participation on the change in fuel-related carbon emissions between pre-CDM years and the years of the first phase of the program: 2006 through 2012. We control directly for pre-treatment trends and characteristics at the firm level, and in an alternate specification implement a nearest-neighbor matching estimator. In both cases we find that participants reduce their emissions intensity of output faster than non-participants and, to a lesser extent, experience a lower growth rate in emissions. The effects are larger in the later years. When we estimate the impact of participation on total factor productivity, we observe costs incurred from the very first periods of the program.

We also find strong heterogeneity across project types. Emissions intensity improves in energy exports, energy efficiency, and, to a lesser extent, waste heat recovery. Firms with projects that reduce emissions per unit output by blending additives into the final product, on the other hand, experience increases in emissions and productivity relative to counterfactual firms. Fuel switching projects show no net benefit.

Finally, we consider rejected applicants. If these firms had submitted non-additional projects, we would expect to see their emissions decrease even though their applications were denied. We see no such effect: their emissions increase, whereas emissions intensity remains unchanged.

This paper is one of first papers to empirically evaluate the supply of carbon offsets. The closest paper to this one is Montero (1999), which documents that firms on pre-policy trends of decreasing SO_2 emissions are more likely to supply credits to the US Acid Rain program. With the exception of a series of empirical studies focused on assessing sustainable development and technology transfer,[3] the CDM literature has to-date been characterized predominantly by case studies. Some key examples are Haya (2009); Shrestha and Timilsina (2002); Schneider et al. (2009); Tanwar (2007); Wara (2008). These previous studies focus on project characteristics, asking *which projects are firms choosing?*. In contrast, this paper emphasizes firm characteristics, asking *which firms opt-in?* It is also jointly the first paper to use counterfactual non-participant firms to test for the additionality of emissions reductions. A parallel project, Colmer et al., looks at wind projects in India. The advantage of our focus on industrial sector credits is that we can observe participants pre-treatment.

The paper proceeds as follows: Section 2 provides a brief background of the CDM. Section 3 explores our expectations for participation and additionality. Section 4 describes the data. Section 5 outlines our empirical strategy and Section 6 presents our results. Section 7 concludes.

[3] De Coninck et al. (2007); Sutter and Parreño (2007); Dechezleprêtre et al. (2008, 2009)

2 Background

The CDM is a system of project-based crediting that can be considered the voluntary "baseline-and-credit" equivalent of mandatory "cap-and-trade" programs. The negotiations leading to the CDM were first discussed in Marrakesh, Morocco in late 2001 and adopted by the Conference of the Parties of United Nations Framework Convention on Climate Change (UNFCCC) in November 2005. The CDM awards offset credits known as Certified Emission Reductions (CERs), to abatement projects in developing (non-Annex I) nations. The credits can be purchased by Annex I nations or by firms in those countries in order to meet emission reduction obligations in the European Union Emissions Trading Scheme (EU-ETS) from commitments made in the UNFCCC's Kyoto Protocol. The CDM provides additional low-cost compliance options for entities in Annex 1 countries and involves non-Annex I nations in global efforts to reduce GHGs.

The CDM Executive Board (EB) is charged with ensuring the credible allocation of CERs. It approves projects on a one-by-one basis by evaluating Project Design Documents (PDD) prepared according to pre-approved methodologies. This process of registration involves significant transaction costs, including the hiring of consultants and auditors. Costs vary project-by-project, but are considered to be on the order of USD \$200,000. For context, at \$3 a CER, a typical industrial energy efficiency project could generate \$20,000 to \$100,000 a year for 10 years. It is common for the transfer of CERs for successful projects to significantly lag the decision to participate. Three year delays from the time the first consultant is hired to the time the project is registered (i.e. approved by the Executive Board) are not uncommon.[4] The project-by-project approval process has been accused of being simultaneously too costly and achieving too little. There are concerns (Haya (2009) and Wara (2008)) that despite the costly oversight, credits are too easy to obtain.

Manufacturing firms participate using a variety of CDM approved project methodologies.[5] Energy efficiency and fuel-switching projects feature prevalently in our sample. These projects mostly involve the installation or retrofit of energy-efficient equipment to directly reduce emissions in production (172 projects), or to recover residual waste products, such as heat, gas or pressure, for in-house energy consumption (152 projects).[6] Capital upgrades may be performed alongside fuel substitution to less carbon-intensive alternatives, or performed as a separate project for existing equipment.[7]

As a fundamental input in construction and development, and an extremely energy-intensive product, cement is a particularly important industry.[8] Biomass projects involving bagasse power or biomass

[4]See Appendix A for a detailed account of the CDM registration process and and an illustrative example.

[5]A complete description of all CDM approved methodologies can be found: http://cdm.unfccc.int/methodologies/documentation/index.html.

[6]See AMS-II.D. *Energy efficiency and fuel switching measure for industrial facilities*, ACM0012/ACM0004 *Recovery of waste heat for energy production*, AMS-III.Q. *Waste energy recovery (gas/heat/pressure) projects.*

[7]See AMS-III.B. *Switching fossil fuels to lower GHG intensity fuel for industrial, residential, commercial or electricity generation applications.*

[8]Clinker production requires significant on-site fossil fuel and electricity consumption in order to achieve temperatures of

briquettes are also common (205 projects). These projects typically involve electricity cogeneration for in-house consumption using manufacturing byproducts.[9] Our final subset of projects involves the blending of additives into clinker, replacing some fraction of the lime with fly-ash or slag byproducts from thermal power plants and steel plants respectively (25 projects).[10]

3 Conceptual Framework

Additionality and baselines

Determining additionality is a major challenge in opt-in programs. The task of identifying which projects are beyond business as usual can be described as the *extensive* margin in crediting abatement efforts. Credits for non-additional projects divert resources away from productive activities to project regulation and registration, without the benefits of emission reductions. When the offsets are linked to a cap-and-trade system, credits for non-additional projects effectively inflate the cap, increasing the total level of emissions in the system.

Haya (2009) examines non-additionality for the energy sector in India, and finds evidence that many projects begin before their CDM registration is complete. She also provides anecdotal evidence that many lenders will only finance CDM projects that are non-reliant on CER incomes, and that consultants recommend that firms to not rely on CERs.

A second challenge with offset programs is determining firm-specific counterfactual emissions trajectories. The task of identifying an appropriate baseline or reference level of emission be described as the *intensive* margin in crediting abatement efforts. Firm-level baselines can be set by historical levels of emissions or, in some cases, as a function of historical emissions intensity and forecasted growth trends. They can also be set as a function of industry averages or leading firm standards, at intensity or absolute levels. Fischer (2005) characterizes the impacts of benchmarks and the incentives for participants given regulator uncertainty. She shows how different crediting systems can systematically over-allocate offsets and lead to inefficient investment decisions, however efforts to more accurately calculate emission reductions can increase the cost of administration and impose barriers to entry.

Bushnell (2011) uses the framing of adverse selection to explore the theoretical sources of non-additional offsets in the CDM, noting that the supply of offsets will also be particularly attractive for firms whose baselines are overestimated. Given that most baselines in the projects that we study are based on a firm's historical emissions or emissions intensity over a one to three year horizon, we would worry about adverse selection if firms that apply to the CDM are disproportionately ones with

up to 1500°C and also releases CO_2 when the limestone $CaCO_3$is converted to lime CaO.

[9] See ACM0006 *Electricity and heat generation in power plants using biomass*

[10] See ACM0005 *Use of blending material in lieu of clinker.*

decreasing trends in pre-treatment emissions or emissions intensity.[11]

Uncertainty regarding the counterfactual scenario and true costs of participation create difficulties in credibly allocating offsets. Policy makers will want to take steps to prevent and minimise both margins for error, particularly given the likely presence of adverse selection. However, such actions require tradeoffs between the accurate assessment of additional emission reductions and the successful encouragement of low-cost abatement. Regulators are limited in their ability to elicit truthful information from firms. The experience of registration in the CDM suggests that bureaucratic processes to filter participants can significantly add to transaction and administration costs. As registration represents a fixed cost of entry, more rigorous processes can result in higher fixed costs, reducing accessibility for both smaller and less productive firms. Regulator efforts to detect adverse selection and optimise efficiency may instead exclude low-cost of abatement firms and increase the aggregate cost of emission reductions.

Previous studies allege that registration in the CDM lacks the rigour to systematically reject non-additional projects (Michaelowa and Purohit, 2007; Zhang and Wang, 2011), while a member of the CDM EB also labels the process as highly subjective and inconsistent (Schneider et al., 2009). Michaelowa and Jotzo (2005) and Krey (2005) claim that firm size is the key parameter for CDM participation in India, as it determines how fixed transaction costs are spread. To the extent that smaller firms are a viable source of low-cost emission reductions, the burden of registration would result in aggregate efficiency losses for the CDM.

Expectations for who participates

There is a limited literature on what drives firms to participate in the CDM. Phillips and Newell (2013) explore the role of institutions and governance in India, and how they may influence the distribution of CDM costs and benefits. They argue that institutional pressures faced by firms may influence their ability or desire to participate. Approaching the selection question from the perception of firms and managers, Hultman et al. (2012) survey 82 firms from the sugar and cement industries in India. They find significant dispersion in the attitudes stated by managers, signalling entry decisions were much more complex than simple net present value calculations, and took into consideration indirect financial benefits such as consumer branding and international reputation. Finally, Schneider (2009) examine firm characteristics of 44 participants in the paper and pulp industry in India. Instead of formal empirical tools, the authors propose and apply a summary analysis based on the "input, process and output" of firms. They find positive correlations between participants and firm size (production capacity).

[11] Bushnell also describes the potential for *moral hazard* involving rent-seeking behaviour in active attempts to adjust baselines or influence the assessment of additionality. We expect that moral hazard is minimal during the first round of CDM projects because the program was unanticipated. It may well play a role in subsequent rounds.

We expect the supply of offsets to originate from two types of firms: those who can afford fixed entry costs, and those with the lowest costs of abatement. As many characteristics will be closely related, we emphasise our expectations *ceteris paribus*.

There are many parallels that can be made between the decision to enter an offset market and the decision to enter an export market. Barriers to entry arise from significant fixed costs, bureaucratic hurdles, and market uncertainties at both the project and political/legal level. Similar diversities separate firms, some of which are hindered by a lack of awareness or managerial constraints, while others face fewer transaction costs and smoother entry from greater international presence. Momentum and neighborhood spillovers can also have a role, as firms that view their competitors entering are incentivized to follow suit. Firms in both markets also receive the benefits of an additional income stream that is less sensitive to domestic market conditions and more exposed to international conditions, including foreign exchange risk.

The CDM is designed to attract firms with low-cost emission reduction opportunities. In an ideal world, participants would have the lowest, but strictly non-zero, marginal costs of abatement. We would expect to see projects that would displace the dirtiest emissions, for example, from firms running diesel generators or with factories located in a region with high grid-level emissions.[12] Investments that phasing out very old vintages of capital stock would yield larger emission reductions than investments that displace more recent vintages.

CDM investments to install new equipment are likely to be less costly than efforts to replace or retrofit existing capital. Participants intent on expanding production capacity may have lower costs of abatement. Younger firms are likely to be expanding and more flexible in adopting new technologies; though older firms could have more opportunities to phase out very old vintages of capital stock. Some firms may have low-cost fuel-switching opportunities due to their access to alternative fuels and inputs.

