Firm Selection and Growth 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 whether they truly reduce emissions. We study carbon offsets sold by manufacturing firms in China under the United Nations' Clean Development Mechanism (CDM). We find that offset-selling firms increase carbon emissions by 49% in the four years after starting an offset project, relative to a matched sample of non-applicants. We explain this increase in emissions by jointly modeling the firm decision to propose an offset project and the UN's decision of whether to approve. In estimates of our model, CDM firms increase emissions due to both the selection of higher-growth firms into project investment (40 pp of the total) and the causal effect of higher efficiency, post investment, on firm scale and therefore emissions (9 pp).

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1 Introduction

To reduce harm from global climate change many countries are trying 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. By 2022, their share had soared to 43%. No global climate agreement can succeed without broad participation in emissions reductions.

This need for global emissions reductions creates an enormous potential market for carbon offsets. Low- and middle-income countries (LMICs) are reluctant to strictly cap emissions or to set carbon prices. A carbon offset is a payment by one party to another party to reduce emissions on the first party's behalf. In principle, rich countries could use offsets to pay for abatement investments in LMICs, both to support LMICs' economic growth and to reduce the global cost of meeting any carbon emissions target. For these reasons, offsets are an important part of global climate agreements under the United Nations Framework Convention on Climate Change.[1]

The use of offsets for climate policy has two main weaknesses. First, offsets may pay for abatement projects that would have happened anyway. In the language of climate policy, only reductions in emissions relative to a firm's unknown, business-as-usual emissions are "additional" reductions that should be counted as an offset. Second, offset projects themselves may act to increase, not reduce, firm emissions. The nature of many offset projects is to increase efficiency by enabling firms to produce the same output with lower emissions and related inputs (e.g., fuel). Since firms choose how much to produce, a project that boosts efficiency in this way may cause the firm to increase its scale and hence emissions in response.

This paper studies firm selection and firm growth 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 study manufacturing firms' selection into CDM offset projects and subsequent firm growth to estimate how much projects reduce emissions compared to a business-as-usual scenario.

The empirical difficulty in studying offset markets is that researchers face the same problem as

[1] Offsets 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.

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 Board'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 generate two main findings from a descriptive analysis of this carbon offset market.

First, the Board attempts to screen on additionality by rejecting projects with high 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. Only 56% of proposed projects in our sample are approved. 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 4.4 percentage points. This result is consistent with the Board attempting to approve only projects that are privately unprofitable and that would therefore offer additional emissions reductions.

Second, despite the Board's screening, carbon dioxide emissions at firms that register CDM projects steeply *increase* in the years after project registration, relative to emissions at a matched sample of non-applicant firms. We use staggered event-studies to estimate that firms that register a project increase emissions by 49% (standard error 0.13%) in the four years after the project start. Firms that propose a project and are rejected increase emissions by 25% (standard error 11%) relative to non-applicants. These estimates stand in contrast to ex ante projections, submitted to the Board, that the average project would reduce emissions by roughly 20%. The striking increase in emissions at firms that register a CDM project, on closer examination, is entirely accounted for by firm growth. Firms that register a CDM project increase their sales and variable inputs 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 therefore stays flat.

These findings show that firms that undertake offset projects do not reduce their emissions, relative to similar firms. However, our event-studies cannot on their own distinguish between the causal effect of an abatement project on emissions and the selection of firms into proposing and registering a project. Event-study estimates capture causal treatment effects only in the absence of anticipation. We study offset projects, long-lived capital investments by forward-looking firms, which we expect to respond to anticipated firm growth.

We therefore introduce a model of firm investment and emissions to separate firm selection from the causal effect of abatement projects on emissions. In the model, a firm produces output using emissions and can choose whether to undertake a project that increases the efficiency 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 from the project. The firm knows both its cost of investment and its exogenous, business-as-usual 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.

In the model, CDM firms, which register offset projects, have emissions growth higher than firms that do not register for two reasons. First, there is *selection on growth*, as the Board's 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 low cost or the firm has high future productivity (like a high demand shock tomorrow). Because the regulator screens out projects with a low investment cost signal, but does not observe growth, firms that are able to register will have higher productivity growth and therefore emissions growth than firms that propose a CDM project and are rejected or firms that do not apply. Second, there is a causal *scale effect* of registered firms growing in response to project investments. Projects raise emissions efficiency and therefore also growth for all firms that undertake them.[2] The CDM causes higher emissions growth for registered firms, in particular, because it induces investments by additional firms.

We estimate the model using our data set that combines UN data on CDM proposal and registration and the manufacturing panel data on firm inputs, outputs and emissions. We use the manufacturing panel to estimate the firm's production function in the pre-CDM period including the key parameter of the elasticity of output with respect to emissions. The main innovation in our estimation is the next step, in which we use our model to match the growth-rate event studies for registered and proposed firms relative to non-applicant firms as well as the registration rate conditional on application. We argue and illustrate that these data moments transparently identify the Board's decision rule, including the strength of the Board's signal of investment costs. The estimated model can therefore reproduce the suite of empirical facts from our reduced-form results including: (i) higher registration rates for low-return projects; (ii) higher emissions growth at registered than proposing firms; (iii) higher emissions growth at proposing than non-applicant firms; (iv) increases in firm scale for registered and proposing firms; (v) constant emissions intensity at

[2]In theory, there could also be a substitution effect of firms using less emissions and more of other inputs when emissions efficiency increases, or of the opposite, if emissions and other inputs are complements. However, we do not find evidence of such an effect, as our empirical analysis suggests that increases in efficiency are factor-neutral.

registered as compared to proposing or non-applicant firms.

