Adverse Selection in Carbon Offset Markets: Evidence from the Clean Development Mechanism in China*

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Abstract

Carbon offsets could reduce the global costs of carbon abatement but there is little evidence on how much they truly reduce emissions. We study carbon offsets sold by firms under the Clean Development Mechanism (CDM) in China by matching offset projects proposed to the United Nations to panel data on emissions and output for manufacturing firms. We have two main findings. First, the CDM attempts to screen out projects that would be profitable without offset payments by rejecting proposed projects with higher stated returns. Second, offset-selling firms steeply increase emissions after registering an offset project, relative to similar firms that proposed a project but did not follow-through. We explain this increase in emissions by jointly modeling the firm decision to propose an offset project and the Board's decision of whether to approve. In the model, CDM firms increase emissions due to a combination of the selection of higher-growth firms into abatement project investment and the causal effect of higher productivity, post investment, on firm scale and therefore emissions.

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1 Introduction

To reduce harm from global climate change the world needs to cut greenhouse gas emissions. High-income countries are responsible for most historical carbon dioxide emissions, but low- and middle-income countries, like India and China, constitute a large and growing share of emissions today. Figure 1 shows a decomposition of global carbon dioxide emissions from 1950 to 2022. China and India comprised only 16% of emissions in 1992, when the first global climate agreement was struck, which has soared to 43% in 2022. No global climate agreement can succeed without broad participation in emissions reductions.

This need for global emissions reductions, coupled with reluctance, from low- and middle-income countries (LMICs), to strictly limit emissions, creates an enormous potential market for carbon offsets. LMICs are not likely to set hard limits on carbon dioxide emissions. China and India have stated goals to limit the emissions intensity of their economies but declined to limit the trajectory of emissions, because they do not want to risk slowing economic growth. A carbon offset is a payment by one party to another to reduce emissions on the first party's behalf. In principle, rich countries could use offsets to pay for abatement investments in lower-income countries both to support their growth and to reduce the global cost of meeting any carbon emissions target.

The main weakness of offsets is that they may not in fact reduce emissions, due to the adverse selection of firms that would have made abatement investments even without offset payments. Suppose a firm in Germany, whose emissions are regulated, pays a firm in China to undertake a project to reduce its emissions. If the Chinese firm would have invested in the project anyway, for some private benefit, then allowing offsets will instead increase global emissions, because the firm in Germany now faces a looser cap, without causing any reduction in emissions in China. In the language of climate policy, only reductions in emissions relative to the Chinese firm's unknown, business-as-usual emissions are "additional" reductions that should be counted as an offset. While this additionality problem is widely recognized, there is little empirical evidence on its importance, and offsets remain an important part of global climate policy.[1]

This paper studies adverse selection in arguably the world's most important carbon offset market, the Clean Development Mechanism (CDM) of the Kyoto Protocol. Under the CDM, firms in rich countries could pay firms in LMICs to reduce emissions. The CDM has paid for 3 thousand offset projects in 80 countries that have issued 2.2 billion tons of Certified Emissions Reductions (CERs) (Institute for Global Environmental Strategies, 2022). We ask whether manufacturing

[1] Offsets continue to feature prominently as a policy tool under the current United Nations' framework climate agreement. Article 6.4 of the Paris Accord governs climate offsets and the framework developing under this article emulates the CDM. Offsets, in this framework, are called the "International Transfer of Mitigation Outcomes" (ITMOs), meaning one country reducing emissions on behalf of another. The rules for ITMOs are an active subject of negotiation in the COP process.

firms that undertook carbon offset projects under the CDM actually reduced emissions, relative to a business-as-usual counterfactual.

The empirical difficulty in studying offset markets is that researchers face the same problem as the market regulator, the CDM Executive Board (hereafter, the Board), of developing a counterfactual for what emissions would have been in the absence of an offset project. This paper addresses this problem by forming a new data set that matches all CDM projects proposed by manufacturing firms in China to a contemporaneous firm-level panel data set of emissions, inputs and outputs. This matching allows us to develop plausible counterfactuals for the emissions trajectories of firms that undertake offset projects. We observe a broad set of control firms and both firms that *propose* an offset project to the United Nations and those firms that follow-through to *register* a project, which allows offset sales. We can therefore study the firm selection into proposing a project, the regulator's decision rule of what projects to register (i.e., approve), and the emissions of firms that propose or register a project relative to firms that do not.

We use this data to generate four main findings from a descriptive analysis of the carbon offset market. First, firms that propose offset projects in China are strongly selected on observable characteristics and have some of the highest firm-level emissions in the Chinese economy. Firms that propose CDM projects have baseline emissions five times higher and baseline emissions growth four times higher than firms in the same industry and province that do not propose a project.

Second, the Board attempts to screen on additionality by rejecting projects with high stated returns. Our data include the original project proposals for each CDM project. In these proposals, firms argue why their project is *additional*—why the firm would not invest in the project on their own without the revenue provided by offset sales. We estimate the Board's probability of registering a proposed project based on baseline characteristics that the project reported to the Board. We find that for each one standard deviation increase in the stated return to the project the probability that the Board registers the project declines by 8 percent. This result is consistent with the Board attempting to approve only projects that are privately unprofitable and that would therefore offer additional emissions reductions.

Third, despite the regulator's attempt at screening, carbon dioxide emissions at firms that register CDM projects grow steeply in the years after project registration, relative to emissions at firms that propose but do not register a project. A unique aspect of our data is that every proposed CDM project has to project, ex ante, how much that project will reduce carbon emissions if implemented. The average CDM project forecasts an emissions reduction of 150 thousand tons per year, which would represent a substantial cut in baseline emissions amongst firms that propose (30% reduction) or ultimately register (12% reduction) a project. Our event-study estimates find, by contrast, that firms that register projects *increase* emissions by roughly 570 thousand tons per year (standard error 170 thousand tons) in the four years after the project start. The change in emissions at CDM firms is therefore roughly four times as large—and of the opposite sign—as is initially projected.

Fourth, the increase in emissions at firms that register a CDM project is entirely accounted for by increases in firm scale. Firms that register a CDM project increase their sales, value of output, cost of goods sold and wage bill in the years after project start, all by a magnitude proportional to that of the increase in emissions. The emissions intensity, or emissions per value of output, of firms that undertake offset projects is therefore roughly flat.

These reduced-form findings show that firms that undertake offset projects do not reduce their emissions relative to similar firms, but our event-studies cannot on their own distinguish between the causal effect of an abatement investment on emissions and the selection of firms into registering a project. Event-study estimates are interpretable as causal treatment effects only in the absence of anticipation. We study offset projects, which are long-lived capital investments by forward-looking firms and should therefore be expected to respond to anticipated firm growth. Firms choose whether to propose an offset project and the regulator chooses which firms to register.

We therefore introduce a model of firm investment and emissions to separate the causal effect of abatement investments on emissions from firm selection. In the model, a firm produces output using emissions and can choose whether to undertake a project that increases the productivity of emissions as an input. The firm may undertake this project privately or apply to the Clean Development Mechanism, at a cost, to seek approval to sell carbon credits. The firm knows both its cost of investment and its productivity growth in the next period. The CDM Board observes a noisy signal of the firm's private cost of investment and sets a threshold rule to reject projects which appear to have high private returns.

We characterize the selection of offset projects in this model. Firms that register offset projects have emissions growth different from that of firms that do not register for three reasons. First, registered firms are more likely to undertake projects, which have a direct *emissions productivity effect* of reducing emissions given fixed input choices. Second, registered firms expand in response to projects. This *scale effect* is due to higher emissions productivity leading firms to choose higher inputs. Third, there is *selection on growth*, as regulatory screening on a signal of investment costs selects for firms that have high growth trajectories. For firms, projects are profitable when either the investment has a lower cost or the firm has high future productivity (like a high demand shock tomorrow). Because the regulator screens out projects with a lower investment cost signal, but does not observe growth, firms that are able to register will have higher productivity growth and therefore emissions growth than the firms that propose a CDM project or firms that do not apply.

We use model simulations to decompose the effect of registration into causal and selection components. We find that the model can produce the suite of empirical facts from our reduced-form results, including: (i) selection on firm size into CDM proposal; (ii) higher registration rates for low-return projects; (iii) higher emissions growth at registered than proposing firms; (iv) increases in firm scale after CDM investment; (v) constant emissions intensity at registered as compared to proposing or non-CDM firms. In an example model calibration that reproduces this suite of facts, we also find significant mistargeting and approval of non-additional projects. In the model, to achieve more abatement, the Board must relax its approval threshold to approve projects with a higher signal of private returns, which are less likely to be additional. The share of abatement that is additional declines, at the margin, as the Board relaxes this threshold, and the abatement cost per ton of actual abatement rises. In ongoing work, we will combine our reduced-form moments on project approval and emissions growth for CDM projects with estimates of firm production functions to estimate the model parameters and characterize what share of offset payments went toward additional abatement investments.

This paper contributes to a thriving literature in environmental economics on incomplete regulation. In theory, environmental regulations are most efficient when they are universal, to equalize marginal abatement costs across all sources. In practice, for reasons of politics, the costs of monitoring, and the like, many regulations have incomplete coverage. One way to broaden coverage is to allow voluntary participation in abatement. An initial wave of research on incomplete regulation, in the context of the US Acid Rain program, showed how regulation should adjust when some sources could voluntarily choose to abate (Montero, 1999, 2000, 2005). More recently, studies of carbon regulation have considered how a regulator with incomplete coverage of emissions should optimally adjust policy when regulated firms can trade (Kortum and Weisbach, 2021; Fowlie and Reguant, 2022; Weisbach et al., 2023). This paper studies carbon offsets as a voluntary mechanism to relax the incompleteness of carbon regulation. We find that adverse selection into offset projects undermines the potential abatement cost benefits of broader coverage.

A major theme in the study of incomplete regulation is the consequences of selection into regulation for economic efficiency. The theory of adverse selection in offset markets delineates a trade-off between the amount of abatement achieved and the information rents transferred to firms (Bushnell, 2010, 2011; Van Benthem and Kerr, 2013; Mason and Plantinga, 2013). In principle, the threat of a tax based on average emissions could be used to induce firms to voluntarily disclose emissions (Cicala, Hémous and Olsen, 2022). Empirically, the literature on problems of selection in offset markets is best developed for land use.[2] We study offset projects in the manufacturing sector and our analysis highlights the ways in which the economics differ in this case, for example due to the endogenous choice of inputs and firm scale in response to higher productivity.

Finally, this paper joins a relatively small empirical literature questioning whether CDM projects

[2]Research has shown that there is strong selection into land use conservation or change contracts based on private benefits to project participants, which can steeply raise program costs or lower the environmental benefits from land use offsets (Jack, 2013; Aronoff and Rafey, 2023; Aspelund and Russo, 2024). An empirical literature using remote-sensing data documents that a large share of payments for ecosystem services from land use go to projects that were not additional (i.e., marginal to these payments) (West et al., 2020; Badgley et al., 2022; Guizar-Coutiño et al., 2022).

specifically reduce carbon dioxide emissions. Calel et al. (2021) estimate that CDM wind power projects are, in many cases, just as profitable as other wind investments that were made without offset payments, and are therefore unlikely to be additional. Jaraitė, Kurtyka and Ollivier (2022) estimate that firms undertaking CDM projects in India increase their emissions. We add to this literature by assembling firm-level panel data on emissions for a broad sample and estimating emissions trajectories for CDM firms as compared to plausible counterfactual firms. We also model the process of selection and approval into the CDM to show that registered firm emissions grow despite the Board's efforts to screen out high-return projects. China, our setting, is the largest originator of CDM projects in the world and has the highest carbon dioxide emissions of any country. Prior research by a subset of the present coauthors studies the effect of domestic Chinese policy on industrial energy use (Chen et al., 2021), but there is little prior work on China's participation in international carbon markets.

The rest of the paper proceeds as follows. Section 2 introduces the Clean Development Mechanism, describes our data and then uses it to document selection into CDM proposals. Section 3 presents empirical results on the screening rule for CDM projects and event-studies of CDM firm emissions and other outcomes. Section 4 introduces our model and uses a calibrated version of the model to interpret our empirical results. Section 7 concludes.

2 Context and data

This section describes the origin and purpose of the Clean Development Mechanism (CDM). We then introduce our data sources and how we match CDM projects to data on the firms in China that undertook those projects. Finally, we walk through the steps in the CDM approval process using our data to illustrate firm selection into the CDM.

2.1 Overview of the Clean Development Mechanism

The Clean Development Mechanism (CDM) is a carbon offset market set up under the Kyoto Protocol, the first operating agreement of the United Nations Framework Convention on Climate Change (UNFCCC) (United Nations Framework Convention on Climate Change, 1997). The architecture of the Kyoto Protocol divided countries into two groups: Annex 1 countries, which are all members of the OECD, agreed to commit to greenhouse gas reduction targets, while non-Annex 1 countries, of low- and middle-income, were exempt from such targets. This division formalized the greater responsibility of industrialized countries for past greenhouse gas emissions and their higher income, and therefore capability to abate, at the time of ratification. The Kyoto Protocol came into force in 2005 with targets for Annex 1 countries to return to 1990 emissions levels, or below, by the end of a first commitment period spanning from 2008 to 2012.

The design of the Protocol included three "flexibility mechanisms" to allow for abatement across international borders, including for abatement in non-Annex I countries. Because GHGs are global pollutants, an efficient program of greenhouse gas mitigation would equalize the marginal cost of abatement all around the world. The division of responsibilities under Kyoto appears to preclude efficiency, as only some countries have abatement targets at all. The Clean Development Mechanism, one of the flexibility mechanisms, therefore allows for carbon abatement projects to be undertaken in non-Annex 1 countries to sell offsets to parties in Annex 1 countries that face emissions reductions targets. The demand side of this market is made up of firms within countries that face binding emissions targets under the European Union Emissions Trading System (EU ETS). The supply side consists of many potential abatement projects in non-Annex I countries. The firms undertaking these projects are under no regulatory obligation to undertake abatement projects but voluntarily choose to sell offsets in the CDM.

The CDM began supporting projects in 2006 and as of 2024 these projects have issued 2.2 billion tons of CO_2 equivalent in carbon offsets, which the CDM calls Certified Emissions Reductions (CERs). China is the largest issuer, by far, with 1.2 billion tons (51%) of this total, followed by India (13%), Brazil (8%) and the Republic of Korea (8%). Projects comprise a dizzying range of possible means of GHG abatement, from renewable energy projects to the flaring of GHG emissions from industrial processes. The rules for eligibility for CDM issuance changed at the end of the first commitment period in 2012, disallowing the exchange of CERs for permits within the EU ETS from new projects in most non-Annex I countries (European Commission, 2024). The issuance of new projects dramatically slowed after this point.

While the CDM market is no longer supporting new projects, the program has spawned succcessors within the UNFCCC process. The Paris Accord introduced a new framework under Article 6.4 to allow abatement in one country to count towards the abatement goals of another country (United Nations Framework Convention on Climate Change, 2015*b*). This framework is similar to the flexibility mechanisms under the Kyoto Protocol in allowing for the "International Transfer of Mitigation Outcomes" (ITMO), which are carbon offsets by another name. The rules to start an offset market under this framework have not yet been agreed upon as of the COP28 meeting in Dubai. The CDM is a compliance offset market because demand in this market comes from regulated firms with compliance obligations to reduce emissions or buy permits. The CDM has also influenced the design of voluntary markets for carbon offsets between unregulated parties.[3] Our findings on the CDM are therefore relevant for shaping regulation towards a range of carbon offset markets.

[3] In voluntary offset markets private companies or individuals who are not obligated to meet an emissions reductions target buy offsets for their own emissions goals, marketing, or other reasons. This voluntary segment has grown enormously in recent years but seen large price fluctuations arguably due to a lack of confidence in the additionality and integrity of offsets (see, for example Greenfield, 2023).

2.2 Data sources

We rely mainly on two sources of data, the United Nations Framework Convention on Climate Change (UNFCCC), for data on CDM projects, and the China Environmental Statistics Database (CESD), for firm emissions. We describe these in turn.

The UNFCCC reviews all proposed CDM projects and publicly releases data and documents on these projects (see `https://cdm.unfccc.int/Projects/index.html`). We use a subset of this data that has been compiled by the Institute for Global Environmental Strategies (IGES) as the IGES CDM database (available at `https://www.iges.or.jp/en/pub/iges-cdm-project-database/en`), and supplement this subset with additional documents from the UNFCCC. The UNFCCC data contain a wealth of information on projects drawn from primary document sources. To propose a CDM project the project proponent has to submit a Project Design Document (PDD) to the CDM Executive Board detailing: the firm that proposed a project, the location of a project, the nature of the project and what kind of investment it will make, and the Certified Emissions Reductions from the project, among other variables. The PDD typically also includes information on the investment ticket size for the abatement project and the internal rate of return for the project, as calculated by the proponent or their consultants.

Our second main source of data is the China Environmental Statistics Database (CESD), from China's Ministry of Environmental Protection. The CESD data are a firm-year panel covering energy consumption in physical units and pollutant emissions for the largest industrial firms in China. We calculate CO_2 emissions by applying fuel-specific emissions factors for China, from the UNFCCC, to the fuel quantities observed in the CESD. The CESD data may be audited by both local and national environmental protection agencies. The main limitation of these data is that they are available from 2001 only up through 2010, limiting the post period for our study of CDM firms to effectively five years. The CESD also contains a measure of output. We supplement the CESD, for additional firm outcomes, with the Annual Survey of Industrial Firms (ASIF) from the National Bureau of Statistics (1998-2009, 2011-2013). The ASIF covers firm-year revenue and inputs like employment.

We find relatively high match rates in merging from the group of CDM proposing firms to the CESD and ASIF datasets (Appendix Table A3). Our merging process manually matched firm names from the English version in the UNFCCC database, to the Chinese version in a firm reference directory (`www.tianyancha.com`), and then to the Chinese names observed in the de-anonymized CESD. The CDM project population in China, restricting to project types likely to be undertaken by manufacturing firms, includes 1049 projects put forward by 894 firms. Of this set, we are able to match 52% of the projects to some firm in the CESD and 80% of the projects to some firm in the ASIF, which has broader coverage.

2.3 Stages of the Clean Development Mechanism approval process

The Clean Development Mechanism has a complex approval process through which the Board and its agents screen projects for whether they will achieve additional reductions in carbon emissions (United Nations Framework Convention on Climate Change, 2015*a*). The main steps are: (i) the proposal of a project by a firm, (ii) validation of the project by a third-party certifier, (iii) review and registration of the project by the Board. Here we briefly describe this process with an emphasis on the proposal and registration steps that are central to our empirical analysis.

The first step in the CDM process is for a firm to propose a project. To propose a project a firm, often with the help of a consultant, needs to draft a Project Design Document (PDD) that describes the investment the firm will make to reduce emissions and calculates how many Certified Emissions Reductions (CERs) this investment will generate.[4] In our sample the most common project types are for waste heat recovery and utilization, fuel switches to various less GHG-intensive fuels, energy efficiency and industrial process improvements (Appendix Table A2). In their PDD, firms argue that their project reduces emissions by undertaking an investment analysis to show that the project, without the additional revenue provided by CERs, would have a low internal rate of return, so that the firm would not invest if it did not get CDM payments. When a firm has prepared a PDD the project then must be cleared by the host country, after which it is forwarded to the UNFCCC, which posts the PDD for the proposal on its website. We therefore observe in our data all proposed projects regardless of whether they were later approved or even submitted for approval.

The second and third steps in the CDM process are validation and registration. Conceptually, these steps are essentially a single, screening stage in which the Board and its agents are deciding whether to allow the project to sell carbon offsets or not. In the validation step, the firm hires a special third-party certifier, called a Designated Operating Entity (DOE), to visit the project site, check the details of the CDM application against the firm's records and plans, and give assurance that the project accords with the rules for its project type. If a project passes validation and the firm chooses to pursue it, the project is then submitted by the DOE, on behalf of the firm, to the CDM Executive Board in Bonn, Germany. The Board and its staff vet the submission (a third party, on reviewing the publicly-posted PDD, can also raise an objection or request a detailed review of the project). If the Board approves the project it is then *registered*. Registration allows the firm to sell CERs after the project is complete and subject to ongoing monitoring of ex post emissions.

[4] The UNFCCC keeps a list of the types of investments that are eligible for the CDM, for example, energy-efficiency upgrades, fuel switching, or changing the industrial process in the manufacture of cement. Each type of investment has an accompanying "methodology," a detailed protocol for what information each type of project has to present in its PDD to calculate baseline emissions and emissions reductions (United Nations Framework Convention on Climate Change, 2021). The methodology gives the rules for how a firm can argue that its project will achieve *additional* reductions in emissions, beyond whatever business-as-usual changes the firm might have undertaken.

2.4 Firm selection into CDM proposal and registration

Our matched data allow us to describe the process of selection into CDM proposal and ultimately project registration. In this subsection we use this data to describe how firms that propose and register CDM projects differ from other firms. Here and below we will call firms that proposed but did not register a project *proposed only* firms. Our control group of non-CDM firms in this part is made up of firms in the same industry and province as any firm that proposed a CDM project *and* which were in the top 10,000 firms by output in at least one sample year.

There are three main findings from this descriptive analysis. First, firms that propose or register CDM projects have at baseline some of the highest firm-level emissions in the Chinese economy. Figure 2 shows the distributions of log carbon dioxide emissions for the control group of firms (in green), firms that only proposed a CDM project (in red) and firms that registered a project (in blue). The median of the distribution of emissions for control firms is 3.04 (log thousands of tons) whereas the median for proposed only firms is 5.45. By contrast, the distributions of baseline emissions between registered and proposed firms overlap considerably. The median log emissions for registered firms is 5.76. The distribution of emissions for registered firms is nonetheless shifted to the right, relative to that for proposed only firms, which can be seen in the right tail, as the very largest firms in the data are more likely to be registered.

Second, proposed only and registered firms dwarf firms in the broad control sample on the basis of inputs and outputs, not only emissions. Table 1 compare mean characteristics (with standard deviations in brackets) between proposed only (column 2) and registered (column 3) firms and the broad sample of control firms (column 1). Columns 4 and 5 show the mean difference between proposed and control firms (column 2 less column 1) and between registered and proposed firms (column 3 less column 2), with standard errors for the difference in means in parentheses. Panel A shows variables from the CESD data. Proposed firms have a value of output of CNY 1221m, about seven times larger than control firms (panel A, output value, column 2 vs. column 1). They are not significantly more likely to use coal, but have higher coal consumption than control firms by a factor of five and have both higher CO_2 emissions and emissions growth. Panel B shows variables from the ASIF, which has broader coverage of firm inputs and outputs. CDM proposed firms have much higher levels of fixed capital assets, wages, employment and revenue than control firms.

CDM registered firms are larger than proposed only firms with respect to output and emissions but are generally more similar with respect to other inputs. The mean registered firm has CO_2 emissions twice as large as the mean proposed firm, but comparable emissions growth in the period before the proposed project (panel A, CO_2 growth). The mean values of inputs like fixed capital assets and the wage bill are higher for registered firms, relative to proposed firms, but these differences are not statistically significant, due to the high variance of these variables among the very largest firms (panel B, fixed assets and wage bill, column 5). The overall picture that emerges is therefore that firms that propose any CDM project are enormous, an order of magnitude larger than other firms in their own industries, whereas firms that end up registering projects, while larger still, are not so dissimilar to proposed only firms. The substantial differences between the broad sample of control firms and proposed only or registered firms will lead us, below, to use matching estimators to establish a control group of firms more like those in the CDM.