Firms with lower debt obligations and capital constraints may have greater ability to invest in additional opportunities in the CDM. Capital-intensive firms may have more capacity for emission reductions versus labor intensive producers, but may also face larger fixed costs for retrofitting or replacing heavier infrastructure.

Multinationals have the advantage of international personnel and greater access to new technologies. Group-owned firms are also more likely to engage in emission "shifting" between regulated and unregulated facilities, thus inflating their reduction efforts and reducing their true abatement costs.[13] Given the similar entry decisions and potential "green" marketing effects from more responsive international consumers, exporters are also likely to participate (Arora and Cason, 1996).

[12] Although regional emission coefficients varied significantly before the CDM, transmission capacity improved and the CEA started issuing reports aggregating all of the non-Southern regions into one region, with an average grid coefficient similar to the one in the South.

[13] This problem is known as *leakage* and features in both mandatory and voluntary regulation. See Bushnell and Mansur (2011) for an examination of the theoretical sources of leakage.

It is unclear whether we should expect state-owned firms to be especially likely to supply carbon credits. As "operational-focused" entities rather than "profit-seekers", state-owned firms may be seeking fewer opportunities beyond their legislated tasks, and be less inclined to apply to the CDM. However, "top-down" directives or support from an environmental department or whole-of-government may encourage entry.

Fixed transaction costs are identified as significant barriers to entry. From our export market analogy, we expect participant firms to be both larger and more productive (Melitz, 2003; Michaelowa and Jotzo, 2005). High-productivity firms may represent industry "leaders" who are likely to be more experienced in efficiency improving projects and searching for profitable opportunities. They may also have superior managerial staff more capable of handling additional administration, or simply better at identifying and exploiting opportunities (DeCanio and Watkins, 1998). On the other hand, low-productivity firms may have particularly old vintages of capital stock to displace, that make CDM projects to be particularly efficiency-improving and attractive investments.

Finally, firms with decreasing emission trends will be more likely to participate as they have already shown an intent to reduce emissions (Bushnell, 2011). These patterns of participation may also be evidence of adverse selection (Montero, 1999) because baselines can be calculated based on emissions or emissions intensity averaged over multiple years.

4 Data

The UNEP CDM Pipeline contains 1057 PDDs for projects in India in industrial energy efficiency, waste heat recovery and use, fuel switching or substitution, blending of additives, and co-generation from biomass. We exclude 152 duplicated projects. We successfully manually link 616 projects (68% of projects) to firms from the CMIE Prowess dataset. Our failed concordances are primarily projects that are prepared by energy consolidators that aggregate projects across firms that are too small to appear in the CMIE (confirmed by manually searching for each consolidated firm in a large random sample of unmatched projects). We form a panel of 291 unique applicants, of which 124 firms have projects that are successfully validated by the CDM. We observe financial and fuel use data for over 3000 non-applicants from 2000 to 2012. Table 1 summarizes the success of our CDM Pipeline to CMIE concordance.

4.1 Variables

We identify a firm as an applicant if it ever submits a PDD to the CDM. Applicants demonstrate the *intention* to supply offsets. We identify as participants the subset of applicants for whom any project is, at any point in the first phase of the program, validated by the CDM. Firms that do not get a single project approved in the first phase are considered to be rejected.[14] Note that the CMIE data is at the firm level and not the factory level, so even if a factory reduces its absolute level of emissions, observed firm-level emissions may still increase. If a firm has factories in multiple locations, we assign the state in which the CDM project takes place. In the case of multiple projects, we assign the state identified by the CMIE as the firm's primary location.

We take advantage of disaggregated data on electricity, coal, natural gas, and petrol expenditures with both prices and quantities. Because we explicitly want to capture input substitution from low-cost "dirty" fuels to high-cost "clean" alternatives, we focus on fuel use disaggregated by type. Aggregate measures of fuel expenditures would confound decreases due to reductions in fuel use with increases due to substitution to more expensive sources. Table 2 shows the factors we apply to impute carbon emissions from fuel use. In our primary specification, we fix grid emissions at the combined margins observed for the North-East-West-Northeast and Southern grids in the first year of the CDM. We use a single coefficient for North-East-West-Northeast because by 2006 that grid was integrated.[15] The combined margin is a 50-50 mean of the operating margin (all sources but baseload nuclear and hydro) and the build margin (all sources added in last 10 years) calculated by the Indian Central Energy Agency (CEA). Table 13 in the Appendix lists the coefficients we used to convert across units observed in the raw data. We impute process emissions in the cement sector using data on limestone inputs. We convert at a rate where 1 ton of $CaCO_3$ produces 44.01/100.09= 0.4397 tons of CO_2.

We measure firm size using capital K_{it}, and construct a capital-labor ratio $\frac{K_{it}}{L_{it}}$ as a measure of the relative capital utilisation in production. Total borrowing over asset values measures the debt-equity ratio $\frac{B_{it}}{K_{it}}$ and debt capacity of the firm. We proxy managerial capacity and the effects of ownership structure using indicators for conglomerates (including multinationals) and government-ownership. An indicator variable for whether the firm exports is used to capture the effects of international consumers and "green" marketing.

Financial data are measured in million rupees at nominal values. We adjust for inflation using CPI deflators[16] for wages and borrowings, and WPI deflators[17] for output, capital and inputs, separated by National Industrial Classification (NIC) codes to three digits. We winsorize outliers at the 0.5 percent level at both left and right tails.[18]

We show summary statistics for participants, applicants and untreated control firms. Table 3 shows

[14] We use the PDD opening date for public comment as the earliest available date from the PIPELINE for the time of entry, but our main results ignore this start date.

[15] We also experiment using different regional coefficients in the selection equation regressions to take into account earlier variation.

[16] Consumer Price Index measures available from Open Government Data India, Ministry of Communications & Information Technology, Government of India; http://www.data.gov.in.

[17] Wholesale Price Index measures available from the Office of the Economic Adviser, Ministry of Commerce & Industry, Government of India; http://www.eaindustry.nic.in.

[18] We use a conservative value of $\rho = 0.005$, to replace the left tail value 0 to ρ with the value at ρ, and the right tail values $1-\rho$ to 1 with the value at $1-\rho$.

statistically significant differences in means between participants and non-participants from 2000 to 2003. Figure 1 present the distributions between firms who apply to the CDM and the control group in 2004, one year before the program began. Treated firms are larger, less productive, more capital-intensive, and have higher fuel expenditures.

4.2 Total factor productivity

We estimate (1) primarily via OLS, described below. We test for robustness using an index-number approach proposed by Aw, Chen and Roberts 2003. In our primary specification, we take natural logs of a standard Cobb-Douglas production function to produce a reduced-form estimation equation:

$$\ln Y_{it} = \gamma_{jt} + \gamma_k \ln K_{it} + \gamma_l \ln L_{it} + \gamma_m \ln M_{it} + \omega_{it} \tag{1}$$

where the dependent variable Y_{it} is the output for firm i in industry j at time t, measured by total sales. Output is a function of observable inputs capital K_{it}, labor L_{it} and materials M_{it}, as well as our unobservable variable of interest, productivity A_{it}. Inputs are measured using asset values, wage bills and raw material expenditures respectively.[19] Each γ measures an output-input elasticity. $\ln A_{it} = \gamma_{jt} + \omega_{it}$ is logged TFP. The constant term γ_{jt} is a baseline measure of common productivity for industry j, while the unobserved residual ω_{it} is firm i's i.i.d. idiosyncratic component of TFP.

5 Empirical Framework

The empirical strategy is split into two stages: the decision to apply and the impact of participation. In the first stage we identify firm characteristics that distinguish applicants who strategically self-select into the CDM. In the second stage, we evaluate the costs and benefits of the CDM by estimating the sample average treatment effect on the treated (ATT) on our outcomes of interest: carbon emissions from fuel use, carbon intensity of output, and TFP. Given the uncertainty around the exact date at which any given firm starts implementing the CDM project that it proposed, we present long differences by year. Our results control for observable determinants of participation via regression with controls and via non-parametric nearest-neighbor matching. Our results are robust to both estimation methods.

Participation analysis

We estimate logit models of both the decision to apply and selection for participation. The decision to apply can credibly be determined based exclusively by pre-policy (t^0) firm characteristics. Described as the "Kyoto surprise", the CDM was a very late inclusion to the Protocol (Werksman, 1998). The word-

[19]See Appendix B for complete definitions of the CMIE PROWESS data.

ing and goals of the policy were ill-defined and interpreted ambiguously among nations. Operational details only appeared after four years of international negotiations leading to the Marrakesh Accords (2001), while significant uncertainty surrounded the policy up until the finalised rules in 2005 (Lecocq and Ambrosi, 2007). Furthermore, only 11 projects from India appeared in the PIPELINE pre-2005, the earliest in late-2003.[20] Thus, we restrict our pre-policy years to before 2003 and check for robustness by repeating our analysis for characteristics from 2000 only, a year prior to the Marrakesh Accords.

Because firms are observed for multiple years pre-policy, we consider both single year and multiple year models and, in the multiple-year case use year fixed effects to capture economy-wide shocks and macroeconomic fluctuations.[21] All specifications include industry and state fixed effects.

5.1 Causal impact of the CDM on emissions

For the second stage we consider a potential outcomes framework. The variable D_i takes on a value of 1 if the ith firm participated in the CDM; D_i takes on a value of 0 if a firm did not participate. We then estimate the sample average treatment effect on the treated for outcomes in post-policy treatment years t^1:

$$\alpha_{ATT} \equiv \mathrm{E}[(Y_{it^1}(1) - Y_{it^1}(0) \mid D_i = 1] \tag{2}$$

where α_{ATT} is the expected value of the difference between the actual outcome of the ith treated firm $Y_{it^1}(1)$, and their counterfactual outcome $Y_{it^1}(0)$ if they had not applied or participated in the CDM. It is the effect of treatment on the subpopulation that is likely to take up the treatment. Given that the counterfactual outcome $Y_{it^1}(0) \mid D_i = 1$ is unobservable to the econometrician, we use pre-policy levels and trends and the observed outcomes of the untreated to estimate α_{ATT} in one of two ways. Our main assumption in both cases is that we are able to fully control for selection using observable variables. To capture unobservable factors like capital vintage and manager experience we include pre-CDM emissions intensity, total factor productivity, and the decision to export.

[20] Lecocq and Ambrosi (2007) describe the interesting emergence of a carbon offset market prior to 2005. However, these were primarily pilot programs completed by developed countries for the AIJ/JI flexibility mechanism of the Protocol (Activities Implemented Jointly, now Joint Implementation), with India hosting only a single bilateral investment project pre-2005. UNFCCC, http://unfccc.int/kyoto_mechanisms/aij/activities_implemented_jointly/items/2094.php, accessed 25.09.2014.

[21] A common alternative for entry decisions is the Cox proportional hazard model. See applications in environmental regulation by Pizer et al. (2008, 2011); Blackman et al. (2010). As the exact timing of entry is unclear and involves considerable lags, we opted for an ever enters vs. never enters logit model.