The model estimates allow us to decompose the observed emissions growth, from the event-studies, into its two key determinants. We find that *selection on growth* makes up roughly 80% of the observed emissions growth of both registered (40 log points) and proposing (22 log points) firms, relative to non-applicants, with the causal *scale effect* making up the balance of 20%. The model estimates dictate that most of the observed emissions growth is *not* causal, because the estimated emissions productivity gains from CDM projects are not large enough for the scale effect to match emissions growth. Moreover, only a subset of registered firms are induced to take-up a project by the CDM. Our model estimates imply that 64% of registered firms are additional and would invest in their project only with CDM support. Conversely, 39% of additional applicants have their projects rejected, due to the Board's noisy signal, and 44% of additional firms do not even apply because of the combination of high application costs and this risk of rejection.

We use the estimated model to predict the effect of counterfactual changes in the screening rule. One reaction to granting CERs to non-additional firms is for the Board to tighten standards by requiring a lower expected return for the firm in order to register a project under the CDM. We find that this approach does not work: as the Board varies the registration threshold to greatly reduce or increase the equilibrium CER issuance, the fraction of CERs granted to non-additional firms varies in a tight range around 30%, falling only slightly as the Board tightens standards. The reason for this result is that an increase in stringency (decrease in the required threshold return for approval) discourages a roughly constant proportion of non-additional and additional firms, at the margin, from applying and being registered. As a consequence, the effective price of CERs per unit of actual abatement is inflated by a factor of one over the share of additional firms, or roughly 40 to 60%, depending on the stringency of the screening rule.

Our model captures a tension between the design goals of the CDM program and its real effect on firms. The Board, despite rigorous screening, grants roughly one-third of CERs to non-additional firms. This share would normally be viewed as wasteful expenditure. In our model, however, payments to non-additional firms have no effect on emissions, whereas payments to additional firms induce investment and emissions growth through increases in firm scale.

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.[3] Studies of carbon regulation have considered how a regulator with incomplete coverage of emissions should optimally adjust

[3] For example, multinational firms respond to more stringent domestic regulation by offshoring production (Hanna, 2010). 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).

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 selection into offset projects and firm growth due to projects undermine 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.[4] We study offset projects in the manufacturing sector and our analysis highlights how the economics differ, in this case, due to the endogenous choice of inputs and firm scale in response to higher productivity.

Finally, this paper joins a small empirical literature questioning whether CDM projects specifically reduce carbon dioxide emissions.[5] We add to this literature by assembling firm-level panel data on emissions 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 rigorous efforts to screen out high-return projects. China, our setting, is the largest originator of CDM projects 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 for CDM firm carbon emissions and other outcomes. Section 4 describes our model. Section 5 estimates the model. Section 6 uses the model estimates to decompose the sources of emissions growth and consider counterfactual screening rules. Section 7 concludes.

[4]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).

[5]Calel et al. (2021) estimate that CDM wind power projects in India 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.

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 proposed the 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 I countries, which are all members of the OECD, agreed to commit to greenhouse gas reduction targets, while non-Annex I 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 I countries to return to 1990 emissions levels, or below, by the end of a first commitment period spanning from 2008 to 2012.

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 Protocol therefore included three "flexibility mechanisms" to allow for abatement across international borders, including for abatement in non-Annex I countries. The Clean Development Mechanism, one of the flexibility mechanisms, therefore allows for carbon abatement projects to be undertaken in non-Annex I countries to sell offsets to parties in Annex I 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 successors within the UNFCCC. The Paris Accord introduced a 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.[6] Our findings on the CDM are therefore relevant for shaping regulation towards a range of carbon offset markets.

2.2 Data sources

We rely on two main 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`).[7] The UNFCCC data contain a wealth of information on projects that we draw from primary documents. To propose a CDM project, the 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 projected 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

[6] 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).

[7] 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.

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 to effectively five years, as practically no CDM projects started before 2006. 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 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.[8] In our sample, the most common project types are for waste heat recovery and utilization, fuel switches to various less GHG-intensive fuels, and energy efficiency and industrial process improvements (see Appendix Table A2). These project types have the character that a project makes firm inputs go farther, raising the effective energy input per unit of actual emissions or fuel used. In their PDD, firms argue that their project reduces

[8] 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.

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, 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 subject to ongoing monitoring of ex post investment and utilization.

2.4 Firm selection into CDM proposal and registration

Our matched data allow us to describe the process of selection into CDM proposal and screening into registration. Here and below we will call firms that proposed but did not register a project *proposed only* firms. Firms that both proposed and registered a project are *registered* 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 two salient findings from this descriptive analysis on selection and screening. First, firms that propose or register CDM projects have at baseline some of the highest firm-level emissions in the Chinese economy. Figure 2, panel A 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 firms (median log emissions 5.76) and proposed firms largely overlap. While CDM registered firms are larger than proposed only firms with respect to output and emissions, they are generally more similar with respect to other productive inputs (Appendix Table B4). 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. Figure 2, panel B illustrates how matching greatly reduces level differences in emissions between non-applicants, proposed only and registered firms.

Second, most screening happens *before* a project is formally submitted to the Board for approval. Table 1 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 proposed only or non-applicant 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

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

Here $Registered_i$ is a dummy variable equal to one if a project is registered, $log(ProjectReturn_i)$ is the log of 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 $log(ProjectReturn_i)$. 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 2 reports estimates of equation (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 registration (approval). The coefficient on the log project return in column (4) implies that a 1% (not 1 pp) increase in the rate of return on a project is associated with a 0.16% decline in the probability of approval. Hence raising a project from the median return (0.15) to one standard deviation above the median (0.23 = 0.15 + 0.08) lowers the probability of registration by 7 pp, or 13% of the mean rate of approval (57%). The last two columns 5 and 6 mirror the specifications from columns 3 and 4 but with a probit model. The estimated marginal effects from the probit are very similar to the corresponding LPM coefficients.