The third finding from our descriptive analysis of selection is that most screening happens *before* a project is formally submitted to the Board for approval. Table 2 shows, for our sample of CDM projects in the Chinese manufacturing sector, the number of projects that were proposed (column 2), applied to the CDM Board (column 3) and were registered in each year (column 4). Columns 5 and 6 calculate the conditional probabilities that a project applies given proposal and that a project is registered given application. The bulk of the projects span from 2006 to 2012. In the last row, we see that 64% of projects that are proposed end up applying to the CDM Board (column 5) and fully 95% of projects that apply are then registered (column 6). Recall, from the discussion above, that after a project is proposed it needs to undergo validation by a certifier (DOE) that then forwards its implicit approval with the application to the Board. We interpret these results as showing that, if a project is going to be rejected, it is effectively rejected pre-emptively, at the validation stage, before the DOE and firm submit a formal application to the Board. This finding accords with the characterization that the Board will approve projects that have applied by default unless a Board member or outside party raises an objection (United Nations Framework Convention on Climate Change, 2015*a*). In our model and empirical analysis of the approval process we will therefore treat the firm's decision to propose as the first stage and the Board's validation and registration decisions as a joint second stage.

3 Empirical analysis of project screening and firm emissions

This section uses our data to estimate the screening rule for what proposed projects are registered. We then use an event-study approach to trace out the emissions trajectories of firms that register CDM projects as compared to firms that propose a project or to a broader set of control firms.

3.1 Screening of offset projects: the CDM registration rule

The CDM approval process is meant to screen out projects that would not achieve additional reductions in emissions. Our setting is well-suited to estimate what screening rule the Board is actually following and to test whether it is plausibly seeking to reject non-additional projects, for two reasons. First, our data encompass both proposed only projects and registered projects. Second, information on all projects, as contained in the Project Design Document (PDD), is a good approximation of the information available to the Board in making a decision. The PDD is the basis of scrutiny of the project and the Board's registration decision.

Empirical approach.—We consider the sample of 620 firms that proposed, or proposed and registered, a CDM project and which matched to the CESD or ASIF data samples. Within this sample we estimate a linear probability model

$$Registered_i = InternalRateReturn_i \beta_1 + X_i' \beta_2 + \alpha_t + \alpha_k + \alpha_c + \alpha_l + \varepsilon_i. \quad (1)$$

Here $Registered_i$ is a dummy variable equal to one if a project is registered, $InternalRateReturn_i$ is a continuous variable measuring the internal rate of return for the proposed CDM project reported by the firm in the PDD, X_i are other project characteristics such as whether a consultant helped prepared the PDD, and the various α's are fixed effects for year of project start α_t, project types α_k, certified emission reduction deciles α_c and the time from project proposal to project start α_l.

The main coefficient of interest is on the variable $InternalRateReturn_i$. As part of the investment analysis in the PDD, firms typically report the rate of return they expect for the project. This calculation is fairly complex since it depends on the cost of the investment, any private benefits to the firms, such as through lower energy savings, and the anticipated carbon emissions savings and hence CER payments if the project is approved under the CDM.

Empirical results.—Table 3 reports the results of the estimation of (1). Column 1 includes fixed effects but no other project-level controls, while columns 2 through 4 progressively add controls for other project characteristics. Across the board, we find that higher reported rates of return on a proposed CDM project are associated with an economically and statistically significantly lower probability of approval. The rate of return is measured like an interest rate and has median 0.15 and standard deviation 0.08. The coefficient of -0.550 (standard error 0.270) on the rate of return, in column 4, for example, then implies that a one-standard-deviation increase in the rate of return lowers the probability of project registration by 4.4 percentage points ($= 0.08 \times -0.55$), or 7.7 percent of the mean rate of approval (57%).

This finding that reporting higher rates of return is associated with a lower rate of project registration is consistent with the Board attempting to screen out non-additional projects. If a project has a very high rate of return, it may be reasoned that the return would still be high even without the added revenue provided by CERs. In that case, the Board may decide that a project is non-additional. This result is especially striking given the contrast with the more common problem in rate-of-return regulation of capital investments. The typical problem in rate-of-return regulation (for example, of electric utilities) is that a regulator must rule out investments that regulated firms propose, to earn a guaranteed return on capital, but which in fact have high costs or *low* rates of return. The problem of the Board in the CDM is the opposite: the Board wishes to screen out projects that have low costs or high returns, since those projects would likely have proceeded in any case and therefore will not generate additional reductions in emissions. Appendix Table 3 estimates equations like (1), but with investment as the independent variable, and finds that projects with high investment costs are indeed more likely to be registered.

We find additional support for the idea of the Board attempting to screen on additionality in the coefficients on other project characteristics of Table 3. Having a consultant help prepare the PDD appears to be associated with a higher probability of registration (column 2). However, this result turns out to be due to consultants taking on projects with a longer time lag from the proposal to the start of the project (i.e., the start of construction). Once we also condition on this time lag (columns 3 and 4), we find that: (i) projects with a longer time lag are significantly more likely to be registered (ii) having a consultant no longer predicts registration. Projects with consultants are more likely to be registered, therefore, because consultants work on projects with longer time lags. A longer time lag, in turn, is associated with project registration because the CDM approval process favors projects that demonstrate "that the CDM was seriously considered in the decision to implement the project activity" (United Nations Framework Convention on Climate Change, 2015*a*). This favoritism was made explicit after 2008, when firms were required to give advance notice of their consideration of a CDM project in order later to be considered for registration. The notice requirement was taken to suppress CDM applications from firms who were undertaking an energy- or emissions-saving investment but were not motivated by the CDM to do so.

3.2 Emissions and output for firms undertaking offset projects

This subsection studies the emissions of firms that proposed or registered CDM projects as compared to control firms that did not pursue a CDM project. The prior result on screening shows that the Board is attempting to screen out firms with high returns that are not likely to be additional. The current subsection examines whether this screening was successful in selecting for firms that reduced their carbon emissions.

Empirical approach.— We use an event-study design with staggered treatment using the imputation-based difference-in-difference estimator of Borusyak, Jaravel and Spiess (2021). Because of the large skewness in the distribution of firm emissions and the concentration of CDM firms in the right tail of the emissions distribution, we favor event-study estimators that first match firms on pre-period emissions and then implement the staggered difference-in-difference estimator post matching.

In the first step of our estimation we limit the sample of control firms using matching. As described in Section 2, the typical CDM proposed only or registered firm is much larger and higher-emitting than the typical non-CDM firm; however, there is a very large pool of candidate matches among non-CDM firms in the data. We use a Euclidean distance match without replacement (Abadie and Imbens, 2012; Abadie and Spiess, 2022). The distance matching selects control firms to minimize the sum of squared deviations between a treated firm and a candidate control firm on the available baseline lags of the outcome variable, for example, baseline CO_2 emissions in years $\tau = -4$ to $\tau = -1$ before the project start. Matching estimators present a bias-variance trade-off between finding the best pre-period match to reduce bias and increasing the number of matches and therefore the precision of estimates. In our baseline specification we use 3 matches for each treated firm and we also report results for 10 matches per treated firm.

After matching we account for the staggered rollout of CDM projects across firms by using a difference-in-difference imputation estimator Borusyak, Jaravel and Spiess (2021). We seek to estimate event-study specifications of the form

$$Y_{it} = \alpha_i + \alpha_{jt} + \sum_{\tau=-5}^{4} \beta_{1\tau} \mathbf{1}[t - Start_i = \tau] Proposed_i + \tag{2}$$

$$\sum_{\tau=-5}^{4} \beta_{2\tau} \mathbf{1}[t - Start_i = \tau] Registered_i + \varepsilon_{it}, \tag{3}$$

where Y_{it} is an outcome variable, such as emissions, α_i are firm fixed effects, α_{jt} are industry-year fixed effects (at the 2-digit level), $Start_i$ gives the start year of the CDM project for firm i, $Proposed_i$ is an indicator equal to one for firms that only proposed a CDM project but did not register, $Registered_i$ is an indicator equal to one for firms that registered a CDM project, and ε_{it} is an idiosyncratic error term (clustered at the firm level). The coefficients of interest are $\beta_{1\tau}$ and $\beta_{2\tau}$ estimating the relative change in the outcome variable in the years before and after the start of a CDM project. In a variant of this specification, we limit the sample to only firms that proposed or registered a CDM project and omit the event-time indicators interacted with $Proposed_i$, such that the coefficients $\beta_{2\tau}$ compare outcomes for registered firms using just proposed only firms as the control group. In this narrower sample of firms we omit the matching step because CDM proposed only firms are already large and comparable to CDM registered firms (Figure 2).

The imputation based difference-in-difference estimator estimates (2) in three steps. First, using only untreated firm-year observations, from non-CDM firms or CDM firms prior to their project start year, estimate the firm and industry-year fixed effects with $Y_{it} = \alpha_i + \alpha_{jt} + u_{it}$. One can also estimate the effect of time-varying covariates in this step. Second, for each treated firm-year, predict $\widehat{Y}_{it}(0)$ using this baseline regression and estimate $\widehat{T}_{it} = Y_{it} - \widehat{Y}_{it}(0)$. Third, estimate any function of the $\widehat{T}_{it}$, such as the mean value of the firm-level treatment effect in each event-year. Borusyak, Jaravel and Spiess (2021) show that this estimator is the unique efficient linear estimator in their event-study setting (under an auxiliary assumption that the errors are homoskedastic).

Empirical results on emissions.—We start by examining the Certified Emissions Reductions (CERs) that CDM firms *proposed* to achieve in their Project Design Documents. An unusual feature of our data is that the PDD for each firm contains their explicit projection of how much their proposed abatement project was supposed to reduce emissions relative to the baseline level of emissions. These projections cover the "project boundary," which may be a plant or a system within a plant (such as the boiler), rather than the whole firm. A typical PDD projection assumes a flat baseline for emissions and then projects CERs relative to this baseline over a period of 7 to 14 years.

Figure 3 shows the coefficients from an event-study specification run on the projected CER data drawn from PDDs, rather than data on actual emissions. A CDM project in our sample on average proposed to reduce emissions by 150 thousand tons of CO_2 per year, on impact, with that reduction remaining steady over the first five years of the project (these projections are typically steady for the entire project life; we truncate the projections to correspond to the horizon for our event studies of actual emissions). The projected CERs represent a substantial chunk of firm emissions at baseline. Table 1 shows baseline emissions of about 500 thousand tons per year for firms that only propose a CDM project and emissions of about 1200 thousand tons for firms that register a project. The proposed CER reductions would therefore represent a 30% decrease in emissions for proposed-only firms or a 12% decrease for registered firms, despite that the proposed CDM project does not necessarily encompass all emissions from a given firm. The second (red) line in Figure 3 shows the actual CER issuance from registered projects ex post. CER issuance naturally lags CER projections because issuing CERs requires follow-up monitoring to confirm equipment installation and measure ex post emissions. CER issuance may also be lower than CER projections, even in the long run, if a firm decides not to go through ex post monitoring or to sell its permits.[5]

Figure **??** shows estimates of the event-study specification (2) restricted to the sample of firms that proposed a CDM project. Panel A shows the event-study coefficients with the level of emissions as the outcome and panel B with the log of emissions. The main finding from the figure is that CO_2 emissions steeply increase at firms that register a CDM project relative to emissions at firms that only propose a project. In levels (panel A), emissions at registered firms are slightly below emissions at proposed-only firms, but grow rapidly in the year of the project start and the four years afterwards. In logs (panel B), emissions at registered and proposed-only firms are balanced in the pre-period, but emissions grow markedly at registered firms and exceed proposed-only emissions by roughly 0.5 log points by four years after the project start.

Figure 4 estimates the event-study specification (2) in a broader sample of firms including firms that did not propose a CDM project. In each figure the blue line shows event-study coefficients for emissions at CDM registered firms and the red line for CDM proposed-only firms, in both cases as compared to a matched sample of control firms. The rows of the figure differ in the estimator

[5] We expect that firms in our sample received a negative shock to the value of issuance between the time of starting their projects, in the 2006 to 2012 range, and the time of monitoring, since CER prices fell at the end of Phase 2 of the EU ETS (Appendix Figure A1).

used, where the first and second rows use a matching estimator prior to estimating the staggered difference-in-difference regression, and the third row omits this step. In each row the left-hand side takes the level of CO_2 emissions as the outcome and the right-hand side takes the log.

The main finding of this figure is that the gap between CDM registered and proposed-only firms is driven by large increases in emissions at registered firms. For example, in levels (panel A), CDM proposed-only firms have flat emissions before the proposed project start date and some modest emissions growth, not sigificantly different from zero in most individual years in the post period. By contrast, emissions at registered firms increase rapidly in the post period. In logs (panel B), emissions are flat for both registered and proposed-only firms in the pre-period. Emissions remain flat for proposed-only firms in the post-period, but grow rapidly for registered firms. Estimators with a broader matched sample, with 10 control firms matched to each treated firm (panels C and D), or with no-matching (panels E and F) show qualitatively similar results. The one exception is in panel F, with no matching, where the difference between registered and proposed firms arises more from declines in emissions among proposing firms (relative to matched controls) than from emissions growth among registered firms. Even in this case, it is clear that emissions at CDM registered firms are higher in the post period as compared to proposed-only firm emissions. Given that CDM firms are so large, we prefer estimators with a matching step (e.g., panels A and B) in order to restrict the control sample of firms to have comparable scale of emissions in the pre-period.

The magnitude of the emissions increases at CDM registered firms in the years after registration is very large. Table 4 presents regression results for carbon emissions that pool the post-period events from (2) into a single post indicator variable and therefore estimate the average change in emissions for registered and proposed firms after the CDM project start date, as compared to a matched set of control firms. In panel A, emissions are measured in levels. In our preferred specification with firm and industry-year fixed effects (column 4), CDM registered firms are estimated to increase CO_2 emissions after the project start date, relative to a matched sample of control firms, by 569 thousand tons (standard error 173 thousand tons) and CDM proposed firms by 190 thousand tons (standard error 124 thousand tons). The former effect is highly significant ($p < 0.01$) while the latter coefficient is not statistically significantly different from zero. In panel B, the outcome is log carbon emissions. Again looking at the column 4 specification, the results are qualitatively similar, with registered firms estimated to increase their emissions after registration by 27 log points (standard error 10 log points). Proposing firms have a small, negative and statistically insignificant change in emissions.

The upshot of these estimates is that, while CDM registered firms project ex ante that they will *reduce* emissions by 150 thousand tons per year, in fact emissions at these firms *increased* by some 570 thousand tons per year after registration (Table 4, column 4). In a sample restricted to only proposing firms, as used in the event studies for Figure **??**, we find an even larger increase in emissions in registered versus proposed firms in levels, of 831 thousand tons per year, and a similar effect, in logs, of 22 log points (Appendix Table **??**).

Emissions growth due to scale versus emissions intensity.—Figure 5 decomposes emissions growth at CDM registered firms into growth in output and growth in emissions intensity (emissions per unit output), using the same (2) specification as for Figure 4. Panel A shows the value of output in levels and panel B in logs. Panel C shows emissions intensity in levels and panel D in logs.

The main finding from the figure is that emissions growth is mainly attributable to growth in scale rather than changes in emissions intensity. In panel A, the level of output in CDM registered firms increases in the years leading up to the CDM project start date and grows more quickly in the years afterwards. In panel B, the log value of output at registered and proposed-only firms is similar in the pre-period, but grows more quickly at registered firms after the project start. The point estimate for the aggregate growth in output in year 4 after the project for registered firms is near 0.5 log points (panel B), which is comparable to, if slightly smaller than, the estimated coefficient on the same event year with log CO_2 emissions as the outcome (Figure 4, panel B). Estimates for emissions intensity (panel C) are roughly flat, but imprecisely estimated, for both registered and proposed only firms. There is some evidence that log emissions intensity increases at registered firms, though, again, the estimates for this ratio are imprecise. We conclude that most emissions growth can be attributed to increases in the value of output produced, though there may be an ancillary role for increases in emissions intensity in some specifications.

Drawing in additional data, we find supporting evidence from input costs that CDM registered firms sharply increase scale in the years after registration. Our main emissions outcomes are measured in the CESD; however, we also observe a broader set of firm inputs in the ASIF. This allows us to go beyond emissions and output as measures of scale. Figure 6 compares the log of revenue, the cost of sales, the wage bill and fixed assets in the ASIF for CDM registered and proposed-only firms to a matched sample of control firms. We find that the revenue and variable inputs (cost of sales, wage bill) are growing quickly for CDM registered firms even prior to the project start date, and in some cases this growth accelerates after the project start (wage bill, panel C). There is no growth in fixed assets in registered firms, which is somewhat surprising, as CDM projects themselves involve capital investments. Capital is difficult to measure and the size of CDM investments is likely small when compared to the entire existing capital stock of the firms. The growth in variable inputs from the project start date to four years after for registered firms is approximately 0.4 log points, similar to the growth in the value of output or sales and slightly smaller than the growth in emissions.

Table B9 summarizes these event studies with regressions that estimate the average change in sales and input demands in the post period for registered and proposed only firms. The independent variable of interest is an interaction between registered firms and the period from 0 to 5 years after the CDM project start date. Each column has a different dependent variable: sales, the cost of sales, the wage bill and fixed assets. We find, consonant with the event-study Figure 6, that all of sales, the cost of sales and the wage bill increase significantly in the period after registration, by amounts ranging from 16 log points for the cost of sales to 29 log points for the wage bill. Given the confidence intervals the increase in all of these measures of output and variable inputs is similar in proportional terms to the estimated increase in CO_2 emissions (of 27 log points, in Table 4, panel B, column 4). There is no growth in fixed assets for registered firms in the period after registration.

Overall, the evidence from two data sources suggests that growth in the scale of firm variable inputs and therefore output and sales accounts for most of, and perhaps the entirely of, the estimated increase in emissions at registered firms.

Discussion of results.— We find a suite of empirical results on selection, screening and emissions in the CDM. First, CDM proposed only and registered firms are much larger emitters at baseline than other firms in the same industries. Second, the regulator attempts to screen out high-return projects, on the basis of the firm's proposal, in order to ensure CDM firms achieve additional reductions in carbon emissions. Third, despite this attempt at screening, emissions at registered firms grows steeply in the years after registration, relative to a control group of firms that only proposed a CDM project or a broad sample of matched firms. Fourth, this emissions growth is mainly due to an increase in firm scale and not emissions intensity.

We do *not* interpret the event-study estimates as providing causal estimates of the effect of CDM participation on emissions growth. CDM projects involve forward-looking investments that trade off capital expenditures today for future private benefits in energy savings and social benefits in emissions savings. For this reason, we believe that firms may select into the CDM based on their own anticipated growth, which would violate the "no anticipation" assumption required to interpret an event-study estimate as the causal effect of a dynamic treatment. While the event-study results show that CDM registered firms did not reduce emissions, in an absolute sense, it remains possible, in the presence of selection, that their counterfactual emissions in the absence of the CDM would have been still higher than we estimate.

Our preferred interpretation of the event-study estimates is that they combine three conceptually distinct forces. First, an *emissions productivity effect*, the causal effect of a technological change on emissions, holding constant firm output. This raw technological effect is what the CDM screening process is designed to measure. Second, a *scale effect*, from variable input choices endogenously responding to an increase in productivity. Third, a *selection on growth effect*, from firms that anticipate higher future growth being more likely to invest in a long-lived project today. The CDM explicitly screens on willingness to invest in abatement capital. In order to formalize these effects and build a framework for measurement, Section 4 provides an explicit model of selection and screening in the CDM.

4 Model of the Clean Development Mechanism

This section presents a model of the Clean Development Mechanism to allow us to measure the effects of firm productivity, input choices and selection on firm emissions growth. In the model, a firm has private information about the returns on its abatement project and the Board attempts to screen projects, to award carbon credits only to firms with additional investments.

4.1 Set-up

Figure 7 describes the structure of the CDM game and the payoffs for the firm at each terminal node. A firm can decide whether to apply at a cost to the CDM. If the firm does not apply, it chooses whether to invest in an abatement project or not, based only upon the private returns to the project. If the firm does apply, the Board draws a signal of the firm's investment costs, and either registers the project or not based on its signal. The Board seeks to register only projects with low private returns. If the project is not registered, the firm faces the same investment decision as if it had not applied in the first place. If the project is registered, the firm now has the prospect of selling certified emissions reductions (CERs), which raises its potential payoff from investment. In what follows, we micro-found the benefits and costs of abatement investment in the firm's production decisions and profits.

Production.—We use a framework where emissions are an input to production (Copeland and Taylor, 2005; Shapiro and Walker, 2018). Firms have a production function

$$y = (1-a)zv \tag{4}$$

where z is productivity, v is a composite input of capital and labor, and $(1-a)$ is the loss of output for abatement effort a. Firm emissions depend on abatement through

$$e = \left(\frac{1-a}{z_e}\right)^{1/\alpha_e} zv \tag{5}$$

Total emissions are proportional to value added zv. However, firms can make abatement effort a to reduce emissions. The effect of abatement effort on emissions is governed by an abatement efficiency factor $z_e > 1$ and the elasticity of emissions $1/\alpha_e$ with respect to $1-a$.

Substituting in the choice of $1-a$, we write the production function as

$$y = z_e[zv]^{1-\alpha_e}(e)^{\alpha_e} \equiv \underbrace{[z_e(z)^{1-\alpha_e}]}_{\tilde{z}} v^{1-\alpha_e} e^{\alpha_e} \tag{6}$$

Firms therefore have a Cobb-Douglas production function in a composite input and emissions. With this form, emissions productivity is factor-neutral: emissions productivity z_e and the general productivity term z combine to form total factor productivity $\tilde{z}$.

Optimal output and emissions.—To solve for firm output and emissions, we assume that each firm faces an inverse demand curve $p = y^{-\frac{1}{\eta}}$ with $\eta > 1$. With this demand curve, the firm maximizes profit by choosing an optimal output of

$$y^*(\tilde{z}) = \left(\left(\frac{\eta-1}{\eta}\right)\frac{\tilde{z}}{C_w}\right)^{\eta} \tag{7}$$

where C_w is a constant depending on factor prices and production parameters. Firm emissions are linear in the chosen output at

$$e^*(\tilde{z}) = \frac{C_w}{\tilde{z}}\frac{\alpha_e}{t_e}y^*(\tilde{z}) = \tilde{\eta}(\eta-1)\frac{\alpha_e}{t_e}\left(\frac{\tilde{z}}{C_w}\right)^{\eta-1} \tag{8}$$

where $\tilde{\eta} = (\eta-1)^{\eta-1}\eta^{-\eta}$ and t_e is the price of emissions. We think of this emissions price as being a shadow cost of existing regulations for air pollution or energy use, although it could also include the prices of inputs like coal that generate emissions. Since $\eta > 1$, the emissions from optimal production are *increasing* in the emissions productivity z_e, due to a scale effect. Emissions intensity, per unit of output and per unit of sales, respectively, can be expressed as

$$\frac{e^*}{y^*} = \frac{C_w}{\tilde{z}}\frac{\alpha_e}{t_e} \qquad\qquad \frac{e^*}{r^*} = \frac{\eta-1}{\eta}\frac{\alpha_e}{t_e} \tag{9}$$

Emissions intensity per unit output is *decreasing* in both productivity $\tilde{z}$ and the emissions shadow cost t_e, while emissions intensity per unit sales does not depend on productivity.