Regression-based conditioning

We first use a conditioning strategy by regressing long differences in outcomes on a vector of pre-policy firm-level characteristics X_{it^0} and our treatment indicator D_i:

$$Y_{it^1} - Y_{it^0} = \beta' \mathbf{X}_{it^0} + \alpha D_i + \epsilon_i$$

The parameter α is the average effect of the CDM on emissions, emissions intensity, and TPF conditional on the observable covariates. We estimate the average change in outcomes differences over sets of year-pairs.

Nearest-neighbor matching

We also implement a semiparametric strategy that draws from the matching estimator techniques applied by Antweiler and Harrison (2007), Fowlie et al. (2012) and Cicala (2015). The aim of nearest-neighbor matching is to pair treated firms with similar but untreated firms, creating a control group with counterfactual outcomes. Matches are formed based on the similarity of characteristics between firm i and potential match m. We use a distance metric to rank matches:

$$\delta_{i,m} = ||X_i - X_m|| = \sqrt{(X_i - X_m)' \ \Omega_X^{-1} (X_i - X_m)}$$

where our scaling metric is the commonly used Mahalanobis inverse of the variance-covariance matrix:

$$\Omega_X^{-1} = \frac{(X_i - \overline{X})' W (X_i - \overline{X})}{\sum_i w_i - 1} \quad , \quad \overline{X} = \frac{\sum_i w_i X_i}{\sum_i w_i}$$

W is a diagonal matrix containing each of the frequency weights w_i, for N_m number of matches to the ith firm, and $\overline{X}$ is the vector of weighted means of the characteristics.

Once treated firms are matched with their N_m "nearest-neighbors", we proxy their counterfactual outcome using the average of outcomes $Y_m(0) \mid D_i = 0$ from the control group:

$$\left[\widehat{Y}_i(0) \mid D_i = 1\right] = \frac{1}{N_m} \sum_m \left[Y_m(0) \mid D_i = 0\right] \tag{3}$$

where $\widehat{Y}_i(0)$ is the estimate of the counterfactual outcome for treated firms if they had not applied to the CDM.

Substituting (3) into (2), and taking the average of the sum, we arrive at the ATT:

$$\widehat{\alpha} = \frac{1}{N_1} \sum_{i \in S_1} \left\{ \left(Y_{it^1}(1) - Y_{it^0}(0)\right) - \sum_{j \in S_0} w_{ij} \left(Y_{jt^1}(1) - Y_{jt^0}(0)\right) \right\} \tag{4}$$

where N_1 is the number of participant firms, S_1 is the set of participant firms, and S_0 is the set of non-participant firms. We weigh each observation by the quality or "closeness" of matches, w_{ij} between participant i and non-participant j, representing by the mean inverse distance $\bar{\delta}_{i,m}^{-1}$.

5.2 Identifying assumptions

The key identifying assumption is that trends and changes in outcomes of both treated firms and untreated control firms would be the same in the absence of the CDM. There are three identifying assumptions that need to hold for our estimation strategy to yield causal interpretations of the treatment effect. First of all, we assume that, after controlling for or matching firms on observables, paired firms will also be matched on unobservables (unconfoundedness). Secondly, the *overlap* requirement posits that every value of a characteristic from the treatment group has a positive probability of being in the control group and can be matched. We apply common methods of winsorising and matching with replacement to reduce outliers and ensure sufficiently close matches. Figure 1 allows us to make a visual check for overlap. Applicants appear to satisfactorily fall within the range of characteristic values of the control group.

Finally, the *stability of unit treatment values* (SUTVA) is the requirement that control firm outcomes not be contaminated by spillover and general equilibrium effects. There are many parallels between SUTVA and "leakage", a term commonly used in the CDM to describe emissions shifting from participant projects to non-participants. If treatment impacts the production of non-participants, then the outcomes of the control group are biased and are no longer an appropriate counterfactual. There are no formal tests for this assumption, although we can test potential failures by considering violations for specific hypothesized scenarios. Our main concerns about a violation of SUTVA are as follows. First of all, because many CDM projects involve a fuel substitution, changes in demand for specific fuel types may lead to a change in fuel prices, and thus impact the fuel expenditure and fuel-use of non-participants. Given that projects are spread across 47 industries and 20 states, and that the fuel use of participant firms makes up less than XX% of total pre-CDM fuel use in our database of firms, we believe it is unlikely that the CDM leads to significant changes in fuel prices. Similarly, there could be general equilibrium effects in the cement sector if cement with a higher blend fraction causes prices to change for both participant and non-participant firms. Using the product-level data on price quantity pairs, we test for price effects among non-participant firms and find no evidence of average prices changing at a faster rate than for participant firms. Secondly, banks may use CDM accreditation to redirect financing to projects that are guaranteed to have an additional stream of project revenues. If this is true, then CDM participants would be observed to doubly outperform non-participants with respect to growth and investment. CDM affiliation may also provide product differentiation, perhaps as positive "green" branding or negative perceptions of inferiority. This differentiation could shift sales between participants and non-participants. In online searches we have yet to find any branding of consumer products or intermediate inputs produced by CDM-recipient firms.

6 Results

6.1 Supply: Characteristics of selected firms

The goal of the first stage is to identify the characteristics of treatment firms as evidence of strategic self-selection in the supply of offsets. Differentiated pre-policy trends may also provide evidence for adverse selection. We use a logit model with firm characteristics from pre-policy years 2001 to 2003 to search for systematic differences between CDM firms and those outside of the policy.

Column (1) suggests that firms who apply to the CDM are on both higher emissions levels and increasing pre-policy emissions trends. After controlling for firm size in column (2), differences in levels are no longer apparent, while the statistical significance of pre-policy emission trends weakens as additional controls are included, column (3). A negative and significant coefficient for trends or levels of emissions would be consistent with a story of adverse selection. However, it is clear that this is not the case in our sample, and we do not find evidence of systematic adverse selection from this source.

We repeat our analysis for the subset of applicant firms whose projects are successfully validated by the Executive Board. Column (4) shows that larger, growing firms which are indeed those that are doubly selected into the CDM, by the firms opting to participate and the Executive Board opting to validate the proposed projects. The importance of firm size is consistent with expectations that the well-recognized fixed costs of participation are a significant barrier to entry. Applicants also tend to have lower debt-to-equity ratios, suggesting that sufficient capital ownership is required to secure financing for both CDM projects and applications, but this effect is barely statistically significant.

CDM firms are also less productive. This is perhaps evidence that industry laggards have the greatest incentives to apply for offset credit incomes, however productivity is known to be correlated with the included characteristics. We also see that conglomerate membership and exporter status is insignificant, and that government-owned firms are no more of less likely to apply to the CDM. Age is also insignificant. Older firms may be the ones that could gain the most from replacing their capital stock, but the CDM may not be enough incentive for them to make the investment.

Applicants are also more likely to be increasing their capacity, which can be interpreted in one of two ways. On one hand, energy efficiency is known to be significantly cheaper at the investment stage than as a retrofit. This is a very positive story. On the other hand, rapid expansion could be a sign that firms are submitting paperwork for projects that they were intending to undertake anyway.

Although we are primarily interested in identifying the significance of firm characteristics, we report marginal effects across all regressions in Appendix: Table 16. Average marginal effects are calculated at the average probability of belonging to a treatment group; 3.9 to 7.0 percent for applicants and 1.9 to 4.2 percent for participants.

Using column (3) as a reference for interpretation, a one percent increase in firm size (capital assets) increases the average probability of being an applicant by 1.6 percent. A one percentage point decrease in the debt-equity ratio increases the average probability of being an applicant by 2.1 percent. Exporters are on average 1.6 percent more likely to be applicants.

We conduct additional regressions in Appendix: Table 14 and Table 15. Our results are robust to using a probit model and to controlling for characteristics from different pre-policy years.

Regression-based conditioning

We then look to the impact of the CDM on firm-level outcomes as a test of project additionality. We first condition for self-selection by including firm characteristics from pre-policy years (2000-2003) as controls for estimating post-policy different in outcomes by least squares. Again these controls include: firm size (capital), TFP, capital-labor ratio, debt-equity ratio, age, exporter status, public sector ownership, conglomerate/MNC status, trends in TFP, carbon-intensity and capital, and state and industry fixed effects. Table 17 presents our results. The dependent variable measures the difference in outcomes from 2004, for the opening date of public comment (earliest 2005) to 2012.

There is clear evidence of decreasing carbon emissions and emission intensity of output, with cumulatively large effects over time. By 2011-2012 the effect on both variables is statistically significant. The cost of compliance is seen in reductions of total factor productivity as early as 2006.

When we parse results by project type we see that firms with projects in all type categories increase sales. The bulk of the emissions reductions come from energy export projects and, to a lesser extent, energy efficiency (Table 6). Table 7 shows that the strongest reductions in emission intensity of output occur in energy export and energy efficiency projects. There is also a small and delayed effect on emissions intensity in waste heat recovery. Similarly, these sectors are the same ones that incur TFP costs associated with projects (Table 8).

On the other hand, CDM participants in fuel switching and blending additives projects increase emissions intensity relative to similar non-participant firms and show improvements in total factor productivity. These results suggest that there is important variation in additionality across project types, with fuel switching and blending additives projects being least likely to be additional.

Nearest-neighbor matching: Identifying counterfactuals

We repeat our analysis using nearest-neighbor matching. We show summary statistics of the match in Table Table 9. Pre-policy characteristics between treatment and control groups converge after matching and weighting pairs by their inverse distance.

Table Table 10 shows the impact of the CDM on firm outcomes for a panel of years from the date of public comment to 2012. These results are very similar to those observed under long differences with controls, except that we now see an increase in emissions and emissions intensity in the first years of the CDM, followed by a subsequent decrease. To the extent that the Executive Board allows firms to base historical emissions for crediting purposes on 2006-2008 values, this result is consistent with strategic overuse in the short term to inflate baselines. Total factor productivity costs are highest in the earliest periods, consistent with an investment model where firms divert resources up-front and receive benefits in later periods.

Figure Figure 4 shows pre and post-treatment outcomes for participants and the control group. Firms apply to the CDM at different times, and undertake projects with varying lags, but we partition trends at 2006 for a neater visual representation. Trends between participants and all other firms represent a naive inspection of the data. After matching pairs and balancing the control group by inverse distance weights, trends and levels converge. We also observe larger changes in TFP and carbon emissions from our balanced controls.

These results are robust to different match covariates. Our base specification matches based on industry group and 2003 levels of capital and emissions intensity. Figure Figure 6 presents the results for different sets of counterfactuals based on the match variables: (1) industry group, multinational status, exporter status, pre-policy trends in TFP and capital, and 2003 levels of capital, TFP, and debt-to-equity ratio, (2) industry group and 2003 levels of capital, (3) same as (1) but without pre-policy trends, (4) same as (1) but without industry group.

6.2 Rejected firms

Finally, we look to a key group of firms: rejected applicants. If these firms were presenting non-additional projects to the CDM executive board, we would expect them to reduce their emissions despite their failure to obtain CDM credits. We apply our nearest-neighbor matching to rejected applicants and re-estimate average treatment effects as though they had been treated. Participant firms are not included as potential control firms. Table 11 shows that emissions *increase* for rejected firms, due primarily to an expansion of output, and emissions intensity remains more or less unchanged. There is no evidence that the rejected projects were non-additional. They may have been additional projects that were incorrectly rejected or rejected on other grounds.