This finding that higher rates of return are associated with a lower probability of project registration is consistent with the Board attempting to screen out non-additional projects. If a project has a high rate of return, the Board is more likely to decide that a project is non-additional, since it would have been privately profitable even without the added revenue from carbon credits.[9] We find additional support for the idea of the Board attempting to screen on additionality in the coefficients on other project characteristics of Table 2. 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

[9] 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.

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 show "that the CDM was seriously considered in the decision to implement the project activity" (United Nations Framework Convention on Climate Change, 2015*a*). A long time lag implies advance consideration of the CDM on a project and makes this requirement easier to satisfy. 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.

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 apply for 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 Gardner et al. (2023). 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. We estimate two event-study specifications

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

$$Y_{it} = \alpha_i + \alpha_{jt} + \sum_{\tau=-5}^{4} \beta_{2\tau} \mathbf{1}[t - Start_i = \tau] Registered_i + \varepsilon_{it} \quad (3)$$

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). For each respective specification, we limit the sample to proposed only firms and their matched counterparts or registered firms and their matched counterparts. 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. We estimate (2) using the two-step estimator of (Gardner et al., 2023) and show the robustness of our results to the closely-related estimator of (Borusyak, Jaravel and Spiess, 2021).

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 business-as-usual case. 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 proposal assumes a flat business-as-usual emissions trajectory for emissions and then projects CERs relative to this path over a period of 7 to 14 years.

Ex ante projections and ex post issuance of CERs.—Figure 3 shows the coefficients from an event-study specification run on the projected Certified Emissions Reduction (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).[10] The second (red) line in Figure 3 shows the projected CER issuance

[10]The projected CERs represent a substantial chunk of firm emissions at baseline. Table B4 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.

accounting for the gap between project start dates and registration dates. Because some projects are registered at a lag, projected CER issuance lags the project start date, but converges to a similar level. Finally, the third (blue) line shows actual CER issuance ex post. CER issuance is lower in magnitude than projected by a factor of about one-third. CER issuance may be less than projected, even in the long run, if a firm decides not to go through ex post monitoring or to sell its permits.[11]

Ex post emissions growth.—Figure 4 shows estimates of the event-study specifications (2) and (3). The panels differ in their outcome variables: the level of CO_2 emissions in tons (panel A), the log of CO_2 emissions (panel B), the log of the value of firm output (panel C), and the log of emissions intensity (CO_2 emissions per value of output).

The main finding from Figure 4 is that CO_2 emissions steeply *increase* both at firms that register a CDM project and, to a lesser degree, at firms that propose a CDM project, relative to matched non-applicants. This finding, based on actual emissions data ex post, is in stark contrast to the ex ante CDM projections that CDM projects would sharply *reduce* emissions (Figure 3). In levels (panel A), emissions at registered firms are well-matched in the pre-period but grow rapidly in the year of the project start and the four years afterwards. In logs (panel B), similarly, emissions at registered and proposed-only firms grow markedly after the project start date. Registered firm emissions exceed those of matched controls by more than 0.5 log points by two years after the project start. Emissions grow roughly half as much at proposed only firms.

The magnitude of the emissions increases at CDM registered firms in the years after registration is very large. Table 3 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 non-applicant control firms. Panel A measures emissions in levels and panel B in logs. Focusing on the panel B, column 4 specification, with firm and industry-year fixed effects, we find that emissions at registered firms increase by 0.40 log points (standard error 0.12 log points), or 49%, in the four years after the project start date relative to matched controls. Emissions at proposed only firms increase by 0.22 log points (standard error 0.10 log points), or 25%, over the same period. Both of these estimates are easily statistically different from zero and from ex ante (negative) projections of emissions growth. The estimates for the two groups in logs are not significantly different from each other at conventional levels (p-value: 0.104), but, along with the event-study Figure 4, strongly suggest that registered firm emissions grow faster.

[11] 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).

Emissions growth due to scale versus emissions intensity.—The proximate cause of emissions growth is an increase in firm scale. Returning to Figure 4, in panel C we learn that the log value of firm output increases with a similar trend and nearly similar magnitude as the log of emissions (from panel B). Therefore, emissions intensity, measured by the log of emissions per value of output, is dead flat in the period after registration (panel D).

Table 4 reports pooled event-study coefficients for registered and proposing firms for the log of output, emissions intensity, sales, and input measures including the cost of goods sold. The sales and input variables are measured in a separate data set, the ASIF, from that used to measure emissions. Figure 5 provides corresponding event-study figures. The main finding of the table is that CDM registered firms and CDM proposed firms both see increases in the value of output, sales and the value of inputs which are roughly—in some cases almost exactly—proportional to the increases in emissions estimated in Table 3. Recall that registered firms increase their emissions by 0.40 log points. They also increase sales by 0.45 log points (standard error 0.10), the cost of goods sold by 0.42 log points (standard error 0.10), fixed assets by 0.26 log points (standard error 0.09) and the wage bill by 0.17 log points (standard error 0.08). Similarly, proposed only firms increase their emissions by 0.22 log points and all output and input measures by around 0.20 log points. Appendix Table B6 runs the same specifications with the ratio of emissions to other inputs as the dependent variable. We cannot reject that either emissions intensity or the ratio of emissions to other inputs are unchanged by CDM registration and proposal. This finding has implications for the form of the production function, which we discuss with our model in Section 4 below.