Abatement project.—Firms, whether or not they are registered in the CDM, have the option to undertake an abatement project to increase their emissions productivity z_e. We now define two periods, with $t = 0$ before the consideration of the project and $t = 1$ after. Let the initial emissions productivity be z_{e0} and the emissions productivity after investment be $z_{e1} = \Delta_e z_{e0}$ for some $\Delta_e > 1$. An abatement project therefore increases the firm's emissions productivity, allowing the firm to make the same output with a lower level of emissions input.

The firm's general productivity changes by $\Delta_z \equiv z_1/z_0$ between periods. We assume that firms have perfect foresight of their productivity growth. Without the abatement project, post-period business-as-usual emissions are

$$e_1^{BAU} = \Delta_z^{(1-\alpha_e)(\eta-1)} e_0 \tag{10}$$

With the abatement project, emissions change to

$$e_1 = \Delta_e^{\eta-1} \Delta_z^{(1-\alpha_e)(\eta-1)} e_0. \tag{11}$$

Firm emissions growth therefore depends on both the exogenous growth in productivity and the endogenous choice to invest in the project.

The private benefit to the firm of undertaking the abatement project is the change in profits that the project would cause. Firm profit is a linear function of emissions $\pi(\tilde{z}) = \frac{1}{\eta-1}\frac{t_e}{\alpha_e} e(\tilde{z})$. The gross private benefit from the abatement project is therefore

$$\frac{1}{\eta-1}\frac{t_e}{\alpha_e}\left(e_1 - e_1^{BAU}\right) = \underbrace{\frac{1}{\eta-1}\frac{t_e}{\alpha_e}(\Delta_e^{\eta-1}-1)(\Delta_z)^{(1-\alpha_e)(\eta-1)}}_{b(\Delta_e,\Delta_z)} e_0 \tag{12}$$

The firm's benefit $b(\Delta_e, \Delta_z)e_0$ therefore depends on the baseline level of emissions, the emissions productivity gain from the project and the firm's anticipated change in productivity.

The firm has to pay an investment cost to do the abatement project. We assume that the investment cost $F(\Delta_e, e_0)\varepsilon$ depends on the emissions productivity gain Δ_e, the firm's baseline emissions e_0 and an idiosyncratic investment cost shock ε. It is necessary to discount the flow benefits of the project to compare them to up-front investment costs. For this purpose, we assume that the project runs for a period of $\widetilde{T}$ discounted years.

Clean Development Mechanism payments.—If the firm invests in the project *and* is registered for the CDM, it can sell carbon credits. The Board grants carbon credits based on what it can measure. We make two key assumptions on how carbon credits are calculated that are consistent with the structure of the model and the CDM rules.

First, we assume that the Board does not have any information about the firm's productivity growth Δ_z, but can observe both baseline emissions and the technical productivity improvement Δ_e from the project. In the CDM approval process, the Board fastidiously measures baseline emissions and the technical characteristics of the project, but does not attempt to forecast growth.

Second, we assume that the Board calculates CERs as the reduction in emissions that would be achieved if the firm produced the same output as at baseline with the same composite input v but the higher emissions productivity given by Δ_e. Using (6) to solve for the implied change in emissions from this rule yields a Certified Emissions Reduction of

$$CER = \underbrace{\left[1 - \left(\frac{1}{\Delta_e}\right)^{1/\alpha_e}\right]}_{\delta_e(\Delta_e)} e_0. \tag{13}$$

The firm is granted more CERs if baseline emissions are high, if the emissions productivity improvement Δ_e from the project is large, and if the elasticity of output with respect to emissions α_e is small. At a CER price of p the CERs have a value $p\delta_e e_0$ to the firm.

4.2 Firm and Board strategies

We solve the game backwards from the firm's investment decisions given registration.

Firm investment decision.—The firm invests when the project is profitable

$$\widetilde{T}\left(b + p\delta\mathbf{1}\{CDM\}\right)e_0 \geq F\varepsilon, \tag{14}$$

where $\mathbf{1}\{CDM\}$ indicates CDM registration and we omit the arguments of project benefits and costs. The net payoffs of the firm's project without and with CERs define a hierarchy of firm profitability. We define three types of firms:

$$\text{Firm type} = \begin{cases} \text{Never invest} & \text{if } \tilde{T}(b + p\delta_e)e_0 < F\varepsilon \\ \text{Additional} & \text{if } \tilde{T}(b + p\delta_e)e_0 \geq F\varepsilon \text{ and } \tilde{T}be_0 < F\varepsilon \\ \text{Always invest} & \text{if } \tilde{T}be_0 \geq F\varepsilon. \end{cases} \tag{15}$$

The *Never invest* firms have projects that are not profitable even if they are registered under the CDM. The *Additional* firms can profitably invest if and only if they are registered. The *Always invest* firms have a profitable project even without CERs and are therefore non-additional.

Board registration rule.—The Board, if it observed investment costs and project benefits, would register only *Additional* firms, since the investment decision is responsive to CDM registration only for these firms. The Board cannot observe the firms' private benefits and costs but attempts to screen for additional firms using imperfect information.

The Board observes δ_e and e_0 as part of the firm's CDM application but does not see two parts of the firm's return. First, the Board does not know the firm's growth rate and evaluates project returns under the assumption that $\Delta_z = 1$, that is, at the firm's baseline scale.[6] Second, the Board observes the average fixed cost of a project, but only receives a noisy signal ε^s of the firm's idiosyncratic cost shock ε.

[6] We provide empirical evidence that this assumption is reasonable. In regressions for project registration, lagged firm emissions growth is found to have no statistically significant effect on registration.

We restrict the Board to follow a screening rule that registers a project if its perceived return is *low enough.* Let $\overline{b} \equiv b(\Delta_e, 1)$ where $b(\cdot,\cdot)$ is the firm's return per unit of baseline emissions (12). The Board registers a project if its perceived annual rate of return is below some threshold $\overline{R}$

$$R = \frac{\left(\overline{b} + p\delta_e\right) e_0}{F\varepsilon^s} < \overline{R}. \tag{16}$$

The logic is intuitive—if the firm has a high return, or appears to have a low investment cost, then the project is likely to be privately profitable and therefore not additional.

It is possible to simplify the model exposition if the abatement project is scale-free, in the sense that the investment costs of the project are linear in baseline emissions. We specify that the cost of a project depends on the amount of CERs it will produce,

$$F(\Delta_e, e_0) = \gamma_0 (\delta_e e_0)^{\gamma_1}. \tag{17}$$

Empirically, we estimate $\hat{\gamma}_1 \approx 1$ (see Appendix B), so we proceed with the assumption $\gamma_1 = 1$. Under this assumption, the log of the registration rule (16) becomes

$$\underbrace{\log\left(\overline{b}/\delta_e + p\right) - \log(\gamma_0)}_{\text{Log observed rate of return}} - \underbrace{\log(\varepsilon^s)}_{\text{Cost signal}} < \log \overline{R}. \tag{18}$$

In Table 3, above, we estimate this registration rule and provide direct evidence for the rule's implication that the registration probability is *decreasing* in observed returns.

Firm application decision.—The first stage of the game is the firm's decision of whether to apply to the CDM or not. From the firm's perspective, the noisy signal ε^S generates ex ante uncertainty in project registration. Let $F(\varepsilon^s|\varepsilon)$ be the distribution of the Board's signal conditional on the firm's draw of investment cost. Then the firm's registration probability is

$$\begin{aligned} Pr(\text{Registered}|\varepsilon) &= Pr\left(\underbrace{\log\left(\overline{b}/\delta_e + p\right) - \log(\gamma_0) - \log\overline{R}}_{\log\overline{\varepsilon}^s} < \log(\varepsilon^s) \,\middle|\, \varepsilon\right) && (19)\\ &= 1 - F(\overline{\varepsilon}^s|\varepsilon). && (20)\end{aligned}$$

We can think of the Board's threshold return $\overline{R}$ implying a corresponding threshold signal $\overline{\varepsilon}^s$, such that the Board registers all firms with a high enough cost $\varepsilon^s > \overline{\varepsilon}^s$ (hence low enough return).

The expected payoff of applying for the CDM differs by firm type (15). *Never invest* firms will not apply since they will not invest even if they were registered. *Additional* and *Always invest* firms expect a profit from application of

$$\begin{aligned} \pi^A(b, \Delta_e, \varepsilon, e_0) &= Pr(\text{Registered}|\varepsilon)\left[\tilde{T}(b + p\delta_e) - (\gamma\delta_e)\varepsilon\right] e_0 && (21)\\ \pi^{NA}(b, \Delta_e, \varepsilon, e_0) &= Pr(\text{Registered}|\varepsilon)\tilde{T}(p\delta_e)e_0. && (22)\end{aligned}$$

The expected profits differ by type because additional firms, if they are registered, earn the profit from the whole project, while always invest firms earn only the incremental profit from being granted carbon credits.

Firms will apply to the CDM if their gain in profit from application exceeds the application cost. We specify a cost Ae_0 of applying to the CDM. We assume that firms know their idiosyncratic investment cost ε and their growth rate Δ_z prior to application. The application decision is

$$\text{Apply} = \begin{cases} 1 & \text{if Additional} \quad \text{and} \quad \pi^{A}(b,\Delta_e,\varepsilon,e_0) > Ae_0 \\ 1 & \text{if Non-additional} \quad \text{and} \quad \pi^{NA}(b,\Delta_e,\varepsilon,e_0) > Ae_0 \\ 0 & \text{otherwise.} \end{cases}$$

Additional and non-additional firms have different application rules because for non-additional firms the expected CER payments only have to cover application costs, whereas for additional firms they also have to compensate for private investment losses.

4.3 Model outcomes by firm type

Firm decisions by type.—Figure 8 characterizes the model outcomes by firm types. The axes of the figure show the two-dimensional firm type space: on the vertical axis, $\log b(\Delta_e,\Delta_Z)$, the gross benefit of investment, and on the horizontal axis, $\log \varepsilon$, the firm's idiosyncratic investment cost shock. Each marker in this space is a simulated firm. The simulations rely on our actual parameter estimates; the estimation procedure will be describend in the following section. The color of the marker indicates the firm type. The type of the marker indicates whether a firm invested ($\times$) or not (hollow $\circ$).

The figure illustrates how firm types dictate decision-making. Firms are delineated into three types according to (15): always invest firms have low costs and high benefits (northwest), never invest firms have high costs and low benefits (southeast), and additional firms lie in between. Firms in the region at the top center of the figure, above the dashed blue frontier, apply for the CDM, because they have high growth rates (private benefits) and moderate investment costs. Firms with high investment costs do not apply to the CDM because their project is too costly to be profitable, even if granted carbon credits. Firms with low investment costs do not apply to the CDM because they anticipate the regulator will receive a signal of their low cost and their project will not be approved.

Firm types interact with application and registration decisions to determine investment If a firm is of the always invest type, its marker has an $\times$, regardless of whether it applies to the CDM, since the project is privately profitable. Among always invest types that apply, some are registered and granted CERs (indicated by $\times$). If a firm is additional, it may apply if the return on investment is high enough; this is the case for firms in the "Apply" space above the blue dashed frontier but below the dashed black line. Because these firms are additional, they only invest (indicated by $\times$) if there project is registered. The model therefore produces a range of outcomes for firm application decisions, registration and investment in abatement projects.

Implied emissions growth rates.—Our event-study results show that emissions at registered firms grow more quickly than emissions at proposing or non-CDM firms. In the model, emissions growth for firms can be decomposed into two forces.

1. *Scale effect* (Endogenous inputs). Firms adjust their variable inputs in response to a change in emissions productivity. If we fix expected growth of $\Delta_z = 1$, but allow firms to adjust inputs, then an increase in emissions productivity will increase emissions by

$$g_e = \Delta_e^{\eta-1} > 1.$$

2. *Selection on growth effect* (Exogenous growth). Firms decide on their investments with information about next periods' productivity growth. If we allow the firm's productivity to have expected growth rate Δ_z, then the growth in firm emissions will be

$$g_e = \Delta_e^{\eta-1}\Delta_z^{(1-\alpha_e)(\eta-1)} > 1.$$

The observed difference-in-differences estimates showing higher growth for registered firms than proposed firms, and proposed firms than for non-applicants, can be rationalized in the model as a combination of these two effects. It is possible to derive analytic formulas for these combinations if we condition on a particular level of ε.[7] In this case, we show that the difference in growth for a registered firm as compared to a non-applicant is given by

$$E[\log(g_e)|\text{registered}, \varepsilon] - E[\log(g_e)|\text{not apply}, \varepsilon] =$$
$$\underbrace{(\eta-1)\log\Delta_e}_{\text{Scale}} + \underbrace{(E[\log b|\log b > b_1(\varepsilon)] - E[\log b|\log b < b_1(\varepsilon)])}_{\text{Selection}},$$

where $b_1(\varepsilon)$ is the minimum private benefit for a firm to apply to the CDM as a function of its investment cost. There is a selection effect in application because only high-growth firms find it worthwhile to apply. In Figure 8, these firms are defined by log benefits, on the vertical axis, above the dashed blue frontier defining the set of applicants. Similarly, the difference in growth between firms that are registered and those that only propose a project is

$$E[\log(g_e)|\text{registered}, \varepsilon] - E[\log(g_e)|\text{proposed, not registered}, \varepsilon] =$$
$$\frac{\omega_1^A(\varepsilon)}{\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)}(\eta-1)\log\Delta_e,$$

[7] We also assume this ε is high enough that the firm will apply to the CDM for some level of b. This rules out the case where the ε is so low that the firm's expected value of CERs is not enough to cover the CDM application cost.

where $\omega_1^A(\varepsilon)$ is the mass of additional firms that apply and ω^{NA} is the mass of non-additional firms that apply. The growth rate gap between the groups is therefore increasing in the fraction of additional firms among all applicants. If more firms are additional then more firms undertake the project when registered, which increases emissions growth for registered as compared to proposed-only firms.

5 Model estimation

We now discuss how we estimate the model. The estimation draws on data from both the firm-level panel data sets and the UN's Project Design Documents. The model is estimated in four parts. In the first part, we estimate the production function parameters using firm-level panel data before the CDM started, with standard techniques. In the second part, we estimate firm investment costs via a linear regression. The third and fourth parts are unique to our model. In the third part, we estimate the mean firm-level emissions productivity improvement. In the fourth part, we estimate the distribution of firm growth and the Board's registration rule and signal structure. We now describe these parts in turn and present our estimates in parallel for each part. The parameter estimates for all parts are gathered in Table 6.

5.1 Production function

We parameterize the composite input function v and the productivity process z to estimate the firm production function. We assume a standard Cobb-Douglas value-added production function such that

$$v_{it} = l_{it}^{\alpha_l} k_{it}^{\alpha_k}. \tag{23}$$

The firm's output is then

$$\log y_{it} = \log z_i^e + (1-\alpha_e)[\log z_{it} + \alpha_l \log l_{it} + \alpha_k \log k_{it}] + \alpha_e \log e_{it} \tag{24}$$

Using the relationship that $\log r_{it} = \left(1 - \frac{1}{\eta}\right) \log y_{it}$, we have

$$\log r_{it} = \alpha_l^* \log l_{it} + \alpha_k^* \log k_{it} + \alpha_e^* \log e_{it} + \log z_i^{e*} + \log z_{it}^* + \varepsilon_{it}^m \tag{25}$$

where $\log z_i^{e*} = \left(1 - \frac{1}{\eta}\right) \log z_i^e$, $\log z_{it}^* = \left(1 - \frac{1}{\eta}\right)(1-\alpha_e) \log z_{it}$, $\alpha_l^* = \left(1 - \frac{1}{\eta}\right)(1-\alpha_e)\alpha_l$, $\alpha_k^* = \left(1 - \frac{1}{\eta}\right)(1-\alpha_e)\alpha_k$, and $\alpha_e^* = \left(1 - \frac{1}{\eta}\right)\alpha_e$. The term ε_{it}^m is an iid measurement or optimization error contained in revenue data.

As is typically the case with data on revenue but not physical output quantities, we will not be able to separately identify η from the rest of production function parameters. We therefore calibrate $\eta = 4$ and use this value to re-scale all the estimated parameters.

We assume that there is a proxy variable, intermediate inputs, that is monotonically increasing in firm productivity, conditional on capital and labor. In other words, $m_{it} = m(k_{it}, l_{it}, z_{it})$. We can then write the revenue equation as

$$\log r_{it} = \phi(l_{it}, k_{it}, e_{it}, m_{it}) + \log z_i^{e*} + \varepsilon_{it}^m$$

where

$$\phi(l_{it}, k_{it}, e_{it}, m_{it}) \equiv \alpha_l^* \log l_{it} + \alpha_k^* \log k_{it} + \alpha_e^* \log e_{it} + m^{-1}(l_{it}, k_{it}, m_{it})$$

Once we obtain the estimate of $\hat{\phi}(l_{it}, k_{it}, e_{it}, m_{it})$, we assume $\log z_{it}^* = g(\log z_{it-1}^*) + \varepsilon_{it}^z$ to yield the quasi-time-difference equation

$$\hat{\phi}_{it} = \alpha_l^* \log l_{it} + \alpha_k^* \log k_{it} + \alpha_e^* \log e_{it} + g(\hat{\phi}_{it-1} - \alpha_l^* \log l_{it-1} - \alpha_k^* \log k_{it-1} - \alpha_e^* \log e_{it-1}) + \varepsilon_{it}^z$$

We obtain an emission elasticity parameter $\hat{\alpha_e^*} = 0.161$ and the labor and capital coefficient $\hat{\alpha}_l^* = 0.456$, $\hat{\alpha}_k^* = 0.175$. With our calibrated value of $\eta = 4$, this implies that the value-added production function has $\alpha_l = 0.724$, $\alpha_k = 0.278$ and is not significantly different from constant returns. Similarly, we can calculate $\alpha_e = 0.215$. It is useful to interpret the emission elasticity parameter as governing the trade-off between output and abatement effort: at an output loss of 5% ($1 - a = 0.95$), a firm could reduce emissions by 21.2%. Our emissions elasticity (share) is greater than that estimated for local air pollutants (Shapiro and Walker (2018)). We believe this estimate is reasonable given the importance of energy use and hence carbon emissions in these energy-intensive industries.

5.2 Investment cost function

We estimate the cost of investment for abatement projects using data from the Project Design Documents (PDDs) submitted to the UN. Our approach assumes that reported investment costs are unbiased measures of the true investment cost, measured up to an idiosyncratic error term.

The investment cost is $F\varepsilon$ where F is given by (17) and ε is an idiosyncratic private cost shock known to the firm but not the Board. As both investment cost and CERs are observed, we estimate the linear regression

$$\log(F) = \log(\gamma_0) + \gamma_1 \log(\delta_e e_0) + \varepsilon. \tag{26}$$

Table D12 reports the results. We find that $\hat{\gamma}_1$ is not statistically different from one, so we can proceed with the multiplicative structure of the investment cost. We also find that the constant in regression is -7.94, which implies an fixed investment cost of 330 USD (approximately 230 EUR during the sample period) per ton of emission saved. Since projects are long-lived, this estimate is reasonable and consistent with the narratives in PDD that a CER price of 10 EUR can meaningfully improve the annual IRR of the projects. If we take the average CER price of 10 EUR, we obtain a normalized parameter of $\gamma_0 = 23$ times the CER price.

Our estimates of investment costs imply reasonable rates of return. We compute the average annual private internal rate of return (IRR) $\bar{b}/(\delta_e \gamma_0)$ on CDM projects to be about 5%. This estimate, despite being derived independently from the production function and investment cost data, is close to the stated private returns in the PDDs.

5.3 Emissions productivity gain

We also use data from the Project Design Documents (PDDs) of all proposed projects to estimate the emissions productivity factor Δ_e from undertaking a CDM project. Equation (13) gives the model expression for CERs as a function of baseline emissions, the emissions elasticity α_e and the emissions productivity factor Δ_e. CERs and firm baseline emissions are observed in the data. Therefore, after estimating $\hat{\alpha}_e$ in the production function, we can solve this equation for Δ_e. We take an emissions-weighted average of the saving rate CER/e_0 across projects to obtain an estimate of $\hat{\Delta}_e = 1.027$ (see Appendix Table D13).

The emissions productivity improvement may seem small, but recall this is the implied productivity gain for the whole *firm* from a single investment *project*. It therefore captures both the technical efficiency gain from the project, which can often be 20–30% or more, and the size of the project-related emissions relative to the firm's total emissions. We can compare the change in emissions productivity to the firm's baseline condition. For the same 5% decline in output that before was associated with a 21% reduction in emissions, the firm, after investment in the project, could instead reduce emissions by 31%.

5.4 Board signal structure and firm emissions growth

Identification.—The final, and most subtle, part of the estimation recovers firm emissions growth and the Board signal structure: the registration threshold and the correlation of the Board's signal with the firm's true investment cost. While firm emissions growth is observed in the data, the Board's signal and the firm's idiosyncratic component of investment costs are not observed. We argue that the model parameters are nonetheless identified from the difference-in-difference of growth rates across registered, proposed-only and non-applicant firms.

Figure 9 presents the identification argument graphically using data from simulations of the model. Each panel shows three data moments: the growth rate of registered firms compared to non-applicants (solid black line, measured against the left axis); the growth rate of proposed-only firms compared to non-applicants (dashed black line, left axis); and the registration rate conditional on application (dashed red line, right axis). The left panel plots these moments varying $\overline{\varepsilon}^s$, the Board's threshold signal of investment cost for registration, and the right panel varies ρ_s, the correlation of the signal with the true investment cost.

The left panel shows that more stringent screening decreases registration rates and raises the growth rates of firms conditional on application. Moving from left to right, the Board requires a higher signal of investment cost (lower return) to register a firm. Hence fewer firms are registered (dashed red line). Because screening is more stringent, the selected set of firms that do apply has higher emissions growth rates, in order for application to be worthwhile despite the lower probability of registration. More stringent screening increases growth rates about equally for both registered and proposed-only firms.

The right panel shows that the gap in growth rates between registered and proposed firms is increasing in the strength of the Board's signal. The logic is as follows. If the Board's signal were random noise, then firms would be assigned to registration or proposed-only status at random. The only growth rate gap between firms would be due to the endogenous adoption of the project by additional firms becoming registered. If the Board's signal is informative, then there will be an additional, selection component of the growth rate gap between registered and proposed firms. This selection component arises even though the Board cannot observe growth. Firms apply to the CDM when their investment cost is moderate and their private benefit (growth rate) is high (Figure 8). The application decision induces a positive correlation between firm growth and investment costs: if a firm has high project costs, it must have especially high growth to bother applying. When the Board rejects low-cost projects, therefore, it also tends to reject low-growth projects. More informative Board screening therefore makes the growth of registered firms relatively higher than the growth of the proposed-only firms whose projects are rejected.