7 Conclusion

We set out to identify the supply of carbon offsets and characterize firms that voluntarily apply to the CDM. After controlling for self-selection, we estimate the post-policy impacts of treatment in the program. Throughout our analysis, we are particularly interested in developing insights for the presence of adverse selection, and the assessment of additionality by the CDM EB.

The first stage of our analysis provides evidence of systematic differences between treatment and control groups. Our results suggest that large firms that are expanding capacity self-select into the supply of carbon offsets. We find no evidence for adverse selection based on pre-program trends of decreasing carbon emissions. The second stage of our analysis shows substantial post-policy impacts on emissions intensity as a direct result of the CDM. Our analysis also suggests that at least some firms experience significant productivity costs as a result of treatment, which may be an indication of the burden and severity of CDM registration. Alternatively, these results could indicate the poor relative productivity of CDM projects, and thus vindicate the award of offset incentives.

Project type appears to be a key driver of additionality, with implications for targeting oversight resources at the types of projects that are ex-post least likely to represent true emission reductions.

Subsequent drafts of this paper will include a section (currently in progress) comparing the credited counterfactual emissions outcomes with the above shown ex-post counterfactuals.

In summary, this paper provides some insights to the operational mechanics of the world's largest project-based crediting program. Further research and discussion is clearly warranted in an otherwise sparse research space.

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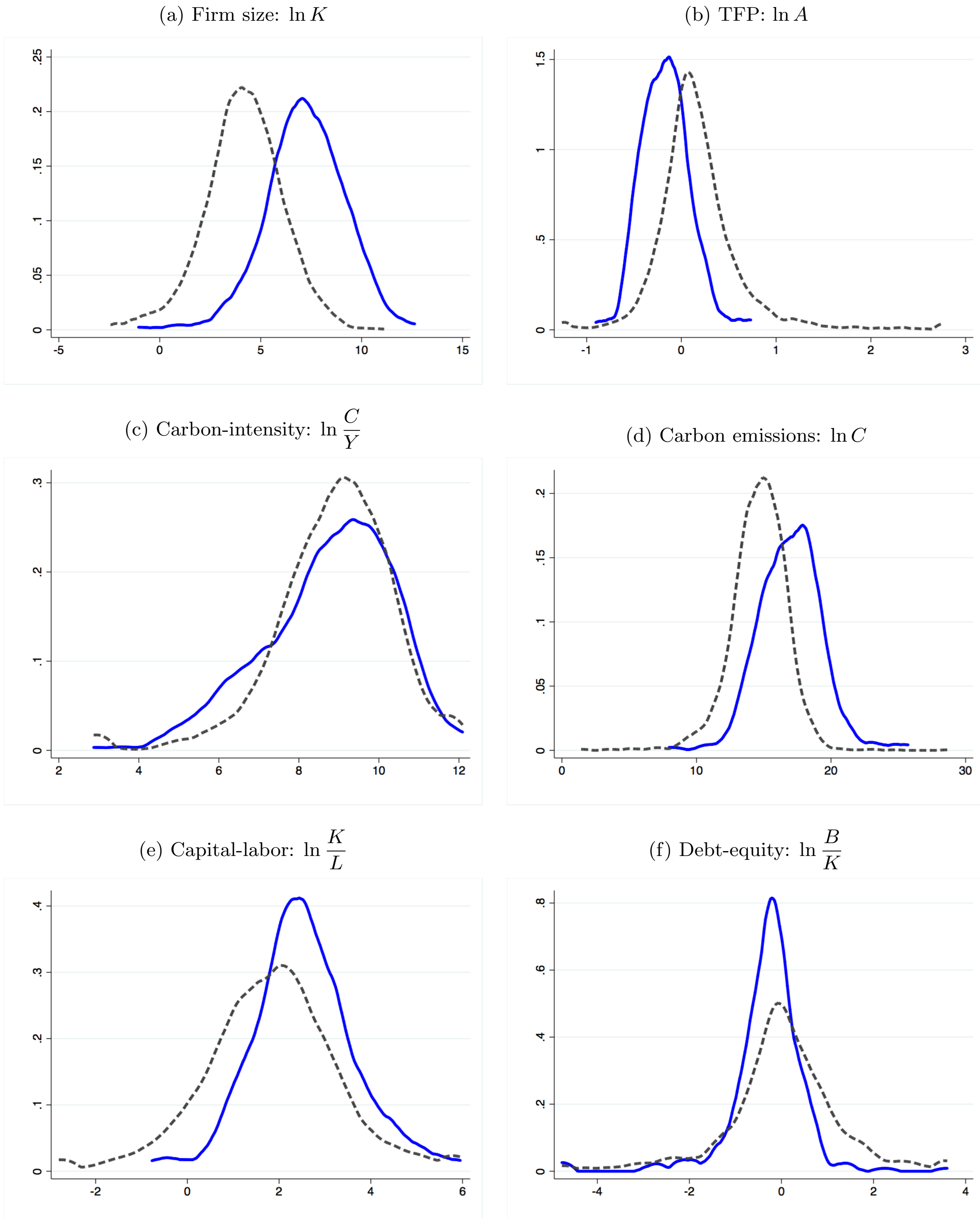
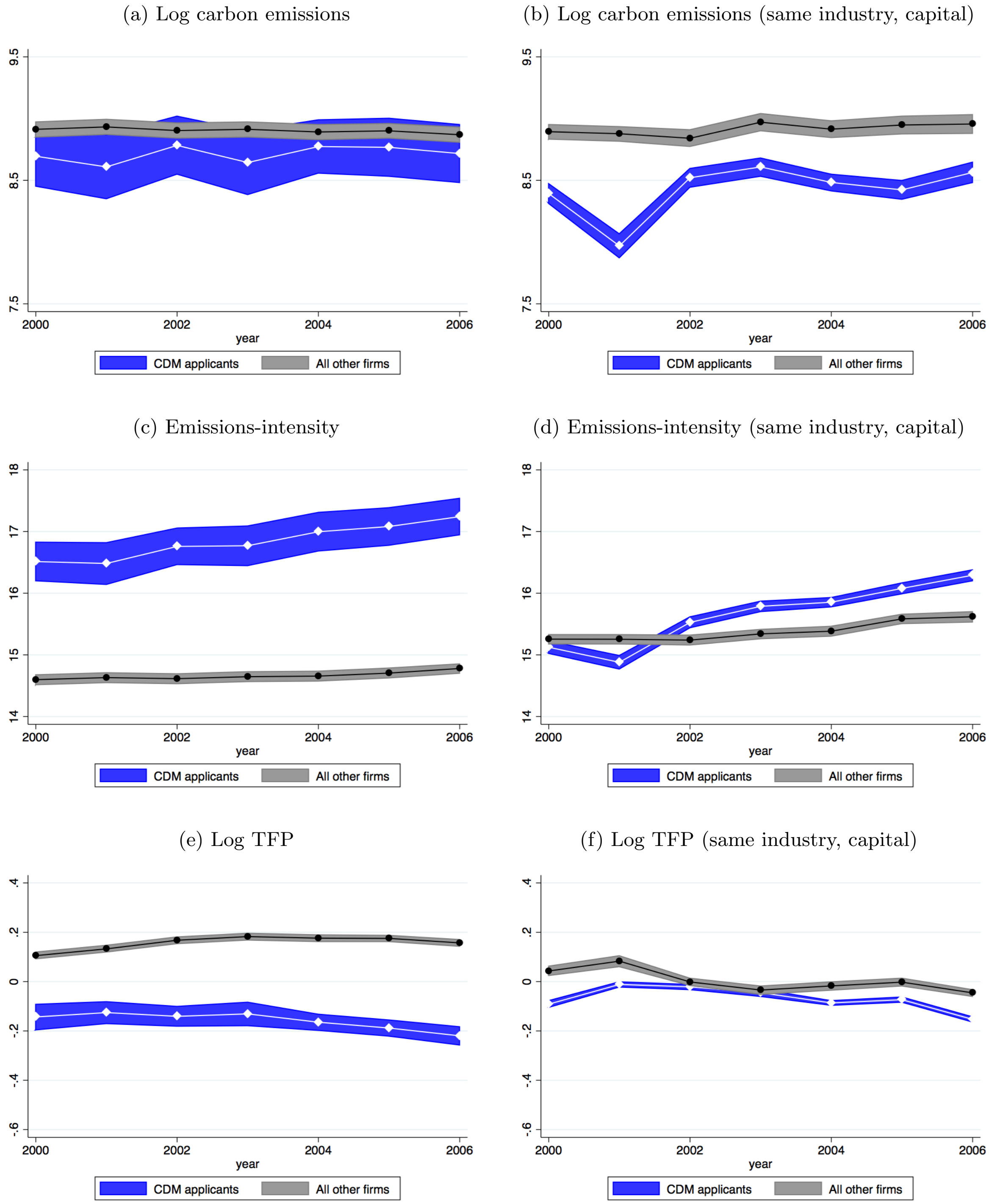
8 Figures

Figure 1: Univariate cross-sections



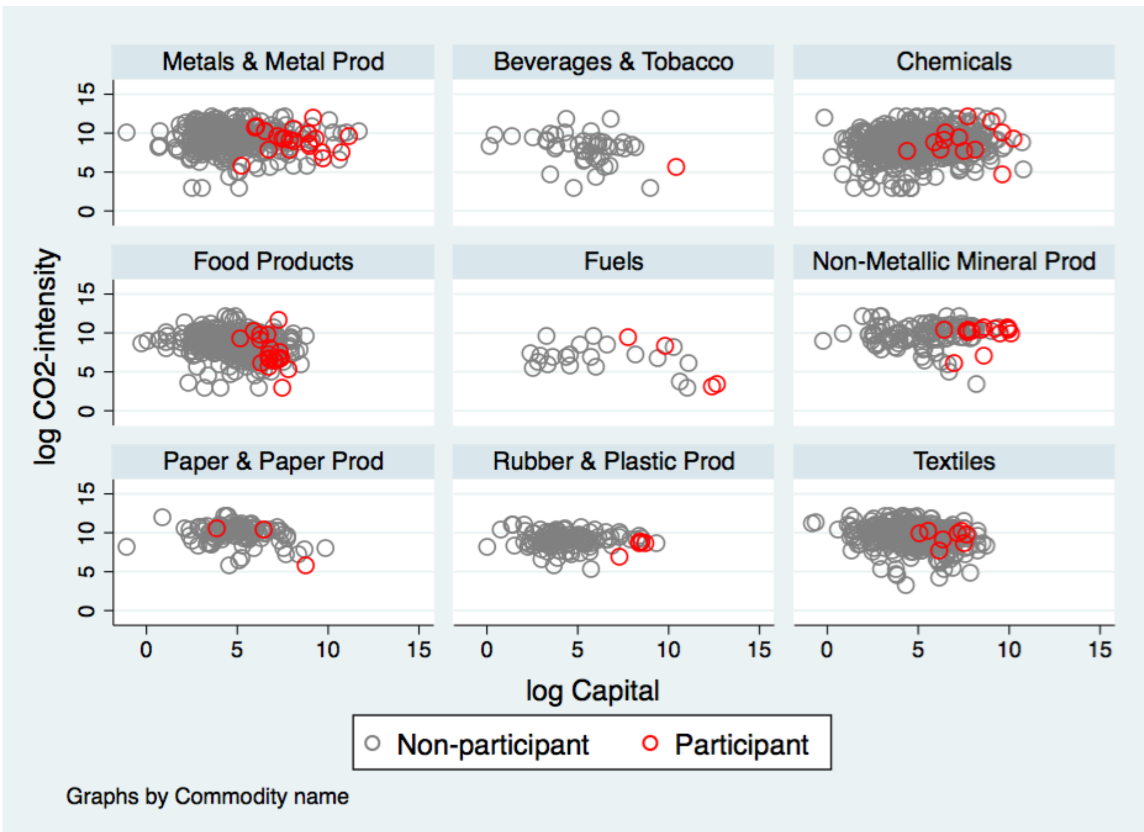
In the cross-section: applicant firms (blue, solid) are larger, less productive, with slightly higher emissions and similar carbon intensity to firms that do not apply (gray, dash): 2004

Figure 2: Pre-policy trends for unmatched and matched applicants



Over time: applicants are, if anything, on an increasing trend of emissions intensity relative to non-applicant firms. Sample means with 95% confidence intervals. Matched sample is based on industry and level of capital stock in the year 2000. Matched observations weighted by inverse distance and the reciprocal of the number of matches.