Discussion of results.—We produce a suite of empirical results on firm selection and growth in the CDM. First, 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. Second, despite this attempt at screening, emissions at registered and proposed only firms grow steeply in the years after registration, relative to a control group of matched non-applicant firms. Third, this emissions growth is entirely due to an increase in firm scale, which is broadly and proportionally observed across multiple measures of output, sales revenue and other inputs. Emissions intensity at CDM firms does not change.

We do *not* interpret the event-study estimates as causal estimates of the effect of CDM participation on emissions growth. CDM projects involve large, forward-looking firms making long-lived capital investments that trade off expenditures today against future private benefits in energy savings and carbon credits. For this reason, we believe that firms may well 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. The large effects of even CDM *proposal* on firm outcomes is itself evidence of selection.

Our preferred interpretation of the event-study estimates is that they combine two distinct forces. First, there is *selection on growth*, from firms that anticipate higher future productivity growth being more likely to invest in a long-lived project today. The CDM explicitly screens on willingness to invest in abatement capital. Second, a causal *scale effect*, from firms changing their input choices endogenously in response to the increase in efficiency that comes with investment in a CDM project. Section 4 introduces a model of the CDM that incorporates both of these forces.

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 efficiency, input choices and screening on the emissions growth of CDM firms.

4.1 Set-up

Figure 6 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 project investment in the firm's production decisions and profits.

Production.—We build 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 the *emissions efficiency* factor $z_e > 1$ and the elasticity of emissions $1/\alpha_e$ with respect to $1-a$. In our model, the CDM, described below, will act through changes in emissions efficiency z_e.

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

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

Firms therefore have a Cobb-Douglas production function in a composite input and emissions. With this form, because the elasticity of substitution between e and v is one, emissions efficiency is factor-neutral: efficiency z_e and the productivity term z combine to form total factor productivity $\tilde{z}$. In general, emissions may be complementary or substitutable with other factors. We select this form because our empirical results, showing that both emissions and the overall costs of goods sold rise in proportion for CDM firms, fail to reject that CDM-induced changes in efficiency are factor-neutral (see Table 4 and Appendix Table B6 and the discussion in Section 3.2).

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

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

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 efficiency z_e, due to a scale effect. Emissions intensity, per unit of sales and per unit of physical output, respectively, can be expressed as

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

Emissions intensity per unit sales does not depend on efficiency, consistent with the empirical result of Figure 4, panel D. Emissions intensity per unit output is decreasing in productivity $\tilde{z}$ and therefore efficiency z_e. The constant emissions intensity per unit sales we observe is consistent with improved efficiency and lower intensity per unit of output, because higher output brings lower prices that raise emissions intensity per unit of sales.

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

The firm's general productivity changes exogenously 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, combining (6) and (8) yields post-period business-as-usual emissions of

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

With the abatement project, post-period 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 Δ_z 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

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

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

The firm has to pay an investment cost for the abatement project. We assume that the investment cost $F(\Delta_e, e_0)\varepsilon$ depends on the efficiency gain Δ_e, the firm's baseline emissions e_0 and an idiosyncratic investment cost shock ε. It is necessary to discount the annual 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, on the rightmost branch of the game tree (Figure 6), it can sell carbon credits. We make two key assumptions on how the Board calculates carbon credits 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 efficiency improvement Δ_e from the project. The Board must grant carbon credits based on what it can measure. 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 Certified Emissions Reductions (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 efficiency given by Δ_e. In other words, the Board does not account for the endogeneity of input choices. Using (6) to solve for the implied change in emissions from this rule yields a CER award 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 efficiency gain 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 for brevity. 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.[12] Second, the

[12] 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.

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.

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 through

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

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) simplifies to

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

In Table 2, above, we estimated this registration rule to 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

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

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

$$\pi^A(b, \Delta_e, \varepsilon, e_0) = Pr(\text{Registered}|\varepsilon)\left[\tilde{T}(b + p\delta_e) - (\gamma\delta_e)\varepsilon\right] e_0 \tag{20}$$

$$\pi^{NA}(b, \Delta_e, \varepsilon, e_0) = Pr(\text{Registered}|\varepsilon)\tilde{T}(p\delta_e)e_0. \tag{21}$$

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 7 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 described in the following section.) The color of the marker indicates the firm type. The type of the marker indicates whether a firm invests ($\times$) 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 Board will receive a signal of their low cost and reject their project.

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 higher emissions growth for registered firms than proposed firms and for proposed firms than for non-applicants. The model can rationalize these findings. Using (11), firm emissions growth $g_e = e_1/e_0$ can be written

$$\log g_e = (\eta - 1)\log \Delta_e + (1-\alpha_e)(\eta - 1)\log \Delta_z, \tag{22}$$

where the first term is the *scale effect* of project investment and the second term is due to exogenous productivity growth.

The difference-in-difference estimates for emissions growth across groups of firms will then depend on what share of each group invests and the selection of firms into each group based on productivity growth. It is possible to derive analytic formulas for group emissions growth rates if we condition on a particular level of ε (see Appendix C.2 for derivations).[13] We show that the difference in growth for a registered firm as compared to non-applicants 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 7, 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

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

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. While these expressions provide intuition, they do not account for the fact that firms select into proposal and registration based on ε also. Appendix D.4 derives expressions for the unconditional emissions growth rates of registered, proposed only and non-applicant firms.

[13] 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.

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 methods. 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 efficiency improvement from the CERs calculated for each project. In the fourth part, we estimate the distribution of firm growth and the Board's registration rule and signal structure. We now describe both our estimation methods and our estimates in parallel for each part. The parameter estimates for all parts are gathered in Table 5.