Estimation.—Using this logic we estimate the parameters $\{\mu_{\Delta_Z}, \sigma_{\Delta_Z}, \rho, \overline{\varepsilon}^s\}$ based on four moments: the emissions growth rates of registered, proposed and non-applicant firms and the registration rate. We match these moments in the model using the Generalized Method of Moments and, as the estimator is just-identified, fit the moments exactly. The model therefore reproduces the difference-in-difference estimates of Table 4 by construction.

We have two comments on the resulting parameter estimates, reported in Table 6. First, the registration threshold $\hat{\overline{\varepsilon}}^s$ implies a threshold rate of return, inclusive of the private benefit and CER payments, around $\overline{R} = 15\%$. This estimate seems empirically reasonable and, again by construction, matches the observed registration rate. Second, the Board is found to be well-informed. The correlation of the Board's signal of investment cost and the true cost is $\hat{\rho}_s = 0.75$, which is quite high. The CDM is an exceptionally costly and rigorous screening mechanism and this expense yields an informative signal.

6 Model results on additionality and screening

With the model estimates we can now characterize the outcomes of the CDM in the status quo and consider how the CDM would perform under counterfactual screening stringency or other conditions. We use the model estimates to produce three main results.

First, most of the growth of emissions reported in the event-study estimates of Table 4 is found, through the model, to be exogenous selection-on-growth. We find that 82% of the differential growth of registered firms and 86% of the differential growth of proposed-only firms, with respect to non-applicants, is due to selection. The model logic for the large share of exogenous growth is straightforward: CDM abatement projects are not large enough contributors to firm's total emissions productivity to endogenously increase growth to the large extent observed. In our model, complete adoption of CDM projects by a group of firms increases emissions by a factor of $\hat{\Delta}_e^{\hat{\eta}-1} \approx 8.6\%$, relative to non-adoption. Most of the observed growth of registered firms must therefore be due to selection, not the causal effect of the CDM abatement project on scale.

Second, a large share of CDM registered projects are non-additional. Table 7 summarizes firm outcomes for application, registration and investment by firm type. We find that most firms are "never invest" (55%) followed by "additional" (28%) and "always invest" (16%). Conditional on being registered, the probability that a firm was non-additional is 36% ($= 5.4/(5.4+9.8)$). The registration also makes Type II errors by rejecting additional firms that have applied. Amongst additional applicants, the probability of registration is only 62% ($= 9.8/(9.8+6.2)$). The screening process therefore generates substantial errors despite that the Board is estimated to have a highly informative signal of investment cost. In part, this is due to the fact that the firm has a two-dimensional type and Board does not observe firm growth.

Third, changes to the stringency of screening would not substantially reduce the share of CERs granted to non-additional firms. Figure 10 traces out a marginal cost curve for additional emissions reductions as a function of the regulatory threshold used in screening $\overline{\varepsilon}^s$. In the left-hand panel we plot mean CERs issued and the fraction of CERs issued to additional firms as a function of the investment cost threshold. We find that lowering the investment cost threshold steeply increases mean CERs issued per firm in the applicant pool. However, the share of non-additional CERs granted is relatively insensitive to screening stringency. The estimated $\overline{\varepsilon}^s$ is indicated by a vertical dotted line. The share of non-additional CERs at this estimated stringency is nearly the same as what it would be if the investment cost threshold was *doubled*.

The reason for this result is that changes in stringency, in the model, exclude more firms but do not have a large effect on the marginal additionality of the firms that are screened out. Consider Figure 8. The dashed blue application frontier defines firm types that apply to the CDM. If the registration threshold rises, only higher-return and higher-cost firms continue to apply, so this frontier shrinks inwards, excluding both non-additional (always invest) firms on the left side and additional firms on the bottom of the frontier. The Figure 10, panel A result is that changing stringency excludes a roughly constant fraction of firms of each type. Panel B then plots the implication for abatement costs. We normalize the nominal price of a CER to one. The payment per CER is constant in the model, but the payment per CER granted to an additional firms varies with the composition of firms that are registered. We find that the actual cost per additional CER is between 1.4 and 1.6 and increases only slightly as the stringency of the screening rule is relaxed. More stringent screening, without more information than the Board presently observes, would not appreciably reduce the registration of non-additional firms.

7 Conclusion

We study the carbon offset market created by the Clean Development Mechanism to encourage abatement projects in low- and middle-income countries. We match data on CDM offset projects, both proposed and ultimately registered, to panel data on firm emissions, inputs and outputs in China, the world's largest emitter of carbon dioxide and the largest offset issuer, by far, under the CDM. We use this matched data to study the screening of firms into offset projects and how firm emissions respond to the registration of an offset project.

Our analysis produces four main findings. First, there is heavy selection into offset proposal and registration on observable characteristics, with CDM firms having higher and faster-growing baseline emissions than other firms in the same industries and provinces. Second, the CDM executive Board attempts to screen out non-additional projects, as it is more likely to reject projects that have higher stated returns or which have a shorter time from application to a project's proposed start date. Third, the emissions at firms which register CDM projects increase steeply after the project start, and on average are 570 thousand tons higher in the four years after a project start relative to the year before, as compared to a matched sample of control firms. Fourth, growth in firm emissions is due to an increase in firm scale which is observed proportionally across sales and other variable inputs such as labor, rather than a change in emissions intensity.

We explain these findings using a model of CDM proposal and screening in which firms differ in their costs of investment and (unobserved) rates of growth. The finding that emissions at CDM firms *go up* initially seems paradoxical given that CDM projects were projected ex ante to reduce emissions by 150 thousand tons per year on average. Our model reconciles this paradox with both a causal and a selection effect. The causal effect is that firms endogenously choose inputs in response to an increase in productivity and so the scale of firm production grows in response to an investment that improves emissions productivity. The selection effect is that the CDM screens on static returns, but not on growth, and therefore the firms that succeed in registering projects will have higher productivity growth than firms that only proposed projects or did not apply. We show in a calibrated version of our model that these effects can produce the empirical results that we estimate in the data. In ongoing work we will estimate the parameters of the model to quantify the relative importance of these effects.

In most parts of the world and in many sectors carbon dioxide emissions are not regulated, which leaves a large potential market for carbon offsets, the purchase of abatement from firms and people producing these uncovered emissions. The integrity of these markets have come into question over whether, for example, certifiers have the right incentives or offset payments are passed through to project participants like small farmers (in the case of land use offsets). Our analysis studies the CDM, which arguably had more extensive monitoring and rigorous screening than any carbon offset market in the world. We highlight that asymmetric information on firm growth or investment costs can produce adverse selection even when monitoring of the technical side of investments and baseline emissions is essentially perfect. Most abatement projects do not happen in a vacuum but are undertaken for a mix of social benefits, through offset payments, and private benefits such as energy savings or technological improvements that raise firm efficiency. Our findings cast doubt on whether even rigorous screening can reliably separate additional from non-additional projects in a dynamic environment where firms make investment decisions in part for such private benefits.

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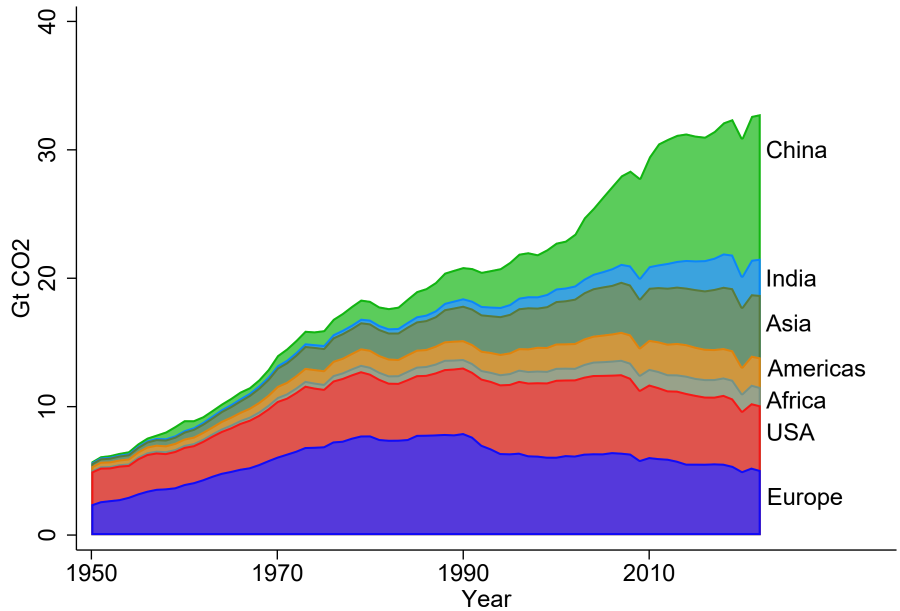
8 Figures

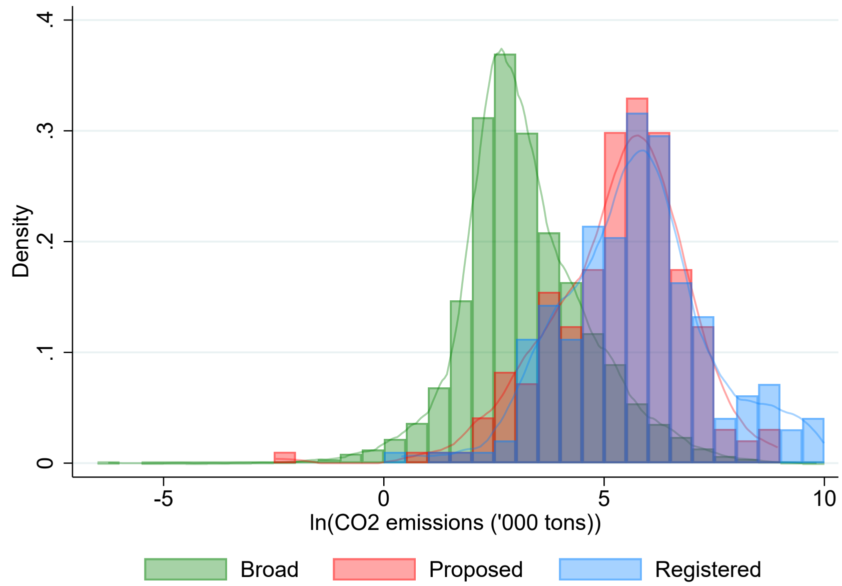
Figure 1: Carbon Dioxide Emissions by Country or Region, 1950–2022



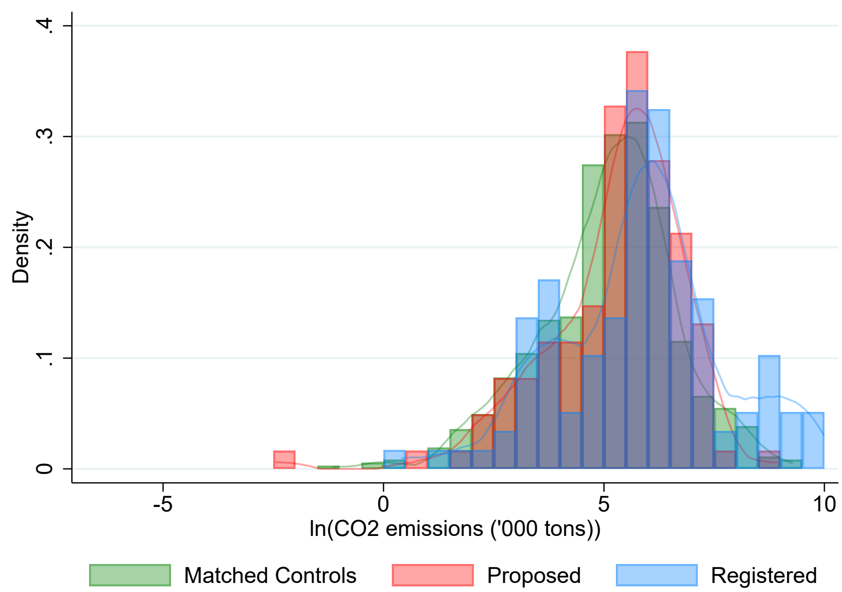
The figure shows CO_2 emissions from coal, oil, gas, cement production and flaring for various countries and regions based on data from the Global Carbon Budget. The Global Carbon Budget uses data from the UNFCCC for the period 1990 to 2022 for Annex I countries and populates data before 1990 with multiple sources including Carbon Dioxide Information Analysis Center (CDIAC), the BP Statistical Review of World Energy and global and national cement emissions from Andrew (2019). The emissions for countries and regions are mutually exclusive and exhaustive with respect to global emissions. The emissions for Asia exclude China and India, which are shown separately, and similarly the emissions for the Americas exclude the USA.

Figure 2: Comparison of Baseline Emissions Between CDM Firms and Other Firms

A. Before Matching

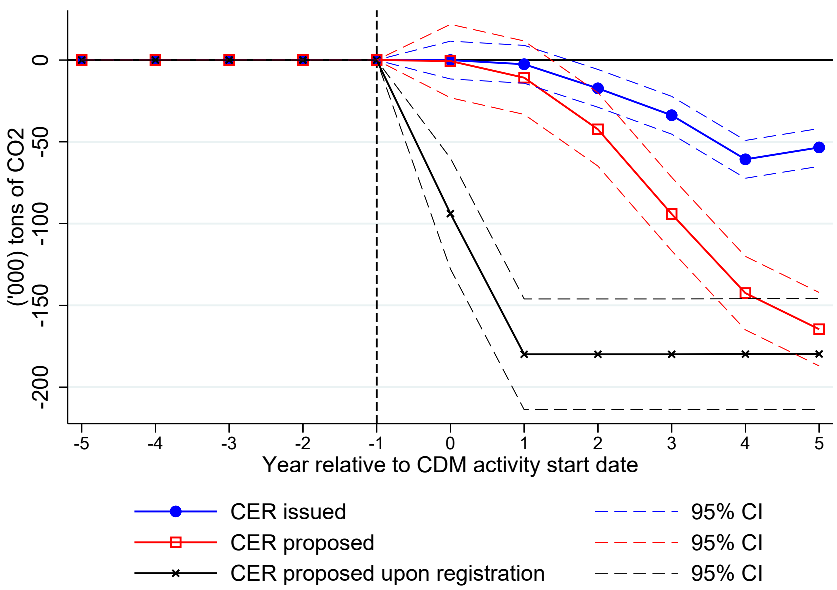


B. After Matching



Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the distribution of carbon dioxide emissions for firms registered under the CDM, before a project was undertaken, distributions for firms that proposed a CDM project that was not registered (what we call proposed only firms) as compared to the large firms that were in the same industry and province of CDM firms but did not propose a project in Panel A, while matched firms in our baseline sample in Panel B. Carbon dioxide emissions are measured in the China Environmental Statistics Database (CESD) in the base year of 2005, one year before the project start year for many CDM projects in our sample, or the year closest to 2005 for firms with no missing emissions in that year. Emissions in the CESD are calculated by applying fuel-specific emissions factors to the physical quantities of fuels consumed.

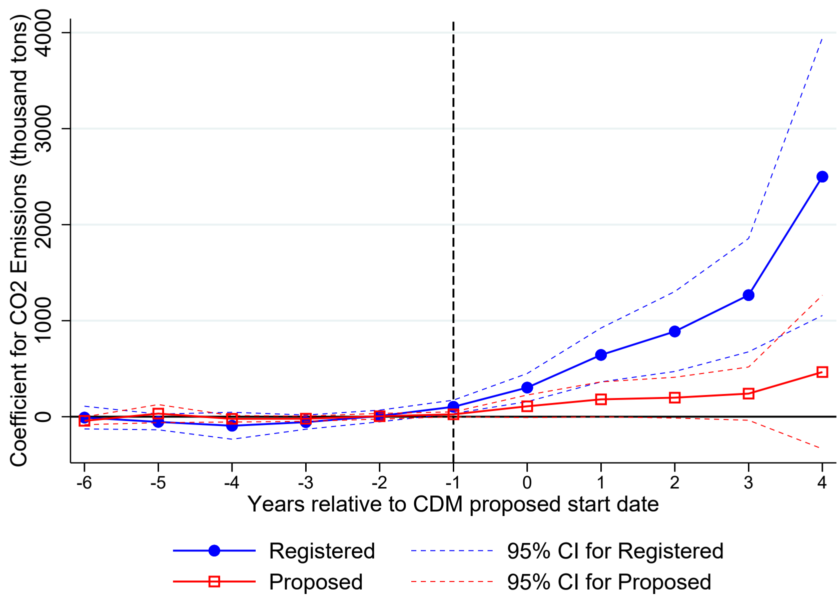
Figure 3: Proposed Certified Emissions Reductions (CERs) ex ante and CERs Issued ex post



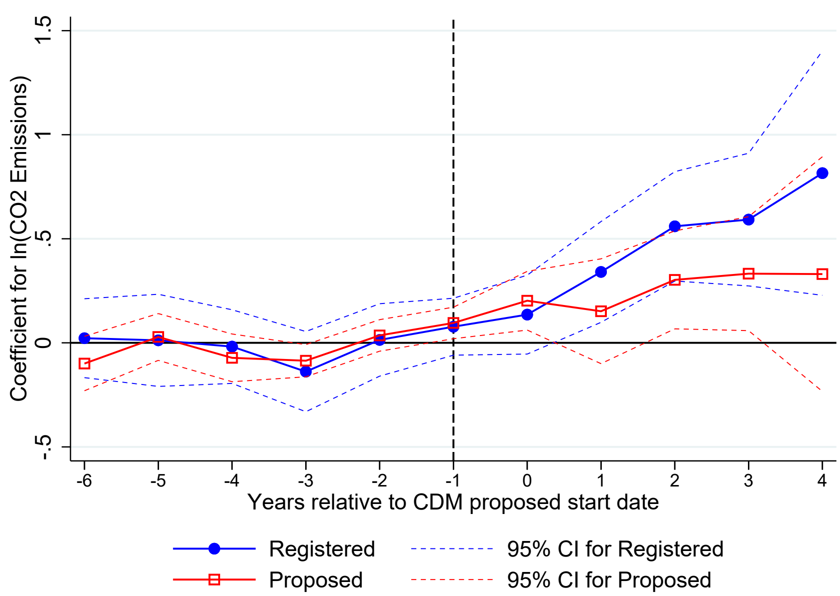
The figure shows the coefficients from an event-study specification for certified emissions reductions (CERs), that is, carbon emissions relative to baseline, using the *stated projections* from each CDM firm in their project proposals (red line) and also CERs supposed that if each firm starts proposing CERs immediately after the CDM activity start (green line). The data on projected CERs are drawn from the Project Design Documents (PDD) filed with the CDM Executive Board. The second event-study (blue line) shows the path of CERs actually issued ex post. Issued CERs can differ from and also lag proposed CERs because ex post verification is required to issue CERs and this takes time.

Figure 4: Event Studies for CO_2 Emissions

A. CO_2 Emissions

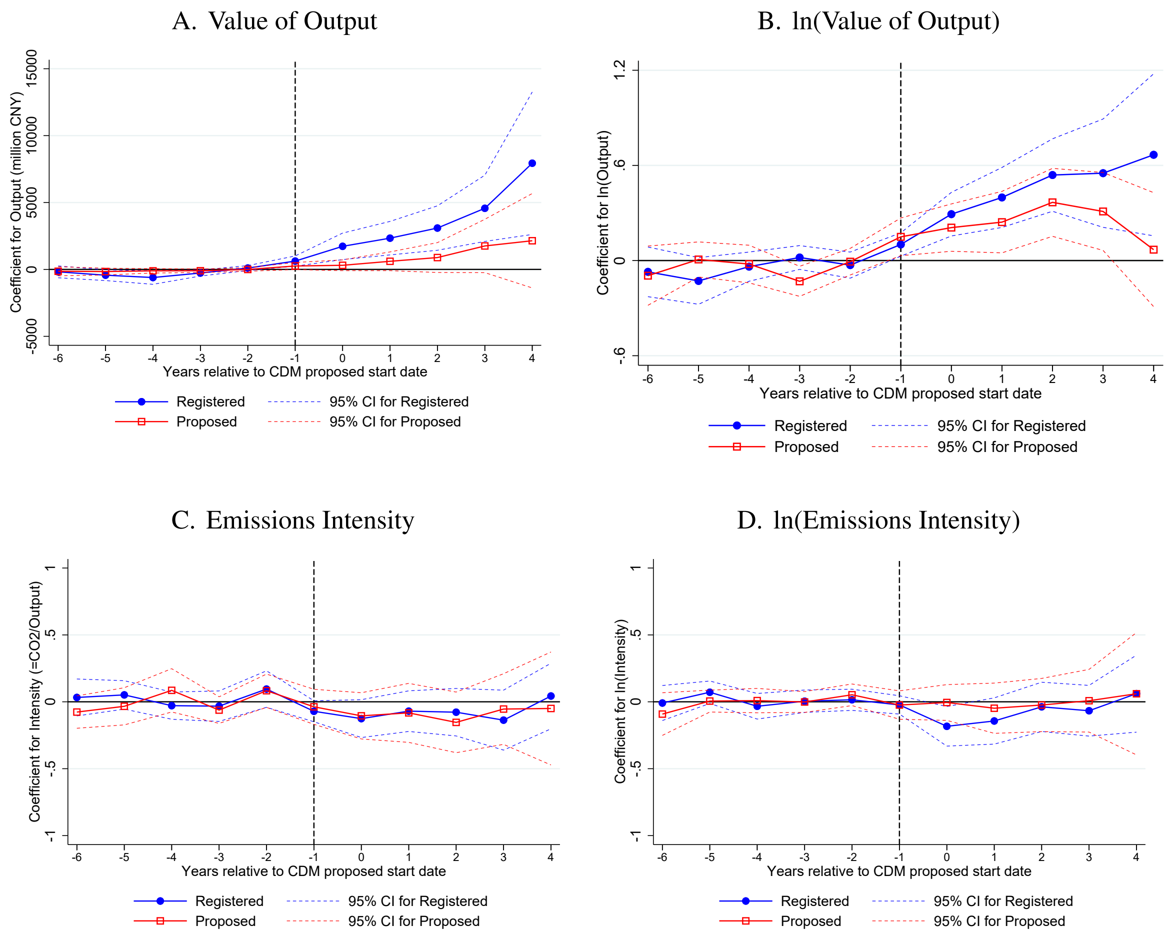


B. ln(CO_2 Emissions)



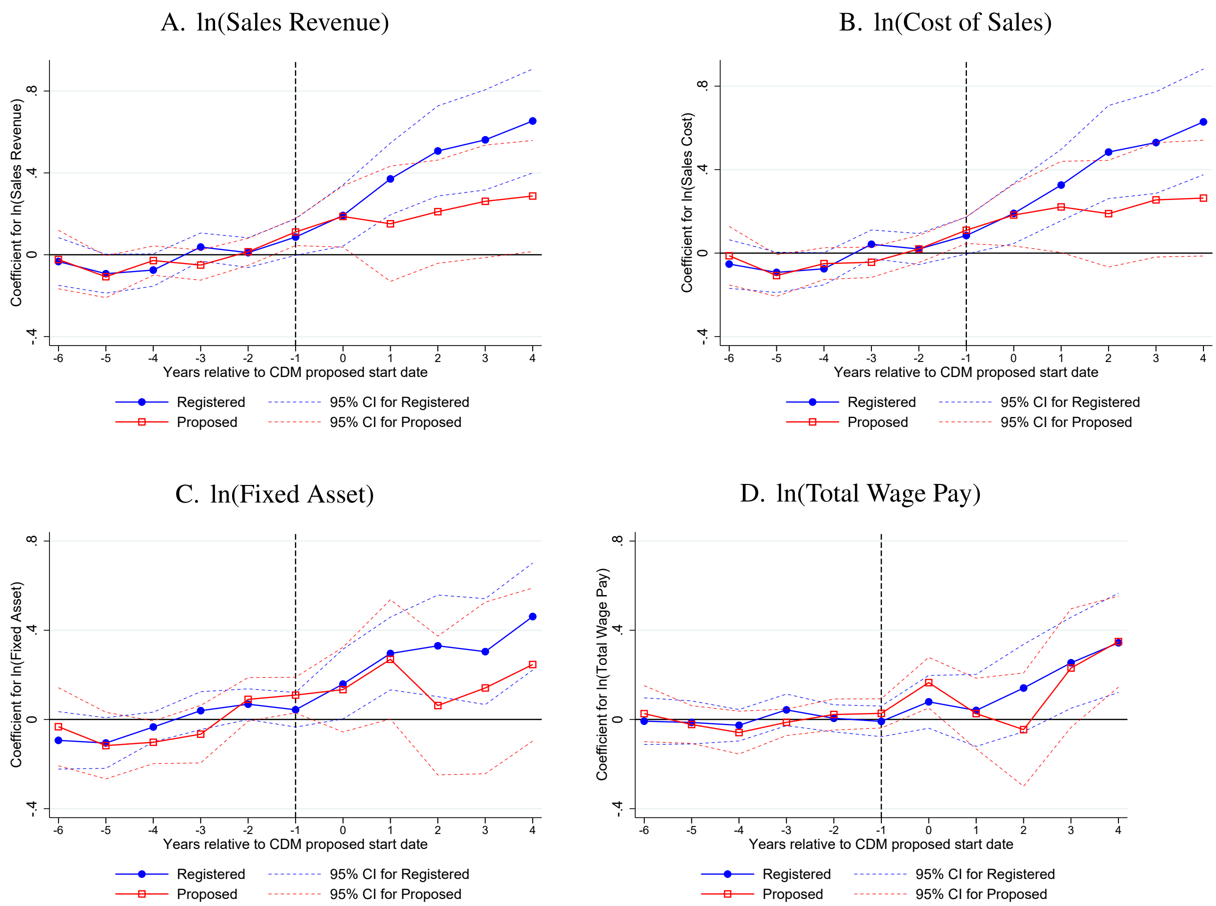
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows coefficients from the event-study specification (2) comparing CO_2 emissions and log CO_2 emissions for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched without replacement to 3 control firms on baseline emissions trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure 5: Decomposition of CO_2 Emissions Into Scale and Emissions Intensity