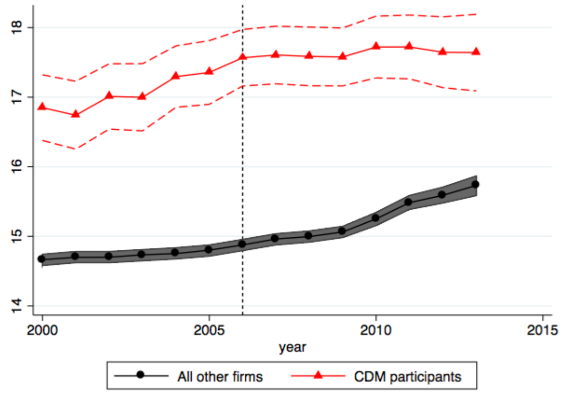
Figure 3: Overlap by match variable



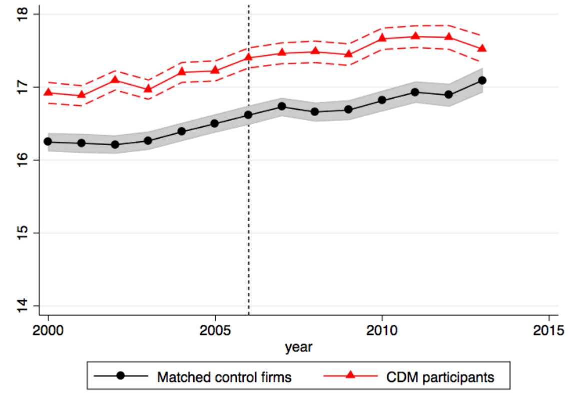
Participant firms (red) and non-participant firms (gray) by quantile of capital stock in 2003 (x-axis) and quantile of emissions intensity of output in 2003 (y-axis) across nine industries.

Figure 4: Pre- and post-policy trends for unmatched and matched participants

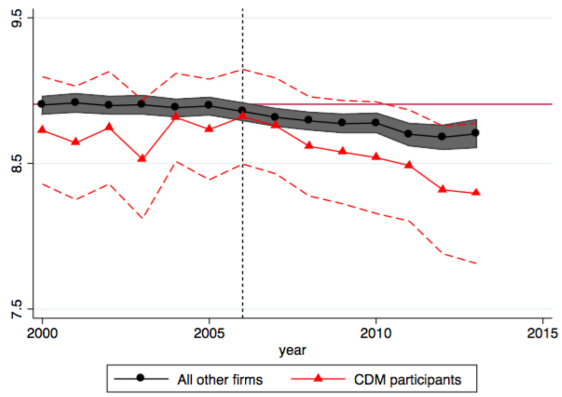
(a) Log carbon emissions



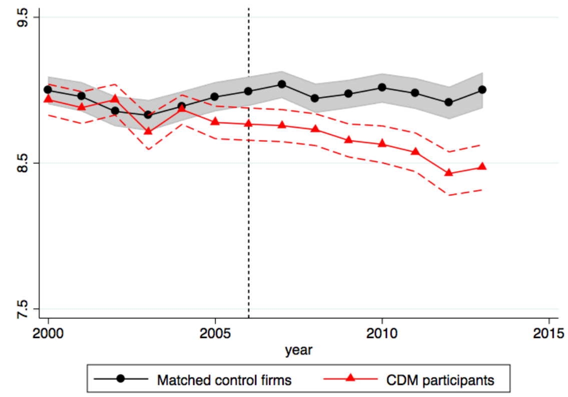
(b) Log carbon emissions (matched)



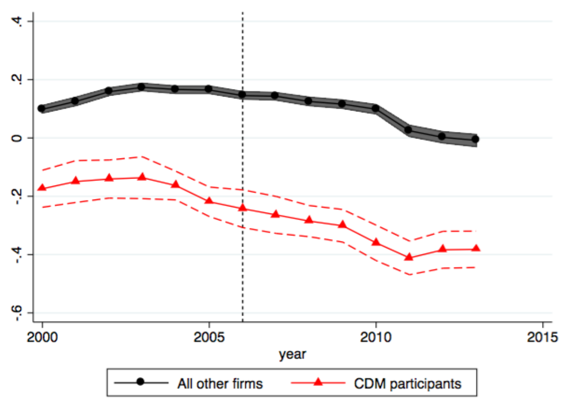
(c) Emissions-intensity



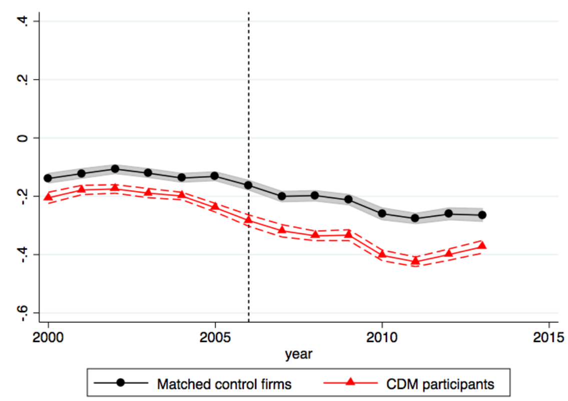
(d) Emissions-intensity (matched)



(e) Log TFP



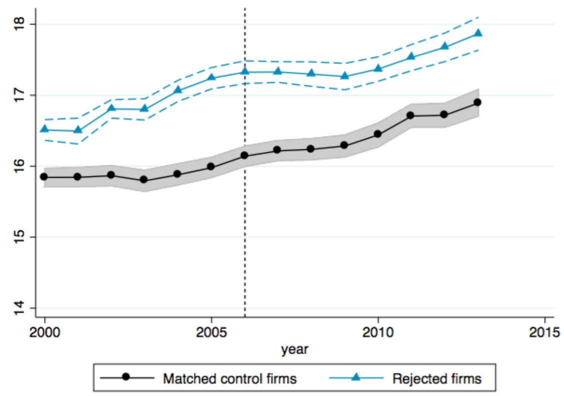
(f) Log TFP (matched)



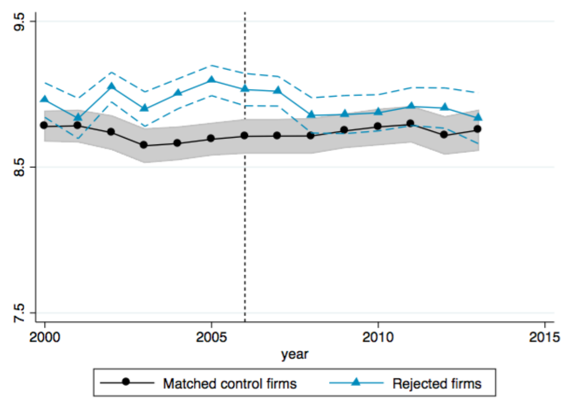
Raw data (left) vs. Matched subsample (right): Comparing outcomes of participants (black, solid) against matched controls (red, dashed). Sample means with 95% confidence intervals. Matched sample means are weighted by inverse distance and the reciprocal of the number of matches. Exact match on industry; match on emission intensity of output in 2003 and capital stock in 2003. Up to 10 closest matches per participating firm. The dashed vertical line represents 2006, the official start of the CDM.

Figure 5: Pre- and post-policy trends for rejected applicants

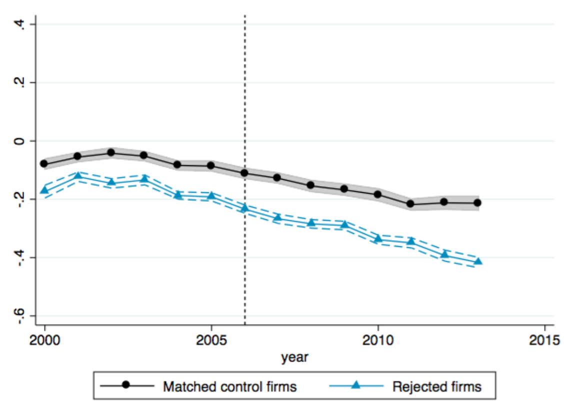
(a) Log carbon emissions



(b) Emissions-intensity



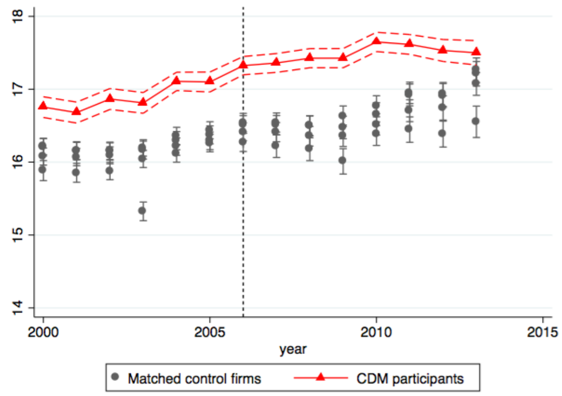
(c) Log TFP



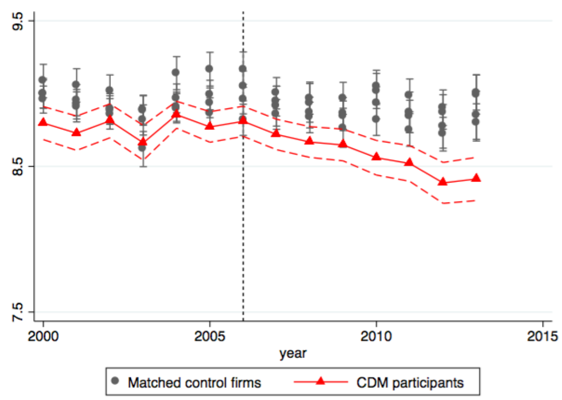
Rejected (left) vs. Successful applicants (right): Comparing outcomes of firms to their matched controls. Sample means with 95% confidence intervals. Sample means weighted by inverse distance and the reciprocal of the number of matches. Exact match on industry; match on emission intensity of output in 2003 and capital stock in 2003. Up to 10 closest matches per participating firm. The dashed vertical line represents 2006, the official start of the CDM.