5.1 Production function

We estimate firm production as a function of emissions and other inputs using proxy control methods (Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). The firm production function is Cobb-Douglas in value added and emissions according to (6). We additionally assume a Cobb-Douglas production function for the value-added input. Taking logs, this yields

$$\log y_{it} = \log z_i^e + (1-\alpha_e)[\log z_{it} + \alpha_l \log l_{it} + \alpha_k \log k_{it}] + \alpha_e \log e_{it}. \tag{23}$$

We estimate this production function using two auxiliary assumptions, described in Appendix D.1. First, because we do not observe physical output, we use sales revenue as the dependent variable. We then need to assume an elasticity of demand η to recover the parameters of the physical production function; we choose $\eta = 4$. Second, to control for the endogeneity of input choices to productivity z_{it}, we use intermediates as a proxy control for productivity. This involves a two-step estimator where we first regress revenue on a flexible function of intermediates and other inputs and then use the fitted proxy function to estimate the production function coefficients.

We obtain an elasticity of output with respect to emissions of $\hat{\alpha}_e = 0.215$, with respect to labor of $\hat{\alpha}_l = 0.724$, and with respect to capital of $\hat{\alpha}_k = 0.278$. The value-added production function is therefore estimated to have constant returns as we cannot reject that $\hat{\alpha}_l + \hat{\alpha}_k = 1$. The emissions elasticity α_e is one of the most important parameters in our model. Our relatively large estimate of $\hat{\alpha}_e$ reflects the importance of emissions for CDM firms' production.[14] To interpret this coefficient, we consider how it governs the firm's trade-off between output and abatement effort. If a firm increased abatement up to the point where output fell by 5% ($1-a = 0.95$), we estimate it would

[14]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, as compared to the smaller role of local air pollutants (and the possibility of end-of-pipe abatement for such pollutants, unlike for carbon).

reduce emissions by 21%.

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

$$\log(F) = \log(\gamma_0) + \gamma_1 \log(\delta_e e_0) + \varepsilon. \tag{24}$$

Table D10 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 efficiency factor Δ_e from undertaking a CDM project. Equation (13) gives the model expression for CERs as a function of baseline emissions e_0, the emissions elasticity α_e and the efficiency 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 D11).

The emissions productivity improvement may seem small, but recall that this is the implied efficiency 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 efficiency 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 novel, 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 8 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 7). 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. Appendix D derives the model moments and constructs the Generalized Method of Moments estimator. As the estimator is just-identified, we fit these moments exactly. The model therefore reproduces the difference-in-difference estimates of Table 3 by construction.

We have two comments on the resulting parameter estimates, reported in Table 5. 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. By the logic of Figure 8, panel B, the an informative signal is required to generate a large gap in growth rates between registered and proposed-only firms. 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 how the underlying distribution of firm types determines the effect of the CDM on emissions growth. We also consider how the CDM would perform under counterfactual screening stringency. Finally, we extrapolate our results for CDM firms to project the effects of the CDM on aggregate emissions in general equilibrium.

Firm types and emissions growth in the CDM.—We use the model estimates to produce three main results. First, a large share of CDM registered projects are non-additional. Table 6 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 Board 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 the Board does not observe firm growth.

The second results from the model is that changes to screening stringency would not meaningfully reduce the share of CERs granted to non-additional firms. Figure 9 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 $\bar{\varepsilon}^s$ is indicated by a vertical dotted line. The share of non-additional CERs at this estimated stringency is nearly the same as it would be if the Board *doubled* its investment cost threshold.

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 7. 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 9, 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.

Third, most of the growth of emissions reported in the event-study estimates of Table 3 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 logic for the large share of exogenous growth is straightforward: CDM abatement projects are not large enough contributors to firms' efficiency, and therefore productivity, to endogenously increase growth to the large extent observed. Our estimates of (i) the emissions share of production α_e and (ii) the importance of CERs relative to baseline emissions $CER/e_0 = \delta_e$ (13), taken together, imply that complete adoption of CDM projects by a group of firms would increase emissions by a factor of $\hat{\Delta}_e^{\hat{\eta}-1} \approx 9\%$, relative to non-adoption. In practice, because many registered firms are non-additional, this estimate is an upper bound on the contribution of project-based efficiency gains to emissions growth. Most of the rapid growth of registered firms must therefore be due to selection, not the causal effect of the CDM.

Implications of the CDM in general equilibrium.—A relevant policy question is to what extent the CDM induced higher emissions in aggregate, as opposed to only at participant firms. Our results show that most emissions growth at CDM firms was exogenous; still, the CDM did contribute to emissions growth by raising efficiency at these firms. The effect of the CDM on aggregate emissions will depend on how much the output of CDM firms substitutes for the output of other firms within the same emissions-intensive sectors and in other sectors.

We lay out a back-of-the-envelope calculation for the effect of the CDM on aggregate emissions in Appendix C.4. We derive that the change in aggregate emisssions due to the CDM is

$$d\ln E = (1-\theta)(1-s_1)d\ln P_1, \tag{25}$$

where θ is the elasticity of substitution between emissions-intensive and non-emissions-intensive manufacturing goods, s_1 is the share of manufacturing expenditure in emissions-intensive (i.e., CDM-eligible) sectors, and $d\ln P_1$ is the change in the price index for emissions-intensive goods due to the CDM. We use our model results to calculate $d\ln P_1 = -0.12\%$. At an assumed $s_1 = 0.20$ and $\theta = 2$, this implies that the CDM increases aggregate emissions by 0.1%, on the order of one part in one thousand. This aggregate projection of the effect of the CDM on emissions is modest, despite the enormous emissions growth at CDM firms, because only a small part of CDM firms' growth is caused by the CDM, CDM firms' growth displaces output from other emissions-intensive firms, and emissions-intensive output is only partly substitutable with non-emissions intensive manufacturing. Still, the implication of our production function estimates, that the CDM increases emissions, carries through in general equilibrium in attenuated form.