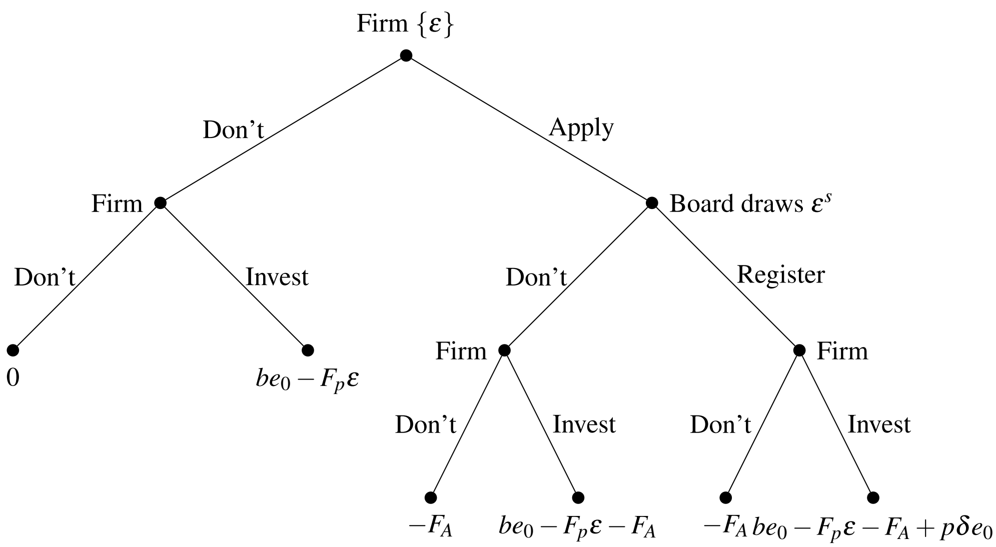
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from the event-study specification (2) comparing output and emissions intensity (CO_2 per unit output) for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched without replacement to 3 control firms on baseline emissions trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure 6: Event-studies for Sales and Input Demands



Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from the event-study specification (2) comparing sales and input demands for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched without replacement to 3 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure 7: Model of the Clean Development Mechanism



The figure shows the game tree for the model of the Clean Development Mechanism application process and firm investment. A firm can decide whether to apply at a cost to the CDM. If the firm does not apply, it chooses whether to invest in the abatement project or not, based only upon the private returns to the project. If the firm does apply, the Board draws a signal of the firm's investment costs, and either Registers the project or not based on its signal (following a rule like that we estimated in Table 3). If the project is not registered, the firm faces the same investment decision as if it had not applied in the first place. If the project is registered, the firm now has the prospect of selling certified emissions reductions (CERs), which raises its potential payoff from investment.

Figure 8: Illustration of firm actions by firm type

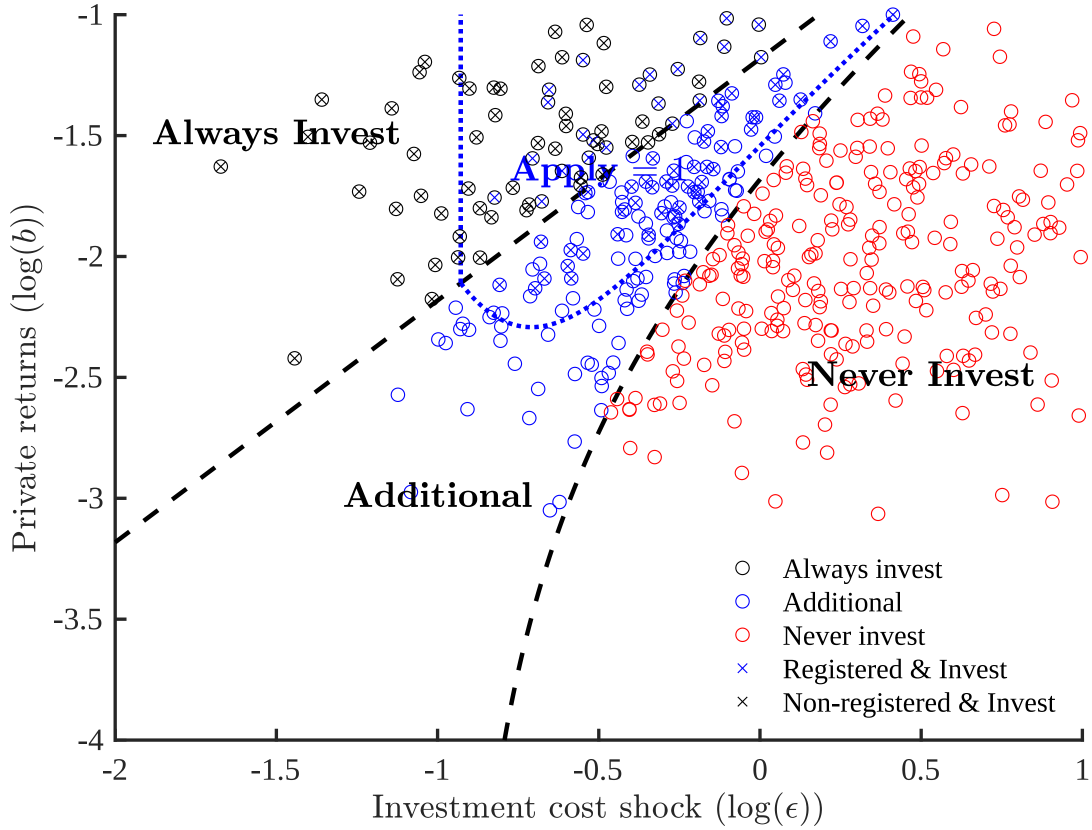
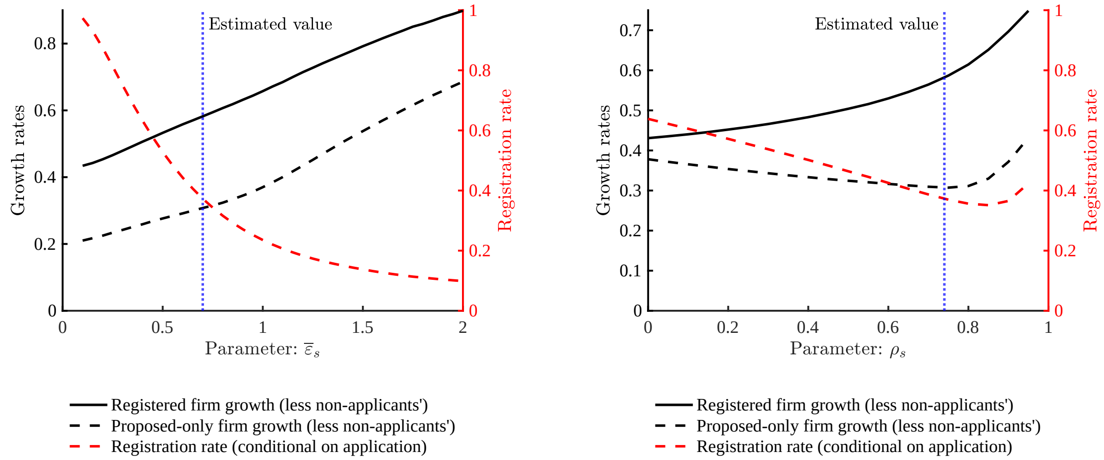


Figure 9: Illustration of Model Identification for Registration Signal and Threshold

A. Moments by $\overline{\varepsilon}^s$ parameter

B. Moments by ρ_s parameter

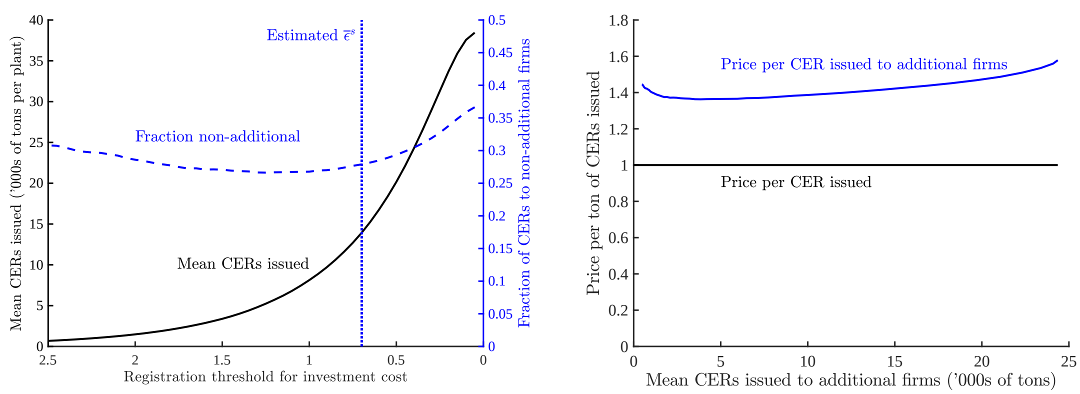


This figure illustrates how the observed data moments on firm growth rates and firm registration rates identify the parameters of the Board's registration rule. Panel A varies the value of $\overline{\varepsilon}^s$, the regulator's cut-off for the investment signal, along the horizontal axis. Moving from left to right the regulator sets a higher cut-off meaning firms have to have a higher observed signal ε^s of investment cost (hence lower return) in order to be registered. Panel B varies the value of ρ_s, the correlation of the regulator's signal of investment cost with the firm's true investment cost. Moving from left to right the regulator's signal is more precise. Within each panel, the data moments are: (i) the difference between the emissions growth of registered firms and non-applicants (black solid line), (ii) the difference between the emissions growth of proposed-only firms and non-applicants (black dashed line), (iii) the registration rate (red dashed line, measured against right-hand axis).

Figure 10: Additionality and Abatement under the CDM

A. CER issuance and Non-Additional CERs by Registration Stringency

B. Abatement expenditure cost curve



9 Tables

Table 1: Comparison of CDM Proposing and Registered Firms to Broad Control Group

	Broad	Proposed only	Registered	Proposed - Broad	Registered - Proposed
	(1)	(2)	(3)	(4)	(5)
		Panel A: CESD variables			
Output value (CNY m)	164.8	1221.0	3764.2	1056.3***	2543.2***
	[1018.4]	[3659.1]	[10343.9]	(261.4)	(773.6)
CO2 emissions ('000 ton)	90.3	511.5	1215.1	421.2***	703.7***
	[358.5]	[922.9]	[3042.8]	(65.6)	(224.0)
Uses coal (=1)	0.93	0.95	0.88	0.015	-0.073***
	[0.25]	[0.22]	[0.33]	(0.016)	(0.028)
Uses liquid fuel (=1)	0.062	0.16	0.15	0.10***	-0.0090
	[0.24]	[0.37]	[0.36]	(0.026)	(0.037)
Uses natural gas (=1)	0.033	0.061	0.12	0.028	0.058**
	[0.18]	[0.24]	[0.32]	(0.017)	(0.029)
Total coal consumption ('000 ton)	44.1	255.7	606.7	211.7***	351.0***
	[172.5]	[472.3]	[1574.1]	(33.6)	(115.8)
Natural gas consumption (million m3)	2.00	6.58	13.1	4.59	6.49
	[61.5]	[50.0]	[64.9]	(3.60)	(5.82)
CO2 growth	0.030	0.16	0.12	0.13***	-0.038
	[0.59]	[0.50]	[0.66]	(0.047)	(0.079)
Observations	29182	197	202	29379	399
		Panel B: ASIF variables			
Fixed assets (CNY m)	126.4	1660.3	2431.7	1533.9***	771.4
	[1086.1]	[6747.6]	[11931.3]	(427.6)	(808.4)
Investment, long-term (CNY m)	16.3	89.3	296.3	73.0	207.0
	[1777.6]	[642.6]	[1782.7]	(59.4)	(171.3)
Investment, short-term (CNY m)	0.98	4.57	13.3	3.59	8.77
	[38.2]	[37.0]	[125.3]	(3.58)	(12.5)
Wage bill (CNY m)	7.93	47.6	158.9	39.7***	111.3*
	[67.3]	[112.9]	[963.3]	(7.85)	(59.7)
Revenue (CNY m)	212.2	1870.4	3163.8	1658.2***	1293.4
	[1305.2]	[5645.9]	[14789.0]	(355.7)	(920.1)
Cost of product sales (CNY m)	181.5	1692.7	2149.0	1511.2***	456.4
	[1184.8]	[5348.6]	[7777.0]	(338.3)	(561.4)
Employment (number)	348.1	1513.4	3085.8	1165.4***	1572.4**
	[1474.7]	[3350.3]	[12575.6]	(215.4)	(774.4)
Observations	89958	251	304	90209	555

This table compares variables in groups. Broad refers to all firms that do not propose a CDM project and are in the same province and industry as a CDM firm. Proposed only firms are firms that have a record in the UNFCCC CDM registry with a status that is not registered. Registered firms are firms are that registered in a CDM project according to the UNFCCC CDM registry. Columns 4 and 5 report the mean difference and the standard errors of different groups. Column 4 compares the set of proposed only firms to firms with on CDM record. Column 5 compares registered firms to proposed only firms. We take the firm-year observation that is closest to 2005 for firms in the broad sample and firm-year observation that is closest to proposed project start year for firms that are proposed only or registered. Panel A are variables in the Chinese Environmental Statistics Dataset (CESD) while panel B are variables in the Annual Survey of Industrial Firms (ASIF). Statistical significance at certain thresholds is indicated by * $p < 0.10$, **$P < 0.05$, ***$p < 0.01$.

Table 2: CDM Project Proposal and Registration by Application Year

	CDM Project Status			Probabilities	
Application Year (1)	Proposed (2)	Applied (3)	Registered (4)	Pr(Applied| Proposed) (5)	Pr(Registered| Applied) (6)
2005	2	1	1	0.50	1.00
2006	58	40	38	0.69	0.95
2007	205	101	90	0.49	0.89
2008	208	78	68	0.38	0.87
2009	180	99	92	0.55	0.93
2010	185	105	101	0.57	0.96
2011	198	135	135	0.68	1.00
2012	193	171	171	0.89	1.00
2013	19	7	7	0.37	1.00
2015	1	1	1	1.00	1.00
2020	10	0	0	0.00	
Total	1259	738	704	0.59	0.95

This table shows the number of CDM projects in China by year of application. The sample consists of CDM projects with project types that are commonly undertaken by manufacturing firms. The projects are distinguished by their application status. A project is “Proposed" if there is a corresponding CDM project record in the IGES dataset. And a project is “Applied" if that project is submitted to UNFCCC executive board for a decision, which implies that its project status is equal to one of RD, RD2, RD3, or RJ. A project is “Registered" if its project status is equal to one of RD, RD2, or RD3. In total, there are 1,036 distinct China-host CDM projects based on the newest version of the IGES dataset.

Table 3: Estimates of the CDM Board's Registration Rule

	Dependent variable: Registered (=1)					
	LPM				Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
log(IRR)	-0.170***	-0.182***	-0.207***	-0.174***	-0.187***	-0.172***
	(0.0606)	(0.0599)	(0.0512)	(0.0527)	(0.0534)	(0.0538)
Consultant on proposal (=1)		0.219***	0.0678	-0.0235	0.0767	-0.0448
		(0.0780)	(0.0834)	(0.0780)	(0.0904)	(0.0671)
Credit buyer lined up (=1)		-0.152***	-0.142***	-0.144***	-0.102**	-0.123***
		(0.0545)	(0.0510)	(0.0479)	(0.0504)	(0.0417)
Build lag			0.329***		0.335***	
			(0.0236)		(0.0264)	
Credit start year effects	Yes	Yes	Yes	Yes	Yes	Yes
Project type effects	Yes	Yes	Yes	Yes	Yes	Yes
CER deciles	Yes	Yes	Yes	Yes	Yes	Yes
Build lag quartiles				Yes		Yes
Mean dep variable	0.571	0.571	0.571	0.571	0.571	0.571
Observations	620	620	620	620	615	615

This table reports coefficients from regressions of log stated rate of return on registration. The first four columns report coefficients from a linear probability model. The last two columns report marginal effects from a probit regression. The sample is the set of projects in IGES that is matched to a firm in the CESD/ASIF dataset. Rate of return is the stated rate of return in the Project Design Documents (PDD) that is submitted as part of the CDM project proposal. Summary statistics for rate of return: median (0.13), mean (0.15), standard deviation (0.08). Consultant on proposal is an indicator for whether a consultant was used in CDM application or not, as stated in the PDD. Credit buyer lined up is an indicator for whether there are buyers of Certifed Emissions Reduction (CER), as stated in the PDD. Build lag measures the number of years from date of public comment of the project to proposed credit start date. Date of public comment is usually a fixed number of days after the project is submitted. Proposed credit start date is when firms expect to start receiving credits for the project; it is a proxy for when the project is built and running. Summary statistics for lag: median (0.97), mean (1.14), standard deviation (0.80). All specifications contain proposed credit start year, project type and deciles of proposed emission reduction fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Point Estimates for CO_2 Emissions

	(1)	(2)	(3)	(4)
Panel A. Dependent variable: CO_2 emissions ('000 tons)				
Registered (=1) ×	1925.9***	1114.1***	940.4***	945.6***
Post (0-4 years)	(639.1)	(267.8)	(265.2)	(237.0)
Observations	3594	3594	3594	3594
Mean dep variable	1008.5	1008.5	1008.5	1008.5
Proposed (=1) ×	266.6*	287.7**	206.3	199.9
Post (0-4 years)	(139.0)	(130.0)	(130.6)	(128.0)
Observations	3656	3656	3656	3656
Mean dep variable	314.5	314.5	314.5	314.5
Difference	1659.4	826.4	734.1	745.7
P-value	[0.0004]	[0.0020]	[0.0056]	[0.0032]
Panel B. Dependent variable: log CO_2 emissions ('000 tons)				
Registered (=1) ×	1.030***	0.559***	0.432***	0.398***
Post (0-4 years)	(0.228)	(0.096)	(0.105)	(0.118)
Observations	3490	3490	3490	3490
Mean dep variable	5.299	5.299	5.299	5.299
Proposed (=1) ×	0.658***	0.433***	0.266***	0.215**
Post (0-4 years)	(0.171)	(0.089)	(0.099)	(0.100)
Observations	3548	3548	3548	3548
Mean dep variable	4.801	4.801	4.801	4.801
Difference	0.372	0.126	0.166	0.183
P-value	[0.0048]	[0.1520]	[0.0660]	[0.0560]
Firm FE		Yes	Yes	Yes
Year FE	Yes		Yes	
Industry-Year FE				Yes

Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched without replacement to 3 control firms on baseline emission trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Point Estimates for Output and Input Demands

	Dependent variable: Ln of . . .					
	Output	Intensity	Sales Revenue	Cost of Sales	Fixed Assets	Wage Bill
	(1)	(2)	(3)	(4)	(5)	(6)
Registered (=1) ×	0.422***	-0.092	0.448***	0.421***	0.259***	0.168**
Post (0-4 years)	(0.100)	(0.073)	(0.102)	(0.102)	(0.089)	(0.081)
Observations	3560	3190	6340	6334	6319	5801
Mean dep variable	5.543	-0.340	6.333	6.125	5.380	2.863
Proposed (=1) ×	0.238***	-0.013	0.236***	0.232***	0.219**	0.177**
Post (0-4 years)	(0.086)	(0.084)	(0.087)	(0.087)	(0.108)	(0.077)
Observations	3616	3242	5847	5842	5836	5325
Mean dep variable	4.960	-0.203	5.755	5.577	4.702	2.353
Difference	0.184	-0.079	0.212	0.189	0.040	-0.009
P-value	[0.0456]	[0.6816]	[0.0708]	[0.0764]	[0.4716]	[0.5708]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched without replacement to 3 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Model parameter estimates

Parameter	Estimate	Data	Description
Production and demand			$y = \left[z_{e0}\Delta_e z^{1-\alpha_e}\right] (l_{it}^{\alpha_l} k_{it}^{\alpha_k})^{1-\alpha_e} e^{\alpha_e}$
η	4		Elasticity of demand
α_e	0.22	CESD	Elasticity of output with respect to emissions
α_k, α_l	0.72, 0.28	ASIF	Elasticity of output with respect to capital, labor
Δ_e	1.028	CESD, UN	Emissions productivity improvement
Investment costs			$F = \gamma_0(CER)^{\gamma_1}\varepsilon$
γ_0, γ_1	23, 1	UN	Investment cost as a function of CERs
σ_ε	0.6	UN	Investment cost shock standard deviation
Productivity growth and Board signal structure			
$\rho_{\varepsilon,\varepsilon_s}$	0.75	CESD, UN	Correlation of signal and investment cost shock
μ_z, σ_z	0.05, 0.19	CESD, UN	Productivity distribution parameters
$\overline{\varepsilon}_s$	0.56	CESD, UN	Registration threshold

Table 7: Plant actions by plant type

	Firm type		
	Never Invest (1)	Always Invest (2)	Additional (3)
All firms	55.4	16.2	28.4
Non-applicants	55.4	4.0	12.4
Apply + registered	0.0	5.4	9.8
Apply + rejected	0.0	6.8	6.2

Online Appendix
Carbon Offset Markets: Evidence on Adverse Selection from the Clean Development Mechanism in China

Qiaoyi Chen, Nicholas Ryan and Daniel Yi Xu.