Figure 6: Sensitivity of results to different matching covariates

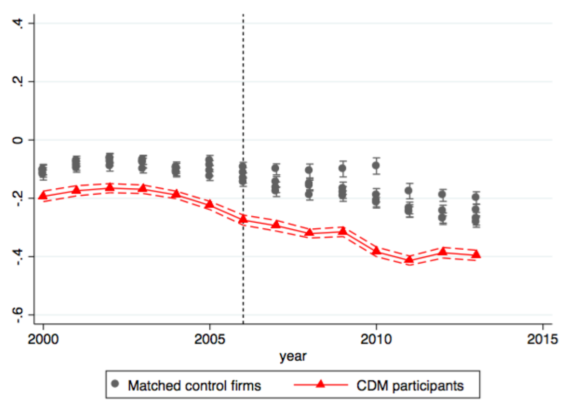
(a) Log carbon emissions



(b) Emissions-intensityd



(c) Log TFP



Sample means with 95% confidence intervals. Sample means weighted by inverse distance and the reciprocal of the number of matches. Matching based on (1) industry group, multinational status, exporter status, pre-policy trends in TFP and capital, and 2003 levels of capital, TFP, and debt-to-equity ratio, (2) industry group and 2003 levels of capital, (3) same as (1) but without pre-policy trends, (4) same as (1) but without industry group.

9 Tables

Table 1: Summary of CDM to CMIE concordance by project type

	Biomass	Cement	Energy efficiency	Fuel switch	HFCs PFCs	Total
Unique projects	362	24	465	45	11	907
Matched	197	24	349	40	7	617
Unmatched	165	0	116	5	4	290
Unique firms	125	20	186	23	6	360
Manufacturing firms	109	19	146	17	0	291

Table 2: Fuel conversion factors

Fuel type	**Detail**	**Unit**	**tCO2 per unit**	**MMBtu per unit**
Coal		tonnes	2.444	25.59
Diesel		kilolitres	2.68	36.65
Electricity		kWh	0.920	0.003412
Electricity	coal	kWh	1.040	0.003412
Electricity	furnace oil	kWh	0.660	0.003412
Electricity	natural gas	kWh	0.430	0.003412
Electricity	own generation	kWh	0.590	0.003412
Electricity	diesel generator	kWh	0.590	0.003412
Electricity	steam generator	kWh	0	0.003412
Electricity	wind	kWh	0	0.003412
LNG		000 m3	1.30	48.00
LPG		tonnes	2.95	46.96
Natural gas		000 m3	1.872	35.30

Table 3: Summary statistics: Firm characteristics for applicants, participants and rejected applicants in pre-CDM years: 2000-2003

	Applicants			*Participants*			*Controls*
	Mean (Std. Dev)	Δ	t-test	Mean (Std. Dev)	Δ	t-test	Mean (Std. Dev)
TFP trend coefficient	−0.021 (0.093)	−0.019	−5.504	−0.021 (0.092)	−0.021	−3.398	−0.005 (0.115)
Fuel trend coefficient	−0.642 (10.840)	−0.606	−2.363	−1.909 (11.173)	−1.953	−7.583	−0.589 (5.491)
Assets trend coefficient	157 (175)	123	51.908	172 (182)	135	39.017	30 (99)
TFP	0.967 (0.996)	−0.313	−3.823	0.985 (1.486)	−0.543	−2.469	1.280 (3.607)
Sales revenue	17271 (24562)	15310	87.704	23004 (28467)	20666	67.538	1610 (5379)
Asset values	22375 (28935)	20265	102.424	28988 (30974)	26561	81.903	1714 (5765)
Wage bill	534 (711)	454	83.063	688 (786)	605	69.988	69 (182)
Raw materials	17280 (76926)	15476	37.747	28131 (112812)	25177	29.255	956 (6238)
Fuel Expenditure	1011 (1324)	929	107.606	1380 (1506)	1273	83.352	64 (227)
Fuel intensity	0.082 (0.074)	0.013	6.593	0.084 (0.076)	0.012	4.613	0.064 (0.121)
Capital-labour	86 (338)	32	9.959	77 (276)	12	3.961	46 (157)
Debt-equity	0.372 (0.299)	−0.311	−2.769	0.346 (0.186)	−0.317	−2.023	0.554 (2.871)
Exporter	0.801 (0.399)	0.246	23.384	0.806 (0.396)	0.250	15.941	0.532 (0.499)
Conglomerate	0.677 (0.468)	0.364	36.348	0.744 (0.437)	0.435	28.907	0.292 (0.455)
Government	0.100 (0.300)	0.064	17.540	0.081 (0.273)	0.036	7.453	0.028 (0.166)
Observations	1,946			805			35,406
Firms	173			71			2,017

"Δ" is the difference between means for the control group and treatment groups. Two-sided "t-test" for means of control and treatment groups. Robust standard errors in parentheses. Values after deflating and winsorising left and right tails for $\rho = 0.005$.

Table 4: Logit regression: Characteristics of applicants and participants

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Applicants	(5) Participants
Pretreatment K trend			0.00431***	0.00398**	0.00627***
			(0.00166)	(0.00169)	(0.00221)
Pretreatment TFP trend			-0.935	-1.109	0.960
			(1.374)	(1.417)	(2.082)
Pretreatment MTCO2 trend	2.03e-07***	1.44e-07***	1.16e-07***	1.32e-07***	4.23e-08
	(4.64e-08)	(4.14e-08)	(4.33e-08)	(4.44e-08)	(5.79e-08)
log Capital		0.814***	0.803***	0.797***	0.880***
		(0.0741)	(0.0800)	(0.0998)	(0.135)
log mtCO2	0.478***	0.0510	0.0485	0.0170	0.00659
	(0.0572)	(0.0542)	(0.0545)	(0.0586)	(0.0870)
log TFP			-0.338	-0.429	-0.356
			(0.257)	(0.264)	(0.371)
log Debt-equity				0.00855	0.0265
				(0.0841)	(0.119)
log Capital-labour				-0.145	-0.188
				(0.104)	(0.140)
Conglomerate				0.269	0.256
				(0.211)	(0.317)
Exporter				0.148	-0.121
				(0.196)	(0.289)
State-owned				-0.0475	-0.678
				(0.514)	(1.097)
Age				-6.64e-05	0.0152**
				(0.00488)	(0.00629)
Observations	7,582	7,115	7,045	6,850	6,850
Industry FE	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
R2	0.231	0.344	0.356	0.362	0.397
CMIE	2934	2798	2772	2712	2712

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: a firm's decision to apply (columns 1-3) or apply and be successfully validated to participate (column 4) in the CDM. All firm characteristics and trends based on 2001-2003 pre-CDM data.

Table 5: OLS long differences from 2004 with controls for selection into treatment

Dependent variable: emissions (log mtCO2)

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
Participants	0.146	0.104	0.0272	-0.0727	-0.0876	-0.0520	-0.259
	(0.140)	(0.146)	(0.297)	(0.237)	(0.237)	(0.232)	(0.340)
Observations	2,249	2,194	2,121	2,060	1,941	1,496	1,249
R^2	0.535	0.512	0.499	0.494	0.507	0.512	0.509
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Dependent variable: emission intensity of output (log (mtCO2 / sales))

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
Participants	-0.120	-0.268*	-0.436*	-0.575***	-0.606**	-0.558**	-0.687**
	(0.163)	(0.133)	(0.199)	(0.166)	(0.220)	(0.191)	(0.301)
Observations	2,156	2,114	2,054	1,970	1,829	1,348	1,154
R^2	0.219	0.198	0.204	0.187	0.193	0.216	0.207
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Dependent variable: total factor productivity

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
Participants	-0.0298	-0.0504	-0.0637	-0.0599	-0.0988	-0.115**	-0.0761*
	(0.0430)	(0.0559)	(0.0502)	(0.0581)	(0.0627)	(0.0465)	(0.0399)
Observations	3,612	3,546	3,434	3,298	3,046	2,274	1,934
R^2	0.533	0.485	0.456	0.409	0.393	0.387	0.390
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

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

Table 6: Heterogeneous effects on total emissions: OLS with controls for selection

	Dependent variable: emissions (log mtCO2)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (apply)	0.109	0.230	0.254	0.209	0.217	0.232	0.150
	(0.232)	(0.214)	(0.264)	(0.231)	(0.202)	(0.207)	(0.253)
Observations	2,249	2,194	2,121	2,060	1,941	1,496	1,249
R^2	0.535	0.513	0.500	0.495	0.507	0.513	0.509
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

	Dependent variable: emissions (log mtCO2)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (Energy efficiency)	0.289	0.182	-0.525	-0.489	-0.438	-0.534*	-1.039**
	(0.213)	(0.276)	(0.463)	(0.402)	(0.370)	(0.285)	(0.459)
Treatment (Energy export)	-1.246***	-1.265***	-1.523***	-1.307***	-1.466***	-1.215***	-1.265***
	(0.187)	(0.172)	(0.160)	(0.198)	(0.289)	(0.247)	(0.316)
Treatment (Fuel switching)	0.714	0.667**	0.789***	0.659***	0.395*	0.619***	0.738***
	(0.531)	(0.249)	(0.147)	(0.185)	(0.215)	(0.118)	(0.106)
Treatment (Blending additives)	0.911***	0.949***	0.804**	0.809***	1.300***	1.142***	1.018***
	(0.201)	(0.251)	(0.264)	(0.218)	(0.217)	(0.208)	(0.0869)
Treatment (Waste heat recovery)	0.611**	0.585	0.778***	0.441**	0.322	0.148	-0.171
	(0.254)	(0.339)	(0.240)	(0.189)	(0.226)	(0.221)	(0.156)
Observations	2,175	2,120	2,047	1,982	1,862	1,423	1,182
R^2	0.521	0.493	0.480	0.478	0.495	0.501	0.501
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Table 7: Heterogeneous effects on carbon intensiy of output: OLS with controls for selection

Dependent variable: emission intensity of output (log (mtCO2 / sales))

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
Treatment (apply)	-0.210	-0.192	-0.311*	-0.370*	-0.389*	-0.376*	-0.457*
	(0.256)	(0.164)	(0.170)	(0.191)	(0.199)	(0.205)	(0.237)
Observations	2,156	2,114	2,054	1,970	1,829	1,348	1,154
R^2	0.219	0.197	0.203	0.185	0.191	0.214	0.204
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Dependent variable: emission intensity of output (log (mtCO2 / sales))

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
Treatment (Energy efficiency)	-0.127	-0.405	-1.277***	-1.272***	-1.236***	-1.340***	-1.722***
	(0.305)	(0.388)	(0.303)	(0.327)	(0.392)	(0.329)	(0.449)
Treatment (Energy export)	-1.325***	-1.220***	-1.542***	-1.622***	-1.831***	-1.496***	-1.566***
	(0.237)	(0.223)	(0.234)	(0.205)	(0.249)	(0.314)	(0.447)
Treatment (Fuel switching)	0.390	0.200	0.248	0.146	-0.132	0.239	0.367**
	(0.574)	(0.289)	(0.245)	(0.211)	(0.317)	(0.135)	(0.139)
Treatment (Blending additives)	0.562**	0.349*	0.427**	-0.109	0.385*	-0.0998	-0.296
	(0.225)	(0.191)	(0.183)	(0.175)	(0.199)	(0.237)	(0.180)
Treatment (Waste heat recovery)	0.388	0.0947	0.120	-0.225	-0.222	-0.455	-0.756**
	(0.265)	(0.172)	(0.161)	(0.276)	(0.300)	(0.284)	(0.245)
Observations	2,082	2,041	1,980	1,892	1,750	1,280	1,094
R^2	0.226	0.201	0.212	0.191	0.197	0.222	0.223
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Table 8: Heterogeneous effects on total factor productivity: OLS with controls for selection