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 three main descriptive findings. First, the CDM Board attempts to screen out non-additional projects by rejecting projects with high stated returns. Second, the emissions at firms that register, or even propose, CDM projects increase steeply in the four years after the project start, contrary to ex ante projections. Third, this growth in emissions is accompanied by proportional growth in 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 anticipated productivity growth. We use the model to match the event-study estimates of the effects of CDM proposal and registration on emissions growth. Using the model, we find that the bulk—more than 80%—of differential emissions growth at registered firms is due to *selection on growth*. Nonetheless, the CDM does have a smaller, positive causal *scale effect* on emissions due to CDM projects raising firm efficiency and hence output.

Our analysis illuminates fundamental problems with using voluntary offsets as a policy tool. The first problem is in screening. The CDM arguably had more extensive monitoring and rigorous screening than any carbon offset market in the world. Nonetheless, firms are better-informed than the Board about their prospects, which makes it difficult to identify additional projects. The second problem is the difference between technical and economic views of the causes of emissions. The CDM view of abatement is as a technical exercise in improving efficiency, which neglects that firm emissions are ultimately a choice. For these reasons, our findings cast doubt on whether even rigorous ex ante screening can reliably quantify emissions offsets in a dynamic environment.

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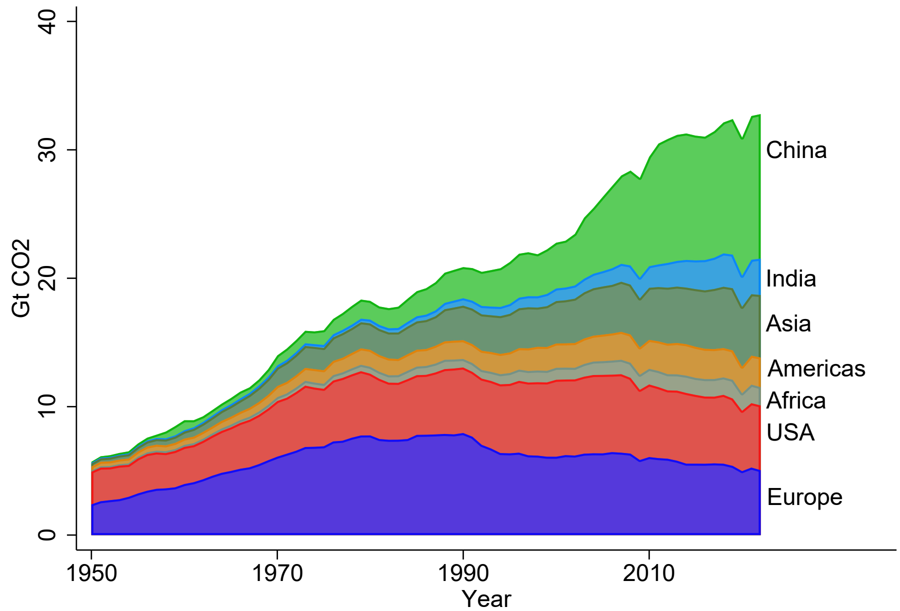
8 Figures

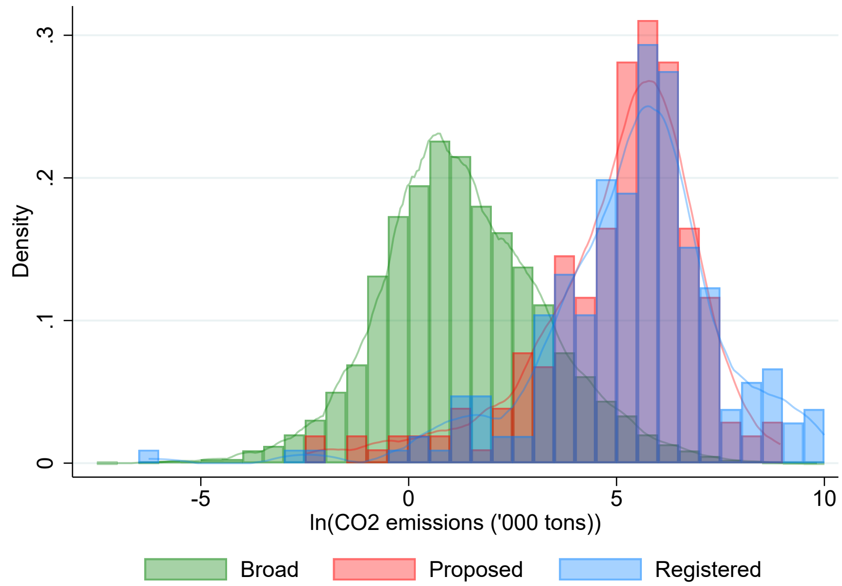
Figure 1: Carbon Dioxide Emissions by Country or Region, 1950–2022