A Appendix: Data

Figure A1: Expected CER Prices and CDM Project Registration, 2005-2015

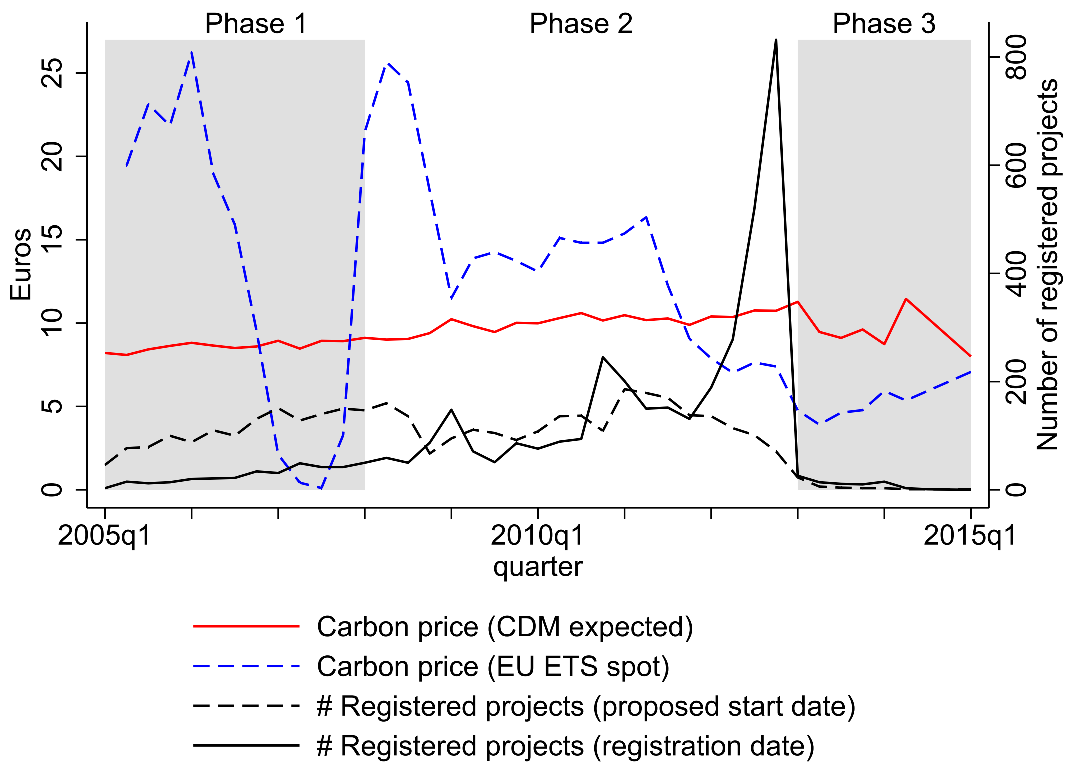
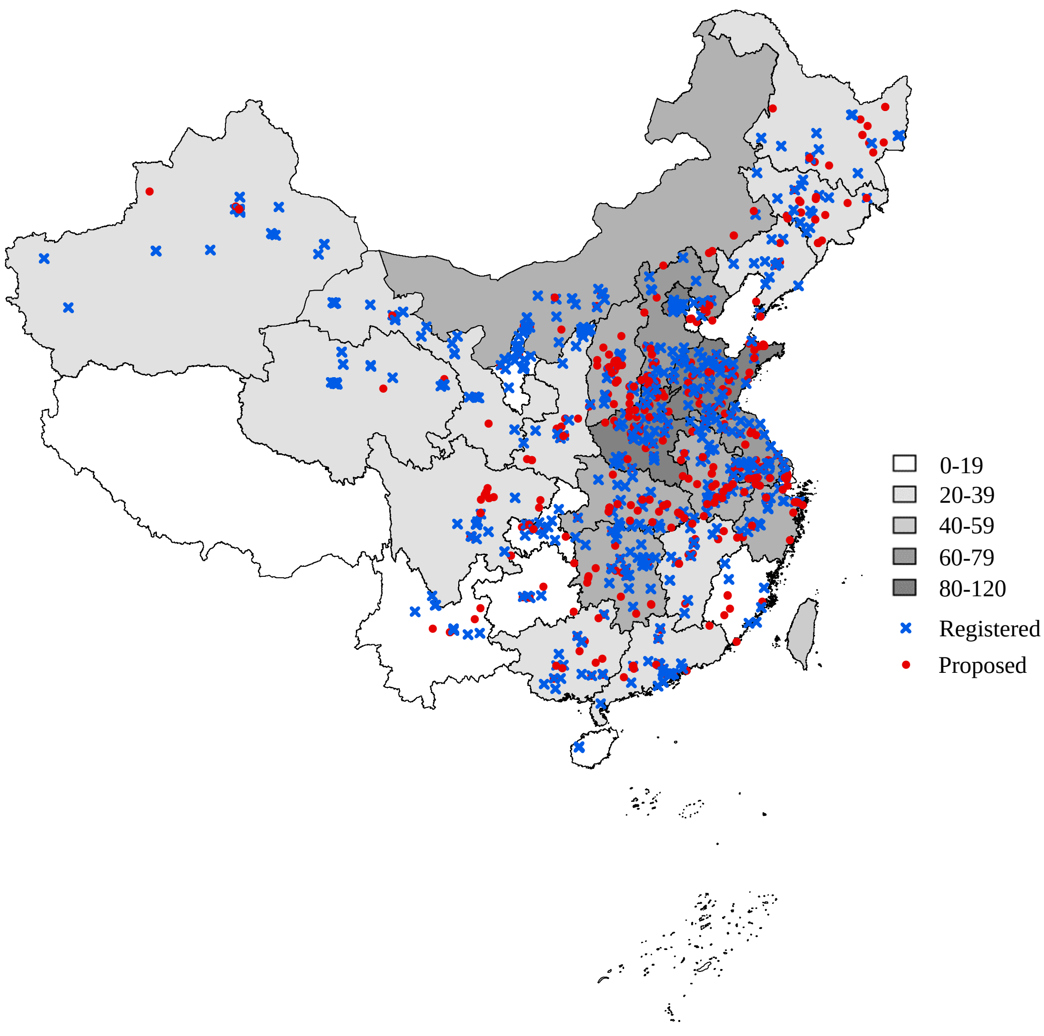


Figure A2: Map of CDM Projects Proposed in China



The figure shows the locations of CDM projects in China. The exact coordinates of the projects are often available in Project Design Documents (PDDs) which are manually downloaded from the UNFCCC CDM database. The figure contains locations for the set of CDM projects matched to our sample and passed the validation stage. Registered implies the project is approved by the board and registered as a CDM project. Proposed implies the project is either rejected by the board or voluntarily withdrawn.

Table A1: Common Industries for Firms Proposing CDM Projects in China

(1) 2-digit industry code and name	(2) Count	(3) %	(4) % (Cumul.)
44 electricity and heat production and supply industry	210	33.9	33.9
31 non-metallic mineral products industry	193	31.1	65
25 petroleum processing, coking, and nuclear fuel processing industries	50	8.06	73.1
32 ferrous metal smelting and rolling industry	43	6.94	80
26 chemical raw materials and chemical products manufacturing	33	5.32	85.3
15 beverage manufacturing	21	3.39	88.7
22 paper making and paper products industry	15	2.42	91.1
13 agricultural and sideline food processing industry	13	2.10	93.2
33 non-ferrous metal smelting and rolling processing industry	10	1.61	94.8

This table shows the frequency tabulation of firms that propose a CDM project in China in the CESD dataset by their 2-digit industry code. A firm is considered to have proposed a CDM project if it has a record in the UNFCCC CDM registry. The CESD dataset is the Chinese Environmental Statistics Dataset that contains information on a firm's energy usage and pollution. The top 10 most frequent industries are shown, along with cumulative percentage, out of a total of 17 industries.

Table A2: Common CDM Project Types in the Matched Sample

(1) Project type	(2) Count	(3) %	(4) % (Cumul.)
Waste gas/heat utilization	305	49.2	49.2
Biomass	96	15.5	64.7
Energy efficiency	48	7.74	72.4
PV	48	7.74	80.2
Biogas	46	7.42	87.6
Fuel switch	35	5.65	93.2
Cement	31	5	98.2
Biofuels	5	0.81	99.0
N2O decomposition	5	0.81	99.8
PFC reduction and substitution	1	0.16	100

This table shows the frequency tabulation of project types for projects in our matched sample. A firm may propose multiple projects, so we include only the first registered project proposed by a firm or the first proposed project (for firms that do not have registered projects). The project types are defined as in the Institute for Global Environmental Strategies (IGES) dataset which extracts publicly available information from the UNFCCC website.

Table A3: Project-Level Documentations

	Frequency	Percentage (%)
CDM Sample (project level)	1,259	100.00
ASIF-CDM merge		
match in the ASIF-CDM sample	834	66.24
match in the ASIF-CDM sample based on output filter	727	57.74
CESD-CDM merge		
match in the CESD-CDM sample	540	42.89
match in the CESD-CDM sample based on emission filter	511	40.59
CDM Sample (firm level)	913	100.00
ASIF-CDM merge		
match in the ASIF-CDM sample	664	72.73
match in the ASIF-CDM sample based on output filter	556	60.90
CESD-CDM merge		
match in the CESD-CDM sample	430	44.91
match in the CESD-CDM sample based on emission filter	399	43.70

B Appendix: Supplementary results

Table B4: Linear probability model on registration prediction

	Dependent variable: Registered (=1)			
	(1)	(2)	(3)	(4)
Stated investment in proposal	0.549**	0.511**	0.273	0.354*
	(0.257)	(0.259)	(0.213)	(0.191)
Consultant on proposal (=1)		0.218***	0.0720	-0.0262
		(0.0768)	(0.0856)	(0.0800)
Credit buyer lined up (=1)		-0.140**	-0.133**	-0.134***
		(0.0560)	(0.0527)	(0.0485)
Lag from proposal to project start (years)			0.323***	
			(0.0249)	
Credit start year effects	Yes	Yes	Yes	Yes
Project type effects	Yes	Yes	Yes	Yes
Certified Emissions Reductions (CER) deciles	Yes	Yes	Yes	Yes
Quartiles of lag from proposal to project start				Yes
Mean dep variable	0.571	0.571	0.571	0.571
R^2	0.187	0.200	0.421	0.492
Observations	620	620	620	620

This table reports coefficients from regressions of stated investment (in billions US dollars) on registration. The sample is the set of projects in IGES that is matched to a firm in the CESD/ASIF dataset. Investment is the stated amount of investment in the Project Design Documents (PDD) that is submitted as part of the CDM project proposal. Summary statistics for investment: median (0.014), mean(0.050), standard deviation (0.14). Consultant on proposal is an indicator for whether a consultant was used in CDM application or not, as stated in the PDD. Credit buyer lined up is an indicator for whether there are buyers of Certifed Emissions Reduction (CER), as stated in the PDD. Lag from proposal to project start measures the number of years from date of public comment of the project to proposed credit start date. Date of public comment is usually a fixed number of days after the project is submitted. Proposed credit start date is when firms expect to start receiving credits for the project; it is a proxy for when the project is built and running. Summary statistics for lag: median(0.97), mean (1.14), standard deviation (0.8). All specifications contain proposed credit start year, project type and deciles of proposed emission reduction fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Robustness for Borusyak Estimator: CESD Data

	CO_2 (1)	$\ln(CO_2)$ (2)	Output (3)	ln(Output) (4)	Intensity (5)	ln(Intensity) (6)
Registered (=1) ×	979.9***	0.466***	3587.7***	0.453***	-0.0766	-0.0747
Post (0-4 years)	(166.9)	(0.114)	(722.0)	(0.0928)	(0.0746)	(0.0699)
Observations	3423	3344	3391	3391	3027	3027
Mean dep variable	1058.7	5.49	2479.5	5.67	1.28	-0.247
Proposed (=1) ×	204.7*	0.229**	952.5	0.232***	-0.0996	-0.0195
Post (0-4 years)	(124.2)	(0.0975)	(602.9)	(0.0822)	(0.0938)	(0.0790)
Observations	3540	3442	3501	3501	3144	3144
Mean dep variable	324.6	4.94	879.9	5.04	1.40	-0.145
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

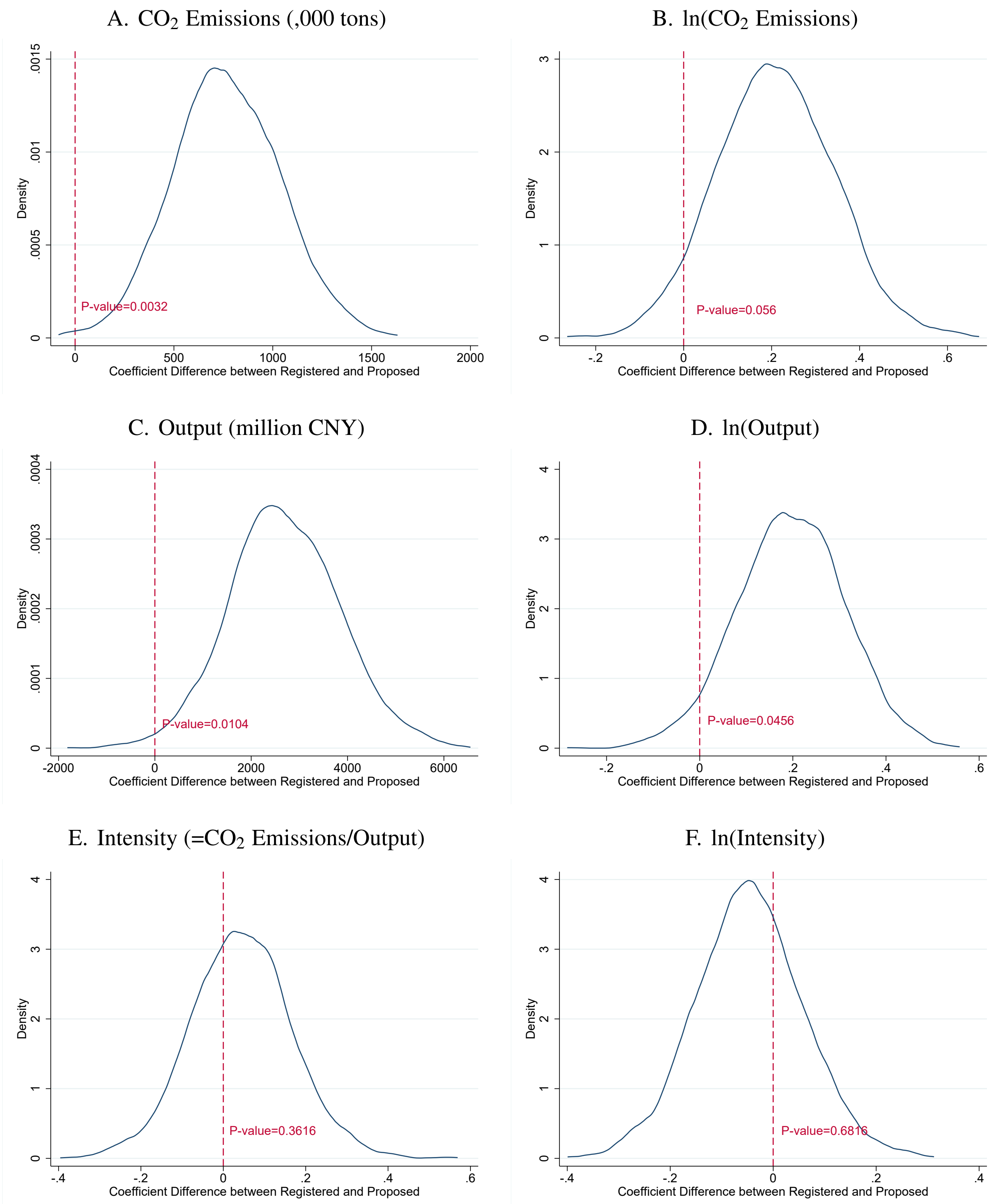
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched without replacement to 3 control firms on baseline emission trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Borusyak, Jaravel and Spiess, 2021). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B6: Robustness for Matching with Replacement: CESD Data

	CO_2 (1)	$\ln(CO_2)$ (2)	Output (3)	ln(Output) (4)	Intensity (5)	ln(Intensity) (6)
Registered (=1) ×	660.6***	0.418***	1776.9***	0.461***	-0.0144	-0.0121
Post (0-4 years)	(191.9)	(0.0856)	(612.9)	(0.0979)	(0.0751)	(0.0693)
Observations	3041	2989	3004	3004	2690	2690
Mean dep variable	822.9	5.3	1956.5	5.47	1.26	-0.203
Proposed (=1) ×	199.1	0.242**	709.7	0.205**	-0.0633	-0.0105
Post (0-4 years)	(133.4)	(0.100)	(658.2)	(0.0868)	(0.101)	(0.0847)
Observations	3518	3420	3481	3481	3118	3118
Mean dep variable	316.9	4.83	963.2	4.94	1.41	-0.160
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

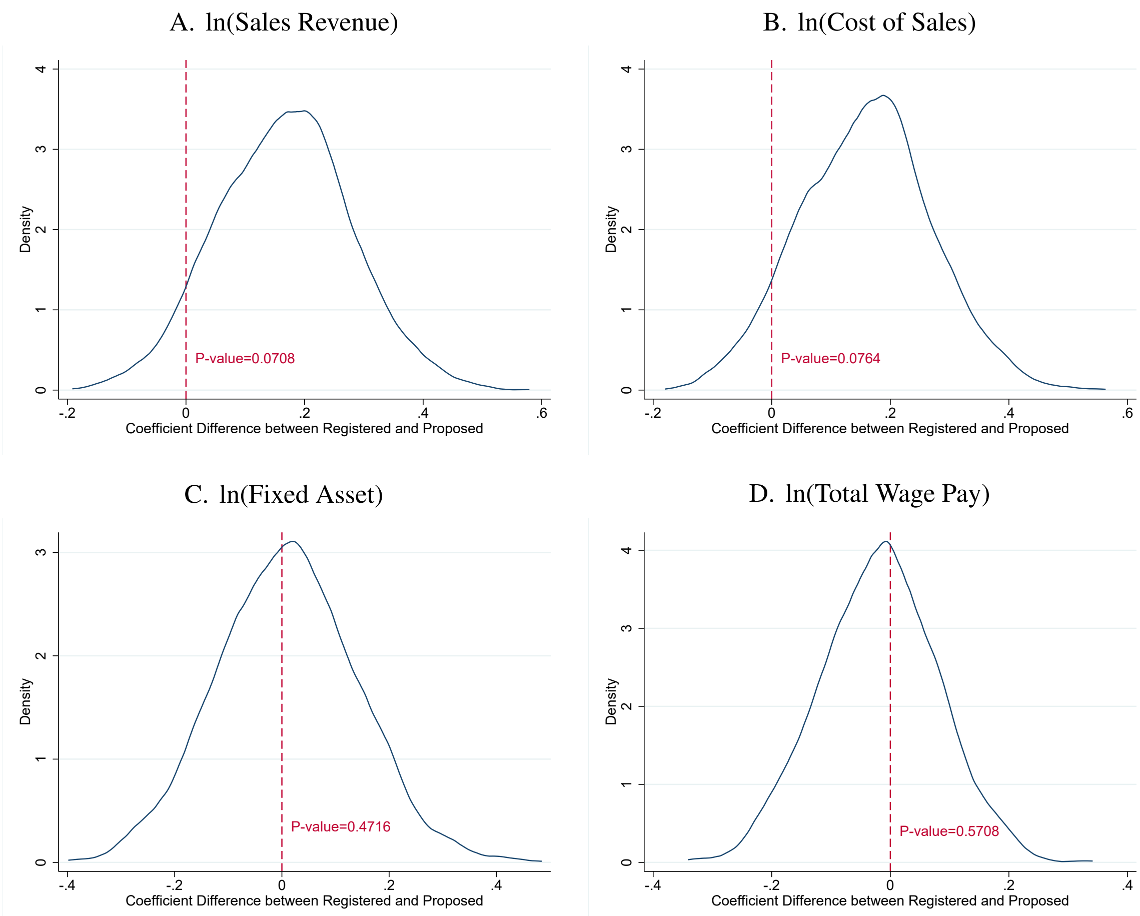
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched with replacement to 3 control firms on baseline emission trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B3: Coefficient Difference between Registered and Proposed Firms: CESD Data



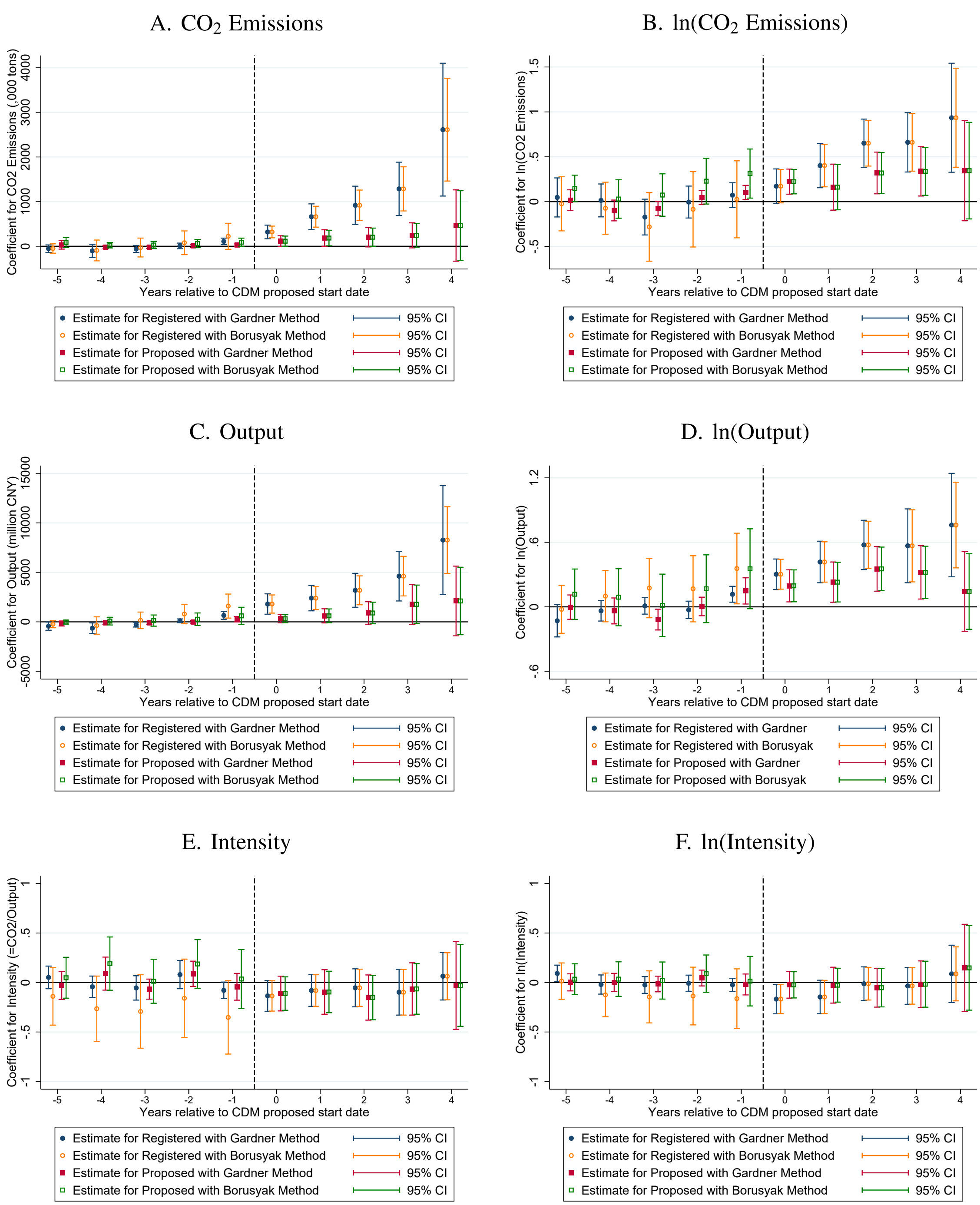
Notes: Authors calculations using data from CESD and UNFCCC. This figure shows results of a 2500 time bootstrap analysis comparing point estimates for registered and proposed firms with our baseline specification. We first generate bootstrap samples for registered (or proposed) firms, and then re-match controls to perform regression analysis with Gardner estimator. Finally, we plot the coefficient difference between registered and proposed firms with these 500 iterations to get the density plot. This figure shows that there is a significant difference between the point estimates for registered firms and proposed firms.