	Dependent variable: total factor productivity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (apply)	-0.0525	-0.0715	-0.0793*	-0.0706	-0.134**	-0.114***	-0.0890**
	(0.0677)	(0.0556)	(0.0422)	(0.0443)	(0.0490)	(0.0344)	(0.0339)
Observations	3,612	3,546	3,434	3,298	3,046	2,274	1,934
R^2	0.533	0.485	0.456	0.410	0.396	0.388	0.392
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

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

	Dependent variable: total factor productivity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (Energy efficiency)	-0.132*	-0.153**	-0.149**	-0.123**	-0.211**	-0.110***	-0.106***
	(0.0675)	(0.0642)	(0.0556)	(0.0495)	(0.0816)	(0.0246)	(0.0281)
Treatment (Energy export)	-0.439***	-0.452***	-0.427***	-0.653***	-0.465***	-0.482***	-0.527***
	(0.0325)	(0.0323)	(0.0267)	(0.0401)	(0.0362)	(0.0364)	(0.0523)
Treatment (Fuel switching)	-0.0166	-0.0356	-0.0586*	-0.0352	-0.136**	-0.202*	-0.111*
	(0.0340)	(0.0287)	(0.0297)	(0.0469)	(0.0447)	(0.0919)	(0.0614)
Treatment (Blending additives)	0.238***	0.219***	0.0941***	0.215***	0.0726**	0.0108	-0.00827
	(0.0309)	(0.0363)	(0.0263)	(0.0332)	(0.0302)	(0.0267)	(0.0282)
Treatment (Waste heat recovery)	0.0626	0.0982**	0.0293	0.0518	0.0305	0.00875	0.0371
	(0.0362)	(0.0392)	(0.0263)	(0.0305)	(0.0325)	(0.0480)	(0.0433)
Observations	3,519	3,455	3,342	3,206	2,954	2,190	1,859
R^2	0.535	0.482	0.451	0.404	0.385	0.383	0.382
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

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

Table 9: Summary of matching results and balancing for participants: 2001-2003

	Raw data			*Weighted by inverse distance*		
	Treatment	Control	Δ	Treatment	Control	Δ
Log emissions	12.888	8.254	4.634	12.681	10.276	2.405
	(0.481)	(0.050)	(0.299)	(0.464)	(0.327)	(0.628)
Log emissions intensity	3.681	2.373	1.308	3.550	2.505	1.045
	(0.036)	(0.263)	(0.209)	(0.255)	(0.274)	(0.384)
Log fuel expenditure	5.421	2.132	3.289	5.415	4.225	1.190
	(0.246)	(0.031)	(0.225)	(0.237)	(0.252)	(0.348)
Log fuel intensity	−3.361	−3.451	0.090	−3.336	−3.309	−0.028
	(0.162)	(0.021)	(0.149)	(0.156)	(0.181)	(0.238)
Log TFP	−0.441	0.287	−0.728	−0.418	0.192	−0.610
	(0.084)	(0.007)	(0.049)	(0.083)	(0.049)	(0.102)
Log capital	9.074	4.504	4.570	8.972	7.030	1.942
	(2.029)	(1.728)	(0.203)	(0.238)	(0.178)	(0.310)
Log capital-labor	3.533	1.787	1.746	3.421	2.451	0.970
	(0.137)	(0.020)	(0.144)	(0.137)	(0.128)	(0.191)
Log debt-equity	−1.133	−0.050	−1.083	−1.095	−0.166	−0.929
	(0.151)	(0.019)	(0.137)	(0.153)	(0.122)	(0.202)
Observations	79	3,985		79	66	

"Δ" is the difference between treatment and control groups. Robust standard errors in parentheses.

Table 10: Nearest-neighbor matches, difference in means by year

Dependent variable: emissions

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
r1vs0.ypart	0.125	0.152	0.154	-0.0600	-0.0871	-0.107	-0.329
	(0.179)	(0.187)	(0.193)	(0.193)	(0.190)	(0.193)	(0.210)
Observations	2,251	2,196	2,122	2,061	1,942	1,497	1,250

Dependent variable: emission intensity

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
r1vs0.ypart	0.0321	-0.00693	-0.0808	-0.277	-0.339*	-0.272	-0.428*
	(0.176)	(0.180)	(0.178)	(0.183)	(0.197)	(0.195)	(0.220)
Observations	2,158	2,115	2,055	1,971	1,830	1,349	1,155

Dependent variable: total factor productivity

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
r1vs0.ypart	-0.0587**	-0.0560*	-0.0591**	-0.0496*	-0.0694**	-0.103***	-0.0647**
	(0.0257)	(0.0292)	(0.0243)	(0.0258)	(0.0273)	(0.0310)	(0.0266)
Observations	3,614	3,548	3,435	3,299	3,047	2,275	1,935

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Coefficients of difference in log emissions between given year and log emissions in 2003 on participation in the CDM. Exact match on industry; match on emission intensity of output in 2003 and capital stock in 2003. Up to 10 closest matches per participating firm. Quadratic bias adjustment for emissions intensity and capital stock.

Table 11: Nearest-neighbor matches **for rejected firms**, difference in means by year

Dependent variable: emissions

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
r1vs0.rejected	0.463**	0.702**	1.084***	0.490	0.358	0.350	0.547*
	(0.233)	(0.300)	(0.419)	(0.325)	(0.302)	(0.287)	(0.320)
Observations	2,155	2,098	2,027	1,968	1,849	1,405	1,163

Dependent variable: emission intensity

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010	(6) 2011	(7) 2012
r1vs0.rejected	0.118	0.303	0.721**	0.164	-0.0175	0.124	0.269
	(0.199)	(0.252)	(0.333)	(0.250)	(0.232)	(0.218)	(0.266)
Observations	2,063	2,019	1,961	1,879	1,737	1,257	1,069

Coefficients of difference in log emissions between given year and log emissions in 2003 on participation in the CDM. Exact match on industry; match on emission intensity of output in 2003 and capital stock in 2003. Up to 10 closest matches per participating firm. Quadratic bias adjustment for emissions intensity and capital stock.

Appendix A: Additional CDM background

CDM registration process

Often with the assistance from an external consultant, each PDD of typically 50-100 pages, consists of all the relevant project details, including expected emission reductions and demonstrations of additionality. This laborious registration process constitutes a major barrier to entry, involving significant transaction costs and lags between the firm's participation decision and the first transfer of CERs.[22]

PDDs are submitted to the host country's Designated National Authority (DNA), where it is issued a "Letter of Approval" if deemed consistent with the nation's sustainable development goals. Firms are then required to hire a Designated Operational Entity (DOE), an accredited auditor who will conduct an independent audit of the PDD. Once the DOE passes the PDD, it is opened to a 30-day public comment period, before submission to the CDM Executive Board for inspection. Projects are evaluated as either "Rejected", "Called for improvement", or "Approved".

This evaluation stage involves the assessment of a PDD's demonstration of additionality, based on one or more of the following methods: positive lists, identification of alternatives, investment analysis for financial attractiveness, barrier analysis, and common practice analysis.[23]

After an approved project is operational and being monitored, typically for a year, the firm is then required to hire a second (different) DOE auditor to verify the actual emission reductions achieved by the project. Once the EB receives a verification report from the DOE, only then are CERs issued to firms, which may then be sold on secondary markets. Projects are typically awarded credits for between seven and 10 years.

Example: CDM project 2905

Optimisation of steam generation and distribution systems through various energy efficiency measures at Anil Products Limited, Ahmedabad, Gujarat.

This project is in industrial energy efficiency. Anil Products, a starch manufacturing plant, uses lignite (coal) to generate steam. The CDM project proposes to reduce coal use by installing an Effimax-2000 (online boiler efficiency analyzer), a blow down heat recovery system, and a condensate recovery

[22] See Gillenwater and Seres (2011); Lecocq and Ambrosi (2007); Olsen (2007); Paulsson (2009) for detailed descriptions of the application process and broader reviews of the CDM.

[23] See Schneider et al. (2009) and Zhang and Wang (2011) for descriptions of these tools for assesement.

system. It also proposes improve steam distribution by installing improved air vents, moisture separators, stop vales, steam traps, thermo-compressors.

In a 64 page PDD, the project proponents argue additionality. As follows:

1. Barrier to prevailing practice: other firms in starch industry in India have implemented either fewer or "less-comprehensive" energy-efficiency measures

2. Investment barrier: historically firm has only made smaller energy-efficiency investments

They propose credits for reductions from baseline emissions calculated from 3 years of historical data. Their monitoring plan commits to weigh incoming trucks to verify actual coal used. They expect as a result to reduce lignite inputs by 5251.91 tons/year, and receive 9.609 ktCO2/year for 10 years (revenues of $30,000 to $50,000 per year).

The project's preparation/approval timeline was as follows:

Table 12: Project preparation/approval timeline

20 Feb 2007	Commission energy audit
26 Mar 2007	Hires CDM consultant
06 Nov 2007	First PDD submission
15 Nov 2007	Host LoA
31 Dec 2008	Official request for registration
3 Feb 2009	Start date for 30 day public comment
5 Mar 2009	Date of registration
5 Mar 2009	Credit start
5 Mar 2016	Last credit accrued

Appendix B: Additional literature on participation in other voluntary emission reduction programs

Given the limited studies performed on the CDM, we survey the empirical work performed on other voluntary programs.

Blackman et al. (2013) undertake case studies of four firms in Colombia's Voluntary Agreements program and find that the threat of stricter mandatory regulation and the desire to influence the country's regulatory transition was the main driver of participation. Likewise, Takahashi et al. (2001) undertake firm surveys of Canada's Voluntary Challenge and Registry program in an effort to understand the participation decision from the firm's perspective. They find that financial institutions, shareholders and boards play significant roles in the extent of emission reduction commitments, while external pressures from environmental groups, the media, or local communities have minor positive effects.

A number of authors use standard logit and probit models of discrete choice to investigate participation in US EPA programs 33/50, Green Lights and Waste Wise.[24] They find that firm size, potential for technological transfer, environmental reputation, consumer goods and public recognition positively correlated with participation, and also that ownership structure may be more important that conventional finance theory suggests.

Brouhle and Harrington (2010) use a dynamic probit model to investigate hysteresis and find limited momentum effects for multiple participation. They also find small significant effects for publicly listed firms, highly toxic emitters and final good producers.

Duration models are also used to estimate hazard rates and the selection of participants, and can be conveniently used to calculate propensity-scores in order to match and evaluate differences among participants and non-participants. Blackman et al. (2010) uses these techniques to find that legitimate threats of fines can drive participation, and that also larger firms, exporters, input importers and firms with government consumers are more likely to participate. They are unable to find a significant change in post-participation emissions however, which may suggest that voluntary-style programs are poor substitutes for mandatory regulation.