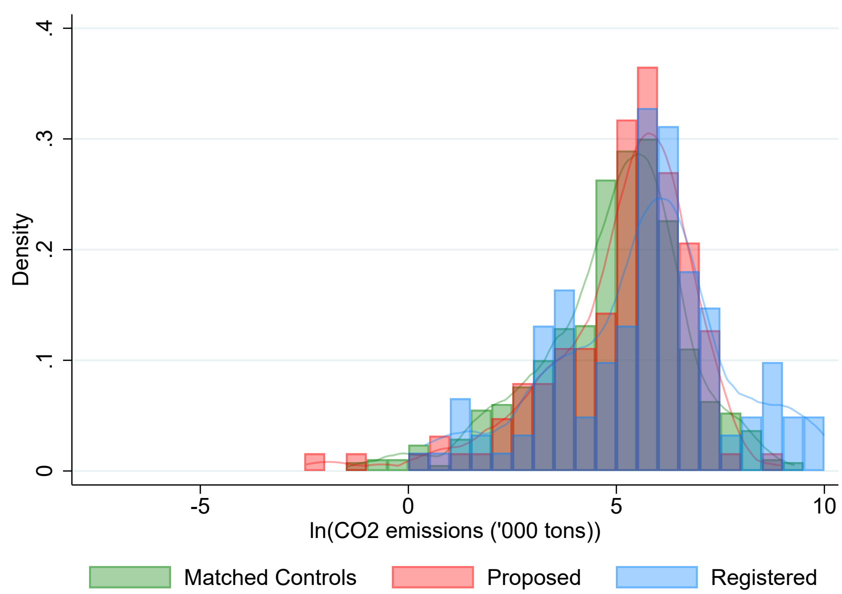
Notes: Authors' calculation using data from the Global Carbon Budget. This figure shows CO_2 emissions from coal, oil, gas, cement production and flaring for various countries among 1950 to 2022.

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

A. Before Matching

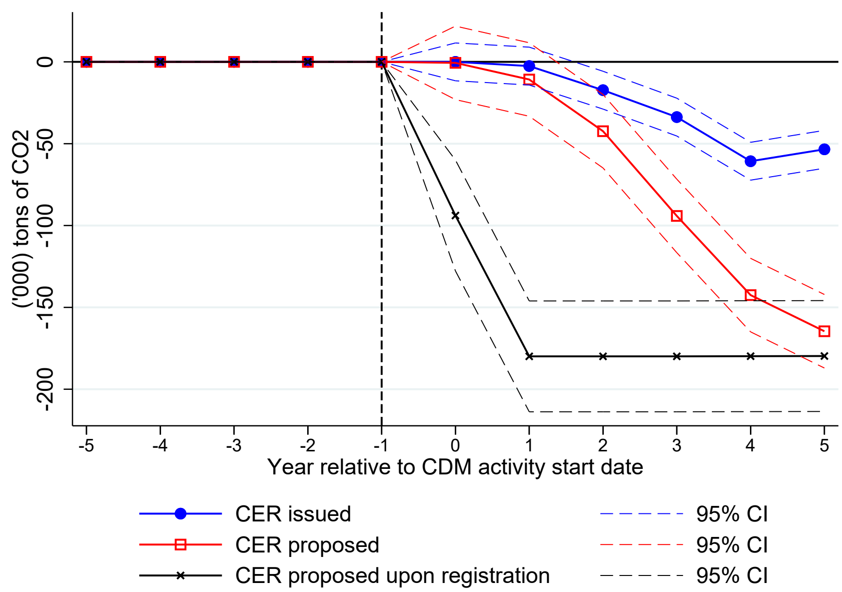


B. After Matching



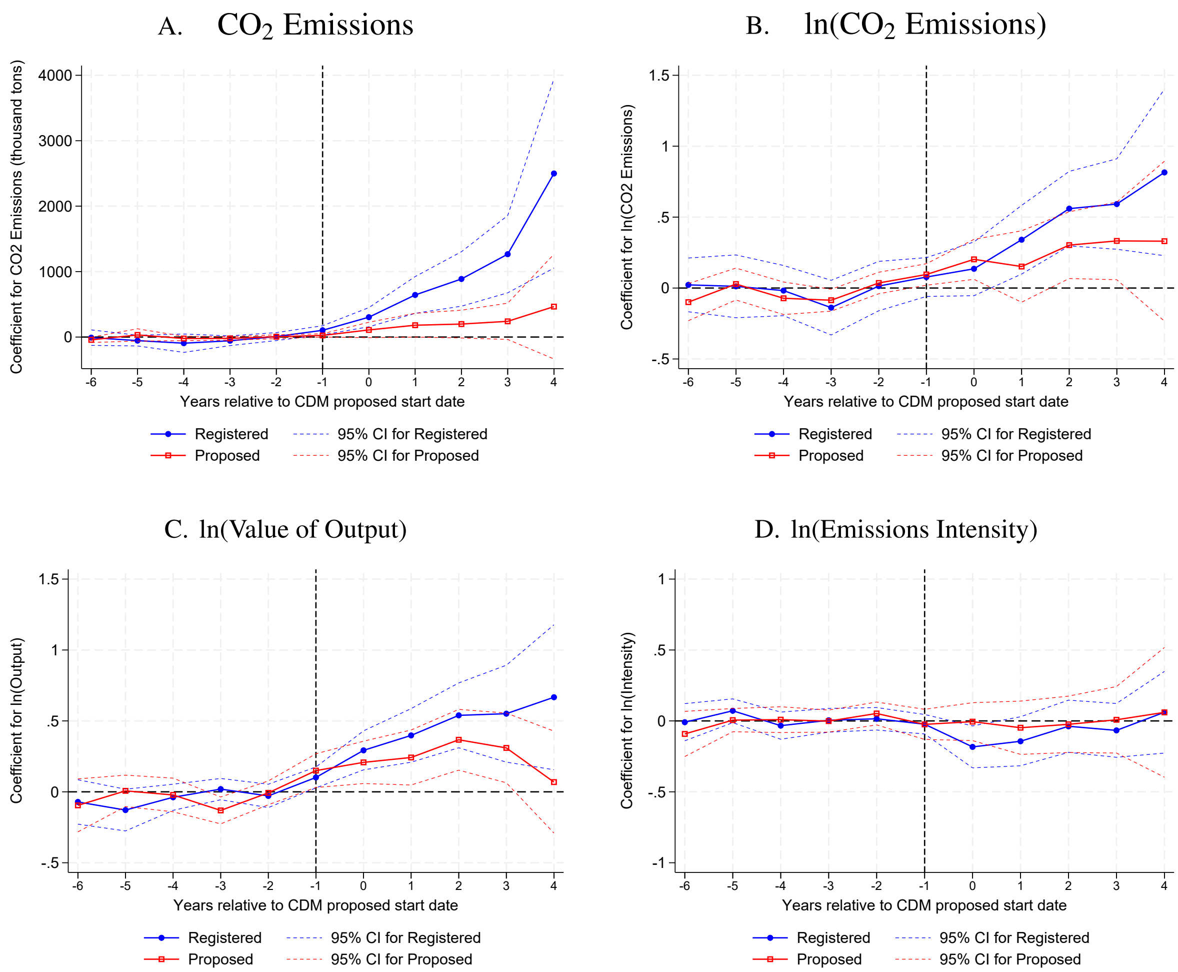
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the distribution of carbon dioxide emissions for firms registered under the CDM program, firms proposed CDM projects but were not registered, as compared to all the other firms in the CESD data that were in the same industry and same province as the CDM registered and proposed 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 start year of the first (registered) CDM project for registered and proposed firms, while the year of 2005 for the other firms. If the base year emissions data is unavailable, we impute the missing values with the most recent year for which emissions data is available. 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