Figure B4: Coefficient Difference between Registered and Proposed Firms: ASIF Data



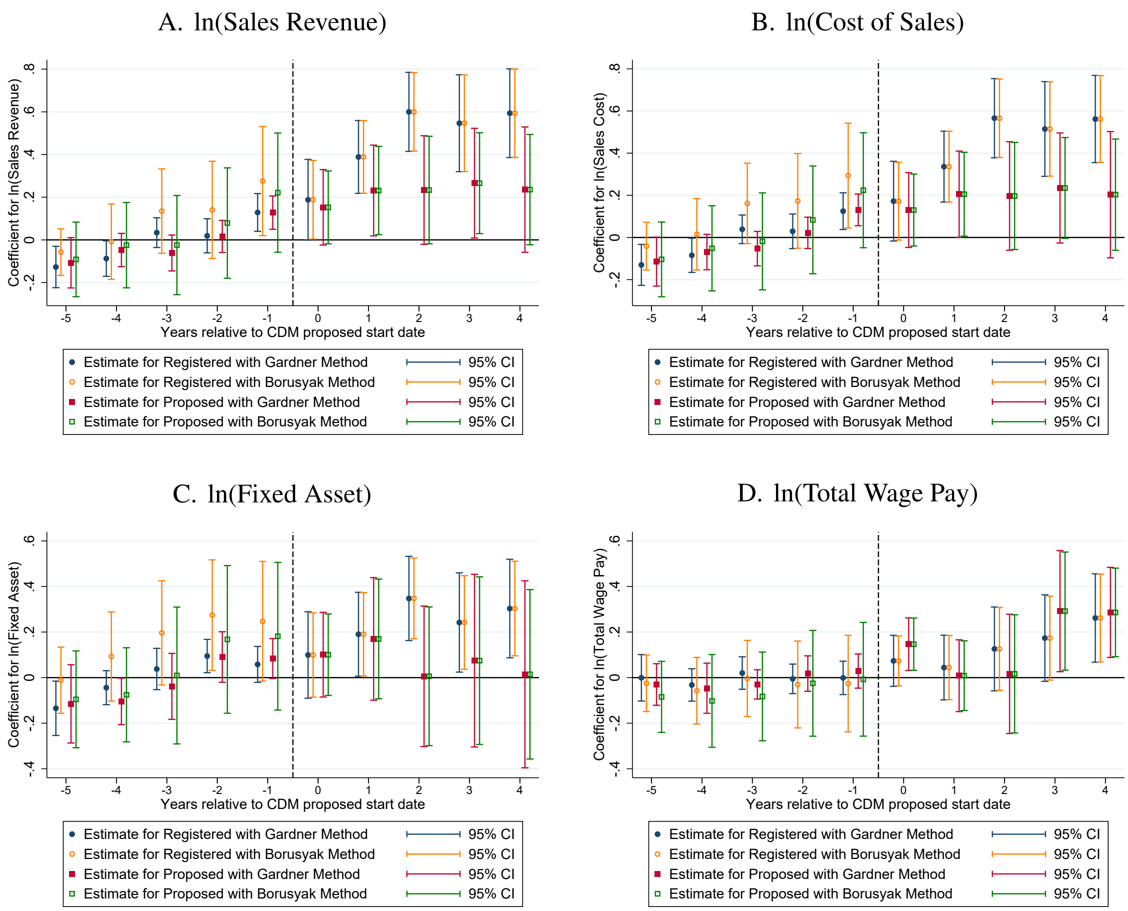
Notes: Authors calculations using data from ASIF and UNFCCC. This figure shows results of a 2500 time bootstrap analysis comparing point estimates for registered and proposed firms with our baseline specification. We first generate bootstrap samples for registered (or proposed) firms, and then re-match controls to perform regression analysis with Gardner estimator. Finally, we plot the coefficient difference between registered and proposed firms with these 500 iterations to get the density plot. This figure shows that there is a significant difference between the point estimates for registered firms and proposed firms.

Figure B5: Robustness for Different Staggered DID Estimators: CESD Data



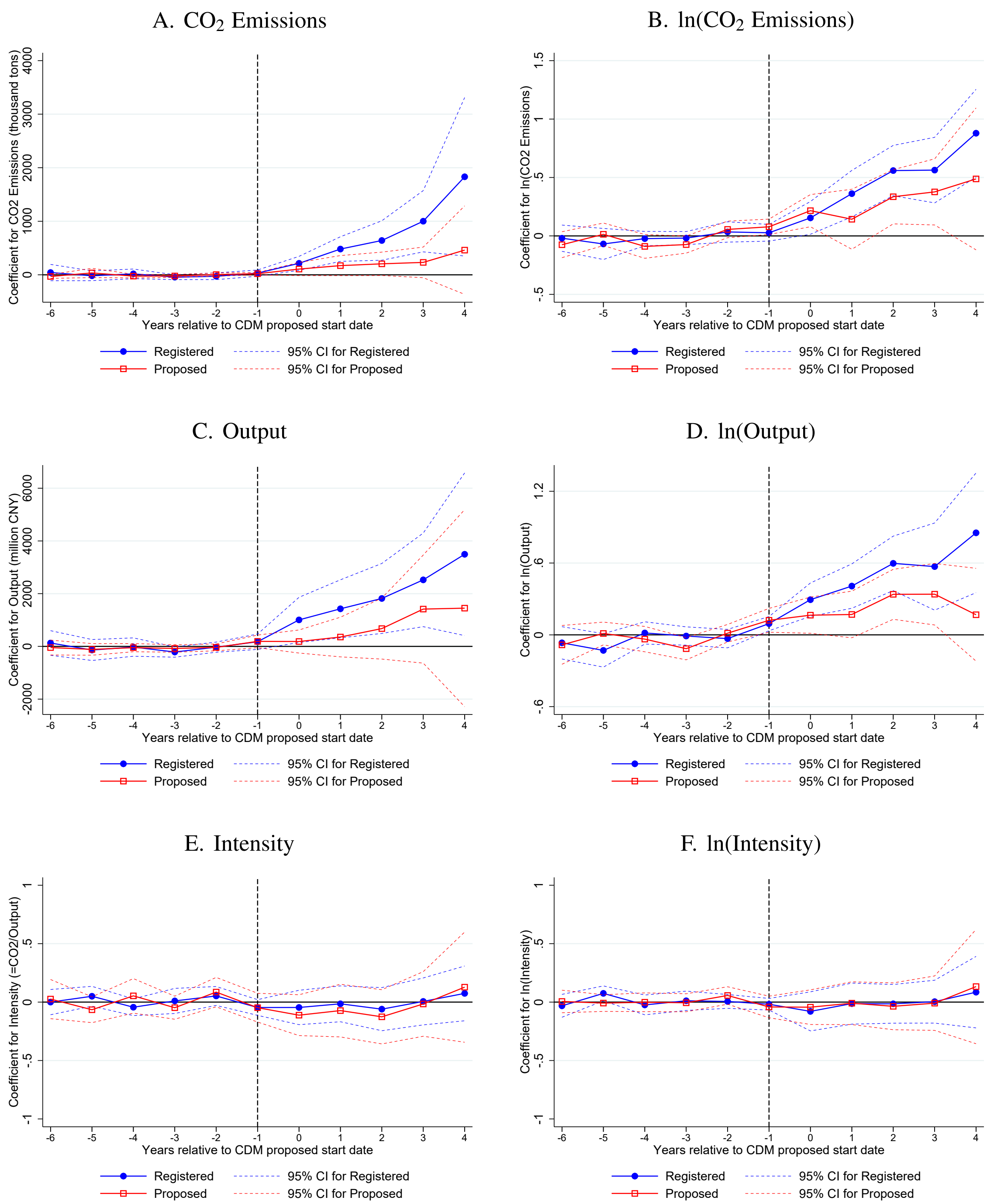
Notes: Authors' calculations using data from CESD and UNFCCC. The figure shows event study comparisons between Gardner et al. (2023) estimator and Borusyak, Jaravel and Spiess (2021) estimator with specification (2) using our baseline sample for CESD data.

Figure B6: Robustness for Different Staggered DID Estimators: ASIF Data



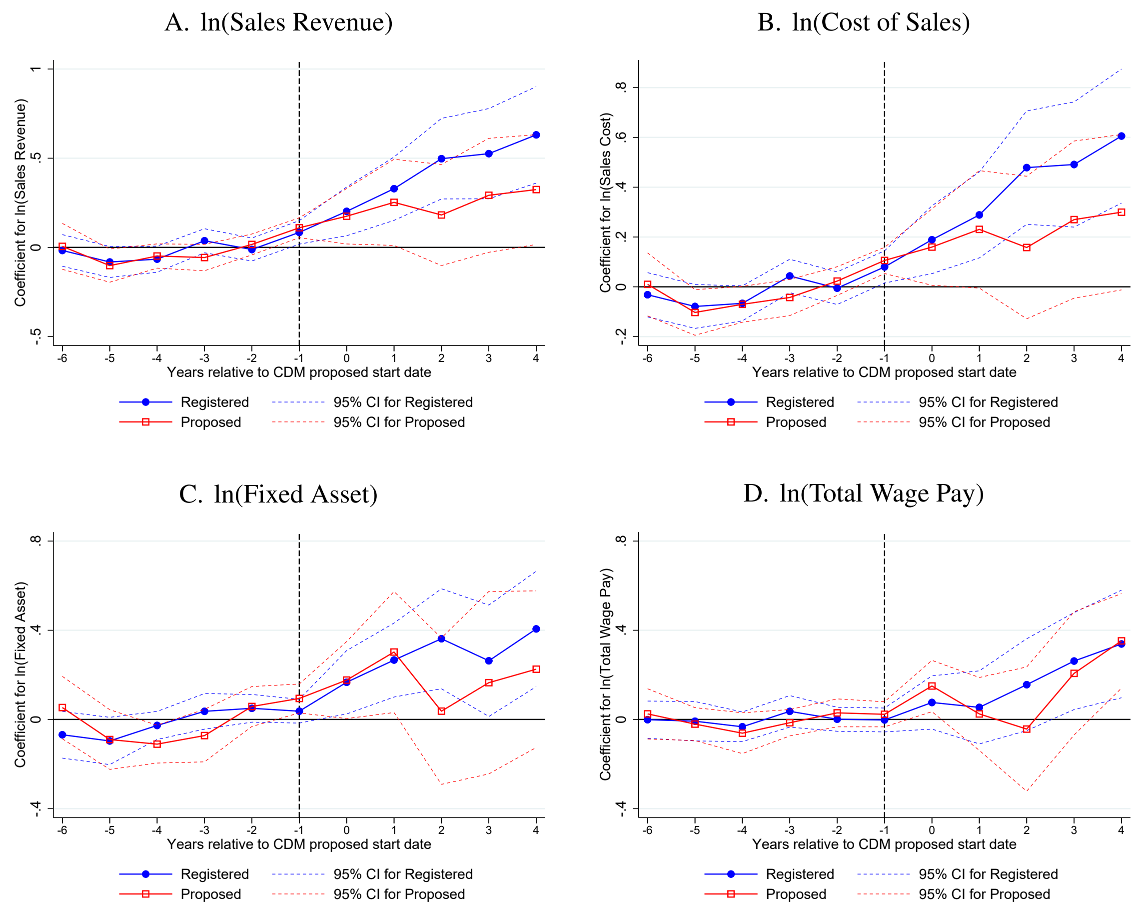
Notes: Authors' calculations using data from AISF and UNFCCC. The figure shows event study comparisons between Gardner et al. (2023) estimator and Borusyak, Jaravel and Spiess (2021) estimator with specification (2) using our baseline sample for ASIF data.

Figure B7: Robustness for Matching with Replacement: CESD Data



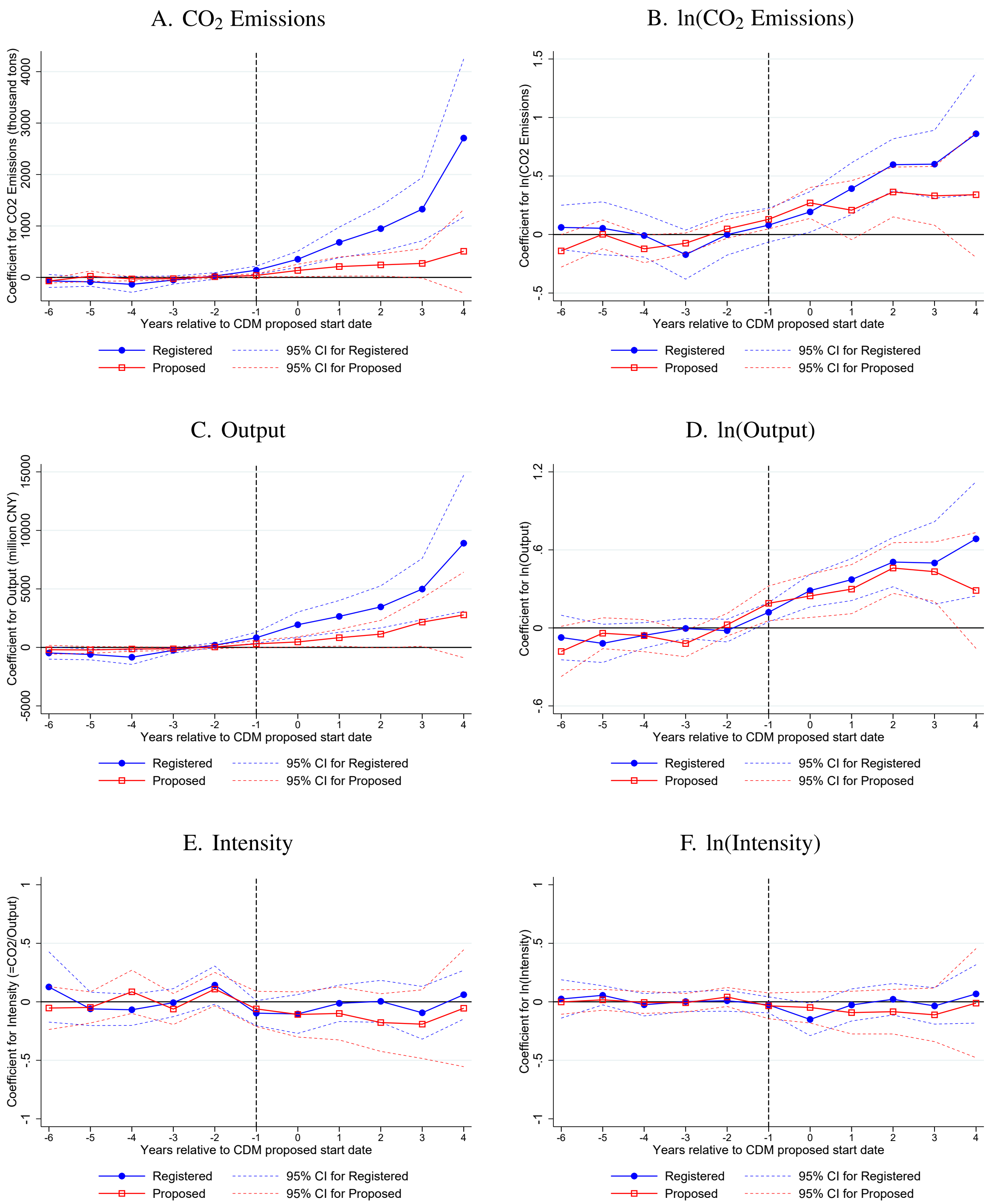
Notes: Authors' calculations using data from CESD and UNFCCC. The figure shows the coefficients from the event-study specification (2) comparing for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched with replacement to 3 control firms on baseline emissions trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure B8: Robustness for Matching with Replacement: ASIF Data



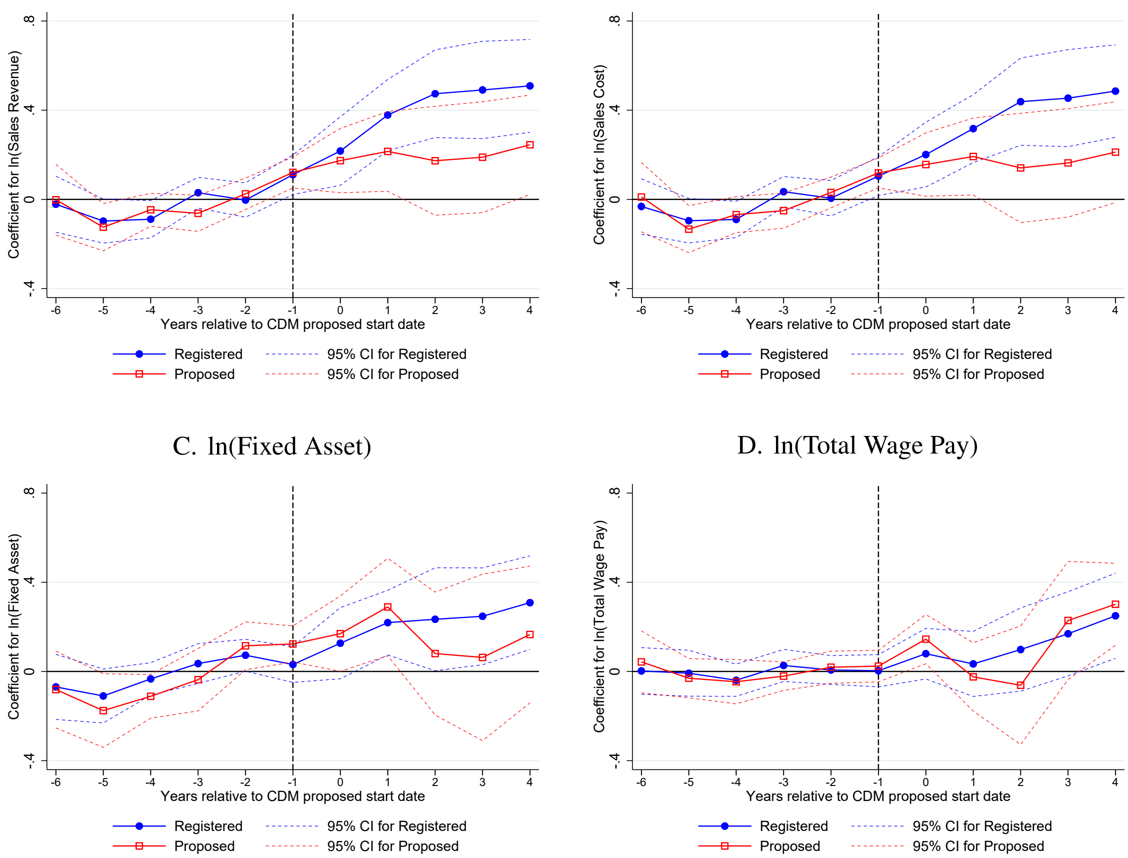
Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from the event-study specification (2) comparing sales and input demands for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched with replacement to 3 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure B9: Robustness for 1:10 Matching: CESD Data



Notes: Authors' calculations using data from CESD and UNFCCC. The figure shows the coefficients from the event-study specification (2) comparing for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched without replacement to 10 control firms on baseline emissions trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure B10: Robustness for 1:10 Matching : ASIF Data



Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from the event-study specification (2) comparing sales and input demands for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched control firm samples. Each CDM firm is first matched without replacement to 10 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Table B7: Robustness for Matching with Replacement: ASIF Data

	Dependent variable: Ln of . . .			
	Sales Revenue	Cost of Sales	Fixed assets	Wage bill
	(1)	(2)	(3)	(4)
Registered (=1) ×	0.430***	0.399***	0.242**	0.172**
Post (0-4 years)	(0.105)	(0.105)	(0.0934)	(0.0839)
Observations	5988	5983	5967	5473
Mean dep variable	6.22	6.01	5.25	2.73
Proposed (=1) ×	0.253***	0.236**	0.236**	0.158*
Post (0-4 years)	(0.0963)	(0.0963)	(0.112)	(0.0811)
Observations	5464	5461	5455	4976
Mean dep variable	5.90	5.73	4.83	2.48
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched with replacement to 3 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8: Robustness for 1:10 Matching: CESD Data

	CO_2	$\ln(CO_2)$	Output	ln(Output)	Intensity	ln(Intensity)
	(1)	(2)	(3)	(4)	(5)	(6)
Registered (=1) ×	1018.7***	0.443***	3892.5***	0.407***	-0.0417	-0.0388
Post (0-4 years)	(253.7)	(0.104)	(1036.2)	(0.0852)	(0.0720)	(0.0566)
Observations	9413	9225	9318	9318	8357	8357
Mean dep variable	648.5	5.25	1443.0	5.32	1.51	-0.121
Proposed (=1) ×	236.1*	0.274***	1225.2*	0.326***	-0.139	-0.0817
Post (0-4 years)	(131.8)	(0.0946)	(647.7)	(0.0832)	(0.109)	(0.0826)
Observations	9655	9331	9538	9538	8560	8560
Mean dep variable	217.5	4.62	658.0	4.70	1.50	-0.166
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched without replacement to 10 control firms on baseline emission trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B9: Robustness for 1:10 Matching: ASIF Data