Pizer et al. (2008, 2011) also use these techniques to account for self-selection by firms into US

[24] See Videras and Alberini (2000); Arora and Gangopadhyay (1995); Arora and Cason (1996); DeCanio and Watkins (1998).

Climate Wise and 1605(b), and assess the outcomes and persistence of each policy. They find small decreases in fuel and electricity expenditure, and no significant effect on energy expenditure following entry into each program. The authors point out the difficulty of measuring realistic baselines for assessing environmental performance.

Antweiler and Harrison (2007) use a logit model to identify the firm characteristics of participants, and find positive correlations between pollution intensity and size, and participation in Canada's Accelerated Reduction/Elimination of Toxins program. They then control for self-selection by including pre-policy trends as covariates in an OLS regression on emissions, and find mixed results for post-policy impacts, with suggestions that participants may be reducing emissions at a slower rate than normal.

Appendix C: Fuel unit conversion factors

Table 13: Converting across fuel units

Fuel type	Units	Units	Multiplier	Notes
Coal	Kgs	tons	0	
Coal	Million kcal	tons	0.16	1 MMBtu = 0.252 million kcal, 1 ton coal is 25.59 MMBtu
Coal	000 tonnes	tons	1000	
Diesel	Litres	kilolitres	0	
Diesel	Tonnes	kilolitres	1.13	
Diesel	000 litres	kilolitres	1	
Diesel	Kgs	kilolitres	0	
Diesel	Billion btu	kilolitres	27.23	x 1e9 BTU/billion BTU / 36720 BTU/liter * 0.001 kiloliters/liter
Diesel	Lakh litres	kilolitres	100	
Diesel	Million kcal	kilolitres	6863	1 MMBtu = 0.252 million kcal
Diesel	Therms	kilolitres	272331	1 MMBtu = 10 therms
Electricity	000 kwh	kWh	1000	
Electricity	Lakh kwh	kWh	100000	
Electricity	Mwh	kWh	1000000	
Electricity	Million kwh	kWh	1000000	
LPG	Kgs	tons	0	
LPG	Kls	tons	0.54	
LPG	000 cu.metres	tons	0.15	1 L of LPG expands of 0.27 m^3
LPG	000 litres	tons	0.54	
LPG	MBTU	tons	0.02	46.96 MMBtu per ton
LPG	Cubic metres	tons	0.54	
Natural gas	Cubic metres	000 m3	0	
Natural gas	Tonnes	000 m3	1.38	
Natural gas	Kgs	000 m3	0	
Natural gas	MBTU	000 m3	0.03	35.3 MMBtu per 000m^3
Natural gas	Million cu.metres	000 m3	1000	
Natural gas	GCAL	000 m3	0.11	0.252 kcal per BTU −¿ 0.252 Gcal per MMBtu, 35.3 MMBtu per 000m^3
Natural gas	Therms	000 m3	0	2.78 m3 gas per therm
Natural gas	Kls	000 m3	0	1 kilolitre per m^3
Natural gas	Cubic feet	000 m3	0	35.3 ft^3 per m^3
Natural gas	Litres	000 m3	0	
LNG	Cubic metres	000 m3	0	
LNG	MBTU	000 m3	0.02	48 MMBtu per 000 m^3
LNG	Kls	000 m3	1	
LNG	TBTU	000 m3	20833	1 TBTU = 10^6 MMBTU
LNG	Kgs	000 m3	0	405 kg per m3

Appendix D: Robustness & marginal effects

Table 14: Robustness to a probit specification and year 2000 only: Applicants

	Year 2000			Probit model		
	(1)	(2)	(3)	(4)	(5)	(6)
TFP trend coefficient	-0.860		-1.981	-0.371		-0.539
	(0.815)		(1.752)	(0.378)		(0.663)
Fuel trend coefficient	-0.0505***		0.0139	-0.0255***		0.000560
	(0.0157)		(0.0155)	(0.00737)		(0.00729)
Assets trend coefficient	0.00964***		0.00450***	0.00488***		0.00205***
	(0.000813)		(0.000880)	(0.000395)		(0.000429)
Log TFP		0.0403	-0.286		-0.0389	-0.136
		(0.267)	(0.307)		(0.123)	(0.133)
Log fuel expenditure		0.354**	0.393**		0.183***	0.197***
		(0.160)	(0.168)		(0.0640)	(0.0634)
Firm size: Log assets		0.716***	0.589***		0.407***	0.324***
		(0.188)	(0.204)		(0.0776)	(0.0808)
Debt-equity		-1.184***	-0.820*		-0.549**	-0.361*
		(0.430)	(0.429)		(0.222)	(0.206)
Log capital-labour		0.349**	0.251		0.176**	0.142*
		(0.169)	(0.175)		(0.0747)	(0.0775)
Conglomerate		0.666**	0.593*		0.186	0.179
		(0.332)	(0.349)		(0.134)	(0.141)
Exporter		0.487	0.463		0.354***	0.338**
		(0.338)	(0.348)		(0.135)	(0.137)
Government		0.234	0.679		0.0788	0.270
		(0.568)	(0.567)		(0.274)	(0.265)
Observations	3,989	2,560	2,560	11,967	8,708	8,708
Industry FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓

Firm-clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Robustness to a probit specification and year 2000 only: Participants

	Year 2000			Probit model		
	(1)	(2)	(3)	(4)	(5)	(6)
TFP trend coefficient	-1.083		-3.475	-0.589		-1.132
	(1.256)		(3.428)	(0.591)		(1.082)
Fuel trend coefficient	-0.0830***		-0.00668	-0.0405***		-0.00549
	(0.0206)		(0.0253)	(0.0103)		(0.0108)
Assets trend coefficient	0.0112***		0.00567***	0.00550***		0.00265***
	(0.00132)		(0.00129)	(0.000585)		(0.000656)
Log TFP		-0.674	-1.154*		-0.259	-0.398**
		(0.489)	(0.596)		(0.181)	(0.176)
Log fuel expenditure		0.561*	0.480		0.113	0.112
		(0.308)	(0.328)		(0.0924)	(0.0899)
Firm size: Log assets		0.713*	0.611		0.528***	0.431***
		(0.370)	(0.439)		(0.124)	(0.133)
Debt-equity		-2.325**	-1.896**		-1.109**	-0.690
		(1.034)	(0.856)		(0.480)	(0.425)
Log capital-labour		0.900**	0.857**		0.357**	0.349**
		(0.409)	(0.422)		(0.140)	(0.146)
Conglomerate		0.787	0.821		0.321	0.330
		(0.631)	(0.793)		(0.226)	(0.245)
Exporter		0.705	0.670		0.519**	0.611***
		(0.645)	(0.680)		(0.221)	(0.224)
Government		0.0877	0.928		0.0130	0.381
		(0.891)	(1.038)		(0.445)	(0.434)
Observations	3,899	2,481	2,481	11,697	8,460	8,460
Industry FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓

Firm-clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: Logit: Average marginal effects: 2001-2004

	Applicants					Participants				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TFP trend coefficient	-0.0242			-0.0292		-0.0128			-0.0241	
	(0.0229)			(0.0359)		(0.0149)			(0.0217)	
Fuel trend coefficient	-0.00142***			-3.85e-05	1.56e-05	-0.000978***			-6.89e-05	2.80e-05
	(0.000442)			(0.000367)	(0.000357)	(0.000243)			(0.000214)	(0.000208)
Assets trend coefficient	0.000271***			9.24e-05***	9.18e-05***	0.000132***			4.11e-05***	3.77e-05***
	(2.33e-05)			(2.11e-05)	(2.06e-05)	(1.57e-05)			(1.19e-05)	(1.11e-05)
Log TFP		0.00199	-0.00182	-0.00665			-0.00168	-0.00381	-0.00613**	
		(0.00584)	(0.00623)	(0.00662)			(0.00333)	(0.00313)	(0.00296)	
Log fuel expenditure		0.00749**	0.0100***	0.01000***			0.000858	0.00196	0.00196	
		(0.00342)	(0.00373)	(0.00364)			(0.00207)	(0.00213)	(0.00193)	
Firm size: log assets		0.0267***	0.0200***	0.0158***	0.0255***		0.0160***	0.0106***	0.00832***	0.0118***
		(0.00387)	(0.00449)	(0.00449)	(0.00261)		(0.00270)	(0.00263)	(0.00262)	(0.00179)
Debt-equity			-0.0317**	-0.0216*	-0.0199*			-0.0243***	-0.0160**	-0.00803*
			(0.0132)	(0.0114)	(0.0104)			(0.00826)	(0.00794)	(0.00427)
Log capital-labour			0.00935**	0.00689*				0.00738**	0.00686**	
			(0.00415)	(0.00416)				(0.00309)	(0.00304)	
Conglomerate			0.0146*	0.0126	0.0129*			0.00738	0.00688	0.00719
			(0.00776)	(0.00782)	(0.00773)			(0.00475)	(0.00491)	(0.00520)
Exporter			0.0173**	0.0158**	0.0159**			0.0112**	0.0119***	0.00857**
			(0.00749)	(0.00727)	(0.00703)			(0.00452)	(0.00433)	(0.00390)
Government			0.01000	0.0170	0.0129			0.000557	0.00653	0.00317
			(0.0134)	(0.0126)	(0.0122)			(0.00761)	(0.00742)	(0.00823)
Fuel-intensity					0.00261					-0.0298
					(0.00995)					(0.0254)
AME (%)	3.9	6.4	7.0	6.9	6.7	1.9	3.6	4.2	4.1	3.8
Observations	11,967	9,189	8,708	8,708	8,850	11,697	8,938	8,460	8,460	8,602

Firm-clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 17: Robustness of OLS long differences from 2004 with controls for selection into treatment using individual-specific start date

Dependent variable: emissions (log mtCO2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (apply)	0.109	0.230	0.254	0.209	0.217	0.232	0.150
	(0.232)	(0.214)	(0.264)	(0.231)	(0.202)	(0.207)	(0.253)
Observations	2,249	2,194	2,121	2,060	1,941	1,496	1,249
R^2	0.535	0.513	0.500	0.495	0.507	0.513	0.509
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Dependent variable: emission intensity of output (log (mtCO2 / sales))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (apply)	-0.210	-0.192	-0.311*	-0.370*	-0.389*	-0.376*	-0.457*
	(0.256)	(0.164)	(0.170)	(0.191)	(0.199)	(0.205)	(0.237)
Observations	2,156	2,114	2,054	1,970	1,829	1,348	1,154
R^2	0.219	0.197	0.203	0.185	0.191	0.214	0.204
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Dependent variable: total factor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	2006	2007	2008	2009	2010	2011	2012
Treatment (apply)	-0.0525	-0.0715	-0.0793*	-0.0706	-0.134**	-0.114***	-0.0890**
	(0.0677)	(0.0556)	(0.0422)	(0.0443)	(0.0490)	(0.0344)	(0.0339)
Observations	3,612	3,546	3,434	3,298	3,046	2,274	1,934
R^2	0.533	0.485	0.456	0.410	0.396	0.388	0.392
Selection controls	yes	yes	yes	yes	yes	yes	yes
Industry and state FE	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1