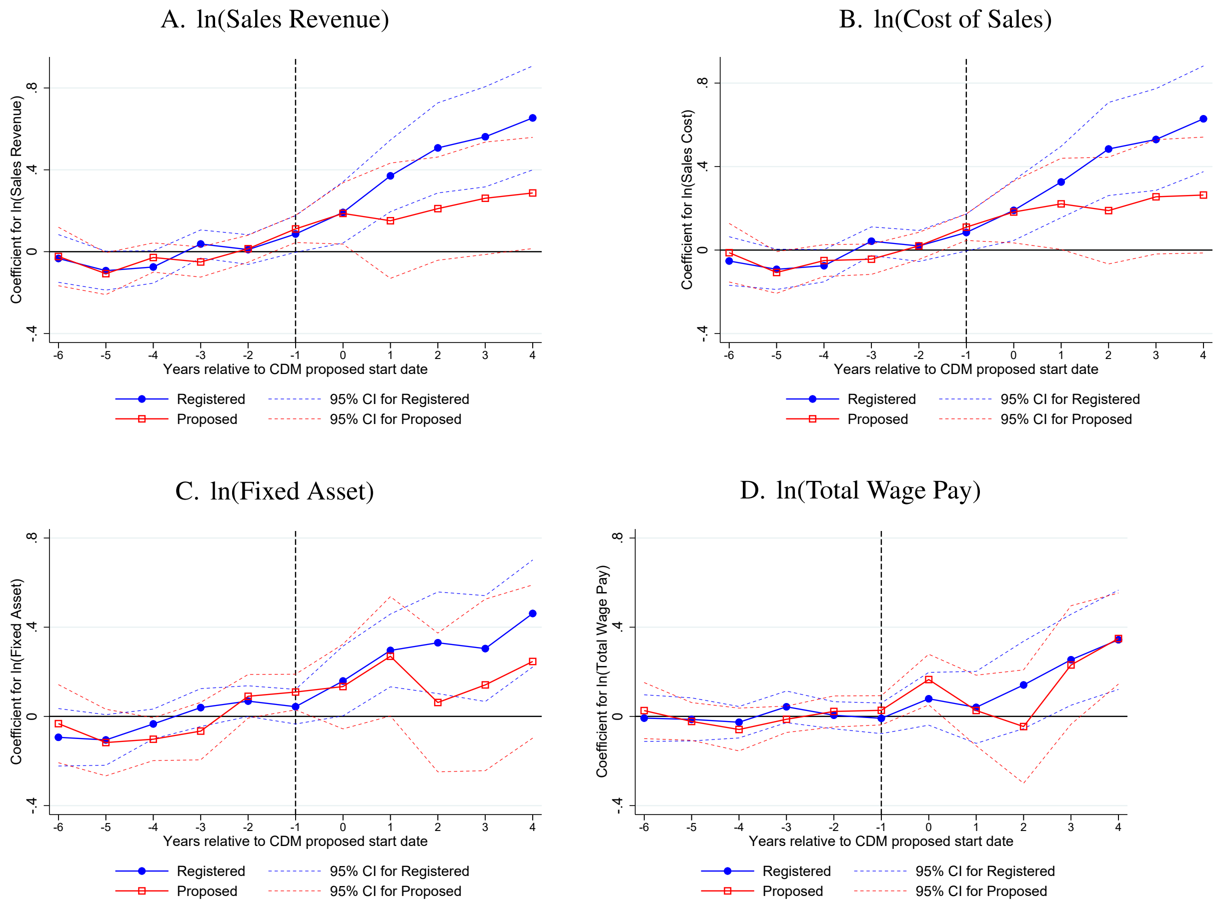
Notes: Authors' calculations using data from UNFCCC. This figure shows the event studies on certified emission reductions (CERs) for all registered projects that matched to CESD and ASIF. The black cross denotes the CERs that a firm proposed to achieve after registration, red square denotes the proposed CERs reported in their Project Design Documents (PDD), while blue circle denotes the actual CERs issued by CDM firms after registration. The lag of the proposed CERs in the PDD is due to that the registration date for a CDM project is generally later than the CDM activity start date since registration usually takes time.

Figure 4: Event Studies for CO_2 Emissions, Output and Emissions Intensity by CDM Status