	Dependent variable: Ln of . . .			
	Sales Revenue (1)	Cost of Sales (2)	Wage bill (3)	Fixed assets (4)
Registered (=1) ×	0.363***	0.330***	0.146*	0.113
Post (0-4 years)	(0.0888)	(0.0872)	(0.0803)	(0.0696)
Observations	16930	16917	16900	15479
Mean dep variable	6.23	6.05	5.12	2.73
Proposed (=1) ×	0.199**	0.173**	0.194**	0.127*
Post (0-4 years)	(0.0778)	(0.0773)	(0.0969)	(0.0735)
Observations	14820	14809	14821	13517
Mean dep variable	5.75	5.56	4.57	2.30
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from ASIF and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year. Each CDM firm is first matched without replacement to 10 control firms on baseline sales trajectories using Euclidean distance matching (Abadie and Imbens, 2012), and then the following difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B10: Robustness for Broad Sample: CESD Data

	CO_2 (1)	ln(CO_2) (2)	Output (3)	ln(Output) (4)	Intensity (5)	ln(Intensity) (6)
Registered (=1) ×	1123.3***	0.475***	4974.4***	0.455***	-0.0444	-0.0608
Post (0-4 years)	(178.2)	(0.0885)	(824.8)	(0.0675)	(0.0546)	(0.0526)
Observations	125147	119522	122901	122901	110188	110188
Mean dep variable	103.5	3.14	273.0	3.43	1.31	-0.366
Proposed (=1) ×	235.5*	0.299***	1260.9**	0.339***	-0.134	-0.0750
Post (0-4 years)	(121.9)	(0.0872)	(602.3)	(0.0720)	(0.0860)	(0.0795)
Observations	125087	119465	122832	122832	110120	110120
Mean dep variable	92.4	3.13	238.2	3.42	1.32	-0.362
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from regressions on indicators for registration and proposal 0 to 4 years after CDM proposed project start year using all firm samples with CO_2 emissions ranking top 10,000 in the CESD data. The difference-in-differences estimates use the staggered estimator of (Borusyak, Jaravel and Spiess, 2021). All standard errors are clustered at the firm level and statistical significance at certain thresholds is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Appendix: Model derivations

C.1 Derivation of firm outputs and emissions

Static cost minimization implies

$$\frac{e}{v} = \frac{\alpha_e w}{(1-\alpha_e)t_e}$$

where w is the per unit composite input cost and t_e is the regulatory shadow cost of emission. The cost function is defined as

$$C(y;\tilde{z}) = \underbrace{\left(\frac{w}{1-\alpha_e}\right)^{1-\alpha_e}\left(\frac{t_e}{\alpha_e}\right)^{\alpha_e}}_{C_w}\left(\frac{y}{\tilde{z}}\right)$$

Profit maximization then gives

$$(1-1/\eta)\times y^{-\frac{1}{\eta}} = C_w/\tilde{z}$$

The optimal output is thus

$$y^*(\tilde{z}) = \left(\left(\frac{\eta-1}{\eta}\right)\frac{\tilde{z}}{C_w}\right)^{\eta}$$

where revenue is

$$r^*(\tilde{z}) = \left(\left(\frac{\eta-1}{\eta}\right)\frac{\tilde{z}}{C_w}\right)^{\eta-1}.$$

C.2 Decomposition of firm growth

The mapping from the estimated difference-in-difference coefficients to these structural parameters depends on the registration rule, firm application and investment decisions. Let us first denote the registration probability of a project with cost shock ε as P_ε. To illustrate the intuition, we consider a specific value of ε that is high enough such that $p\delta_e > \frac{(A/\tilde{T})}{P_\varepsilon}$[8]. For notation convenience,

[8] If $p\delta_e < \frac{(A/\tilde{T})}{P_\varepsilon}$, then the expected benefit from the CDM program is lower than application cost for even the Non-additional projects. As a result, we can define $p\delta_e = \frac{(A/\tilde{T})}{P_{\bar{\varepsilon}}}$ such that no firms with $\varepsilon < \bar{\varepsilon}$ will choose to apply.

we can define a few threshold values for *logb* that characterize firm's decisions given ε.

$$\log b < \underbrace{\log((\gamma\varepsilon/\tilde{T} - p)\delta_e)}_{b_0(\varepsilon)} \quad \text{Never invest and not apply}$$

$$b_0(\varepsilon) \leq \log b < \underbrace{\log((\gamma\varepsilon/\tilde{T} - p)\delta_e + (A/\tilde{T})/P_{\bar{\varepsilon}}))}_{b_1(\varepsilon)} \quad \text{Additional project but not apply}$$

$$b_1(\varepsilon) \leq \log b < \underbrace{\log((\gamma\varepsilon/\tilde{T})\delta_e)}_{b_2(\varepsilon)} \quad \text{Additional project and apply}$$

$$b_2(\varepsilon) \leq \log b \quad \text{Non-additional project and apply}$$

The fraction of each type of firms (conditional on ε) can then defined by

$$\omega^{NI}(\varepsilon) = \int_0^{b_0(\varepsilon)} dF_{\log b} \quad \text{fraction of never invest firms}$$

$$\omega^{A}(\varepsilon) = \underbrace{\int_{b_0(\varepsilon)}^{b_1(\varepsilon)} dF_{\log b}}_{\omega_0^A(\varepsilon)\text{: } \textit{not apply}} + \underbrace{\int_{b_1(\varepsilon)}^{b_2(\varepsilon)} dF_{\log b}}_{\omega_1^A(\varepsilon)\text{: } \textit{apply}} \quad \text{fraction of additional firms}$$

$$\omega^{NA}(\varepsilon) = \int_{b_2(\varepsilon)} dF_{\log b} \quad \text{fraction of non-additional firms}$$

The discussion above highlights that there is clearly selection on growth effect at the application stage. The firms that expect to have higher productivity growth Δ_z (and thus higher private return b) sort into the application of the CDM projects. We can show that the non-CDM firms (our control group) has an expected log growth rate of

$$E[\log(g_e)|\text{not apply}, \varepsilon] = \left[\int_0^{b_1(\varepsilon)} \log b(\Delta_z) dF_{\log b}\right] / (\omega^{NI}(\varepsilon) + \omega_0^A(\varepsilon)) - \log \bar{b}$$

Since the registration probability P_ε is orthogonal to the unobserved firm growth $\log b(\Delta_z)$, we have the expected log growth rate of the registered firms as

$$E[\log(g_e)|\text{registered}, \varepsilon] = \left[\int_{b_1(\varepsilon)} \log b(\Delta_z) dF_{\log b}\right] / (\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)) + (\eta - 1)\log \Delta_e - \log \bar{b}$$

The registered project firms benefit from the improvement in abatement productivity $(\eta - 1)\log \Delta_e$, i.e. the scale effect, but their faster growth relative to the non-CDM firms also reflects the selection on unobserved productivity growth Δ_z. Contrasting the growth of emission by registered firms vs non-applicant firms gives

$$E[\log(g_e)|\text{registered}, \varepsilon] - E[\log(g_e)|\text{not apply}, \varepsilon] =$$
$$(\eta - 1)\log \Delta_e + (E[\log b | \log b > b_1(\varepsilon)] - E[\log b | \log b < b_1(\varepsilon)])$$

which includes both the scale effect and the selection effect. The selection effect depends on cutoff of program application $b_1(\varepsilon)$.

The more interesting group is the firms that propose the CDM projects but are not registered. For these firms, their growth outcome depends on whether the firm is an "additional firm" or "non-additional firm".

$$E[\log(g_e)|\text{proposed, not registered}, \varepsilon] =$$
$$\left[\underbrace{\int_{b_2(\varepsilon)} (\eta-1)\log\Delta_e + \log b(\Delta_z) dF_{\log b}}_{\text{Non-additional}} + \underbrace{\int_{b_1(\varepsilon)}^{b_2(\varepsilon)} \log b(\Delta_z) dF_{\log b}}_{\text{Additional}}\right] / (\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)) - \log\bar{b}$$
$$= \left[\int_{b_1(\varepsilon)} \log b(\Delta_z) dF_{\log b}\right] / (\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)) + \frac{\omega^{NA}(\varepsilon)}{\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)}((\eta-1)\log\Delta_e) - \log\bar{b}$$

It follows that contrasting the growth of emission by registered firms vs proposed (but not registered) firms gives

$$E[\log(g_e)|\text{registered}, \varepsilon] - E[\log(g_e)|\text{proposed, not registered}, \varepsilon] = \frac{\omega_1^A(\varepsilon)}{\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)}(\eta-1)\log\Delta_e$$

If only the non-additional firms apply for CDM projects, then these rejected projects would be implemented even in the absence of the CDM subsidies – the difference between registered vs proposed above would be close to zero. The growth rate difference between registered vs proposed projects widens when there are more additional firms ($\omega_1^A(\varepsilon)$) in the mix of applicants.

C.3 Equilibrium implications of CDM offsets

We assume that industrial composite good is produced with a CES technology across each producer variety i

$$Y = \left[\int_i y_i^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$

which is consistent with our imposed residual demand curve $y_i = \frac{1}{P^{-\eta}}(p_i)^{-\eta}$[9]. The equilibrium price index is defined as $P = \left[\int_i p_i^{1-\eta}\right]^{\frac{1}{1-\eta}}$.

Since firm's decision in the initial equilibrium only depends on their $\tilde{z}$, the industry aggregate emission can be expressed as

$$E = \tilde{\eta}(\eta-1)\frac{\alpha_e}{t_e}\left(\frac{C_w}{P}\right)^{1-\eta}\left[\int(\tilde{z})^{\eta-1} dF_{\tilde{z}}\right]$$

[9] We normalized the industry expenditure to be 1 here.

Table D11: Parameter values used in Simulations

Parameter	Value	Description
α_e	0.2	Elasticity of output with respect to emissions
η	3	Inverse elasticity of demand
t_e	1	Regulatory shadow cost of emission
p	1	Price of Certified Emissions Reductions
γ	1	Scale parameter that relates investment cost to size of CER
Δ_e	1.05	Emissions productivity growth rate
e_0	50	Period 0 firm emissions
N	100,000	Number of firms in simulation
ρ_s	0.8	Correlation between fixed cost and its signal
$(\mu_\varepsilon, \sigma_\varepsilon)$	(0, 0.5)	Mean and standard deviation of log idiosyncratic fixed cost
$(\mu_{\varepsilon^s}, \sigma_{\varepsilon^s})$	(0, 1)	Mean and standard deviation of signal of log idiosyncratic fixed cost
(μ_{FA}, σ_{FA})	(-3.5,0)	Mean and standard deviation of log fixed application cost distribution
$(\mu_{\Delta_z}, \sigma_{\Delta_z})$	(0, 0.5)	Mean and standard deviation of log productivity growth rate

With constant markup pricing, we can write $p(\tilde{z}) = \frac{\eta}{\eta-1}\left(\frac{C_w}{\tilde{z}}\right)$ and the aggregate price index is

$$P^{1-\eta} = (C_w)^{1-\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta}\left[\int(\tilde{z})^{\eta-1}dF_{\tilde{z}}\right]$$

So in this simple setting, the industry aggregate emission is proportional to aggregate industry expenditure where $E = \left(\frac{\eta-1}{\eta}\right)\frac{\alpha_e}{t_e}$. As a result, similar to Shapiro and Walker (2018), the industry emission intensity is proportional to price index

$$\frac{E}{Y} \equiv E \times P = C_w\left(\frac{\alpha_e}{t_e}\right)(\tilde{Z})^{-1}$$

where $\tilde{Z} = \left[\int(\tilde{z})^{\eta-1}dF_{\tilde{z}}\right]^{\frac{1}{\eta-1}}$.

The effect of the CDM on aggregate emissions in the economy will therefore depend on the elasticity of substitution between the output of the energy-intensive sectors covered by the CDM and other sectors. This substitution margin dictates how large is the aggregate response to the emissions productivity improvements caused by CDM projects.

D Appendix: Model estimation

D.1 Fixed cost of investment

In the model, we had assumed that the fixed cost of investment is linear in the proposed certified emissions reductions (CERs) such that $F_p = \gamma(\delta_e e_0)$. Here we test this hypothesis with a regression of log (investment) on log(CER):

$$\log(F_p) = \log(\gamma) + \beta_1 \log(\delta_e e_0) + \varepsilon$$

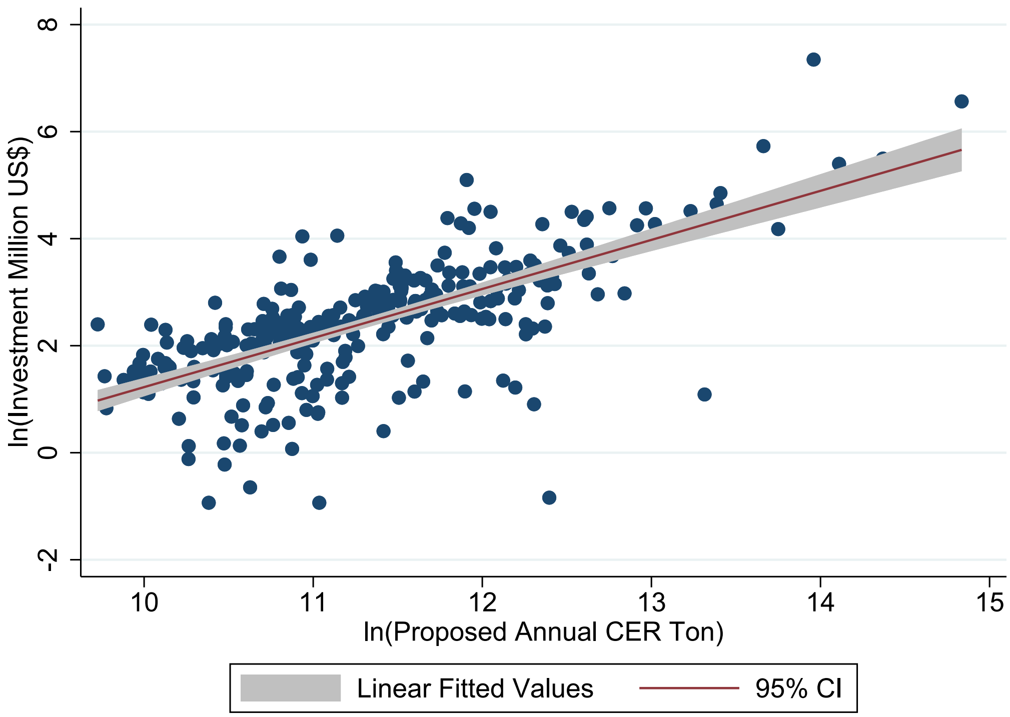
Table D12 shows the results of the regression and a test of the null hypothesis that $\beta_1 \neq 1$. For specifications with start year effects, we fail to reject the null hypothesis, which supports our model assumption that $F_p = \gamma(\delta_e e_0)$.

Table D12: Regression of log(investment) on log(CER) for CDM firms

	Dependent variable: log(investment)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(proposed CER)	0.917***	0.898***	0.896***	0.871***	0.914***	0.900***
	(0.0559)	(0.0469)	(0.0578)	(0.0629)	(0.0659)	(0.0684)
Project Type		Yes	Yes	Yes	Yes	Yes
Indsutry			Yes	Yes	Yes	Yes
Province				Yes	Yes	Yes
Start Year					Yes	Yes
log(CO2)						Yes
$\log(\gamma)$	-7.94					
RMSE	0.83	0.67	0.61	0.60	0.60	0.60
R^2	0.47	0.67	0.77	0.80	0.81	0.81
p-value $H_0 : \beta_1 \neq 1$	0.14	0.031	0.072	0.042	0.19	0.15
firms	301	301	301	301	301	301

This table reports coefficients from regressions log(stated investment) on log(proposed CER). The sample is the set of firms in CESD matched to a CDM project and has emissions record before the proposed CDM start year. The root mean squared error, which is our measure of σ_ε, is taken to be 0.60. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure D11: Scatter plot of log(investment) on log(CER)



Notes: This figure scatters log(stated investment) on log(proposed CER). The sample is the set of firms in the CESD matched to a CDM project and has emissions record before the proposed CDM start year. The line of best fit is plotted and has a slope close to 1, which supports our assumption that the fixed cost of investment is linear in proposed CER.

D.2 Improvement in emissions productivity

Table D13: Estimation for δ_e

	Original Value			*Winsor Value*		
	All	Waste	Others	All	Waste	Others
CER	34.97	27.23	7.73	31.07	25.37	5.71
	(3.34)	(3.19)	(0.80)	(3.27)	(3.17)	(0.52)
Initial CO_2	233.6	219.2	14.38	233.6	219.2	14.38
	(35.97)	(35.36)	(1.89)	(35.97)	(35.36)	(1.89)
δ_e = CER/Initial CO_2	0.150	0.124	0.538	0.133	0.116	0.397
	(0.019)	(0.017)	(0.086)	(0.017)	(0.016)	(0.048)
	303	230	73	303	230	73

D.3 Board's signal structure

In the empirical part, we will assume that ε and ε_s are jointly log-normal, with

$$\log\left(\begin{bmatrix}\varepsilon\\ \varepsilon^s\end{bmatrix}\right)\sim\mathcal{N}\left(\begin{bmatrix}0\\0\end{bmatrix},\begin{bmatrix}\sigma_\varepsilon^2 & \rho\sigma_\varepsilon\\ \rho\sigma_\varepsilon & 1\end{bmatrix}\right).$$

We normalize the variance of the signal to one. The parameter ρ is the correlation of the signal of idiosyncratic investment costs with the true investment costs; as $\rho\to 1$ the regulator is completely informed. With this assumption, the registration probability can be written

$$Pr(\text{Registered}|\varepsilon) \quad = \quad 1-\Phi\left(\frac{\log\overline{\varepsilon}^s-\frac{1}{\sigma_\varepsilon}\rho\log\varepsilon}{\sqrt{1-\rho^2}}\right).$$

A lower threshold $\overline{\varepsilon}^s$ on the Board's investment cost signal increases the probability of registration.

Parametric Assumption of Δ_z We proceed with a parametric assumption of the firm growth Δ_z to derive closed-form expressions of the above. Specifically, we assume that $\Delta_z\sim\text{Lognormal}(0,\sigma_z^2)$. It is then straight-forward to show that $\log b\sim\text{Normal}\left(\log(\bar{b}),\sigma_b^2\right)$, where $\sigma_b^2=[(1-\alpha_e)(\eta-1)\sigma_z]^2$

Conditional on ε, we can evaluate the fraction of firms that do not apply for the program as

$$\omega^{NI}(\varepsilon)+\omega_0^A(\varepsilon)=\int_0^{b_1(\varepsilon)}dF_b=\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)$$

Similarly, the fraction of firms that apply for the program is

$$\omega^{NA}(\varepsilon)+\omega_1^A(\varepsilon)=1-\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)$$

The control firms with ε have the expected growth rate

$$E[\log(g_e)|\text{not apply}, \varepsilon] = E[\log b|\log b < b_1(\varepsilon)] - \log\bar{b} = -\sigma_b \frac{\phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}{\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}$$

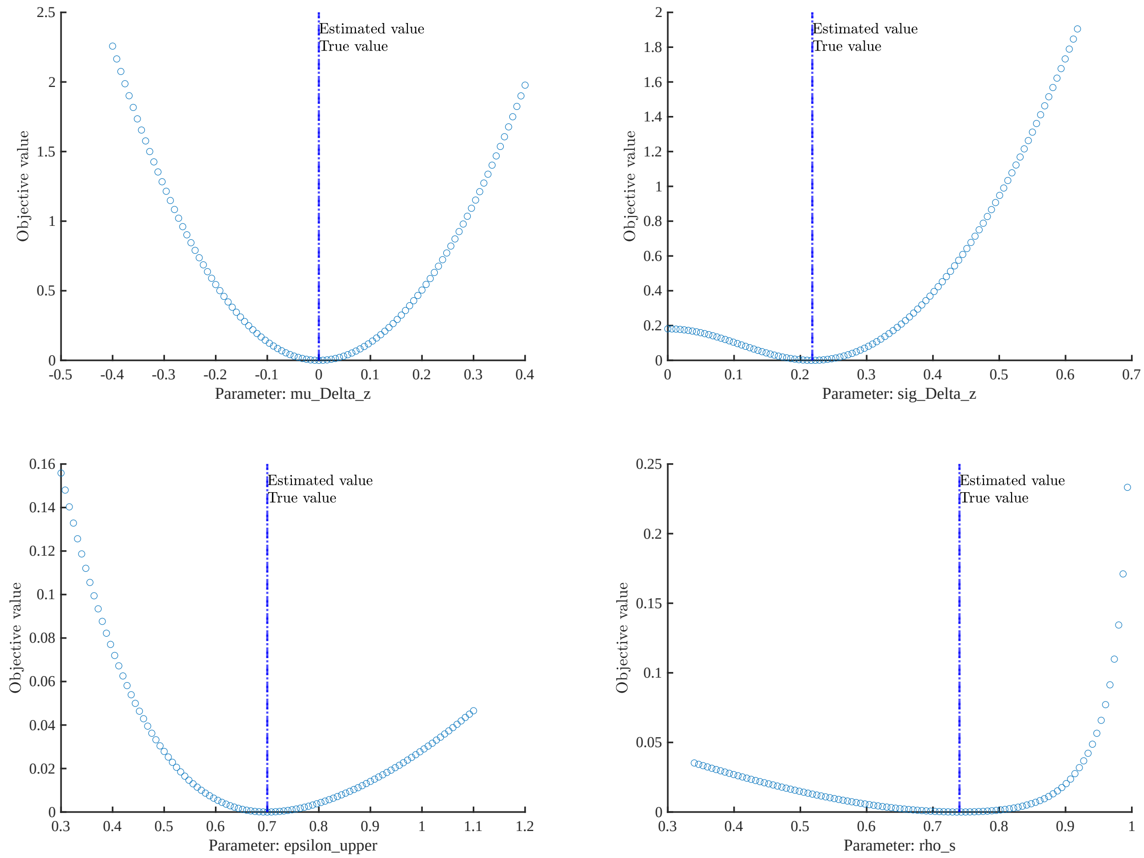
The registered firms with ε have the expected growth rate

$$\begin{aligned} E[\log(g_e)|\text{registered}, \varepsilon] &= E[\log b|\log b > b_1(\varepsilon)] + (\eta-1)\log\Delta_e - \log\bar{b} \\ &= (\eta-1)\log\Delta_e + \sigma_b \frac{\phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}{1-\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)} \end{aligned}$$

In addition, the proposed but rejected firms have the expected growth rate

$$\begin{aligned} E[\log(g_e)|\text{proposed, not registered}, \varepsilon] &= \\ E[\log b|\log b > b_1(\varepsilon)] + (\eta-1)\log\Delta_e \frac{1-\Phi\left(\frac{b_2(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}{1-\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)} - \log\bar{b} \\ = (\eta-1)\log\Delta_e \frac{1-\Phi\left(\frac{b_2(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}{1-\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)} + \sigma_b \frac{\phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)}{1-\Phi\left(\frac{b_1(\varepsilon)-\log(\bar{b})}{\sigma_b}\right)} \end{aligned}$$

Figure D12: Monte Carlo estimates: Objective function



D.4 Data Moments: Objective Functions

Figure D13: Matching data moments: Objective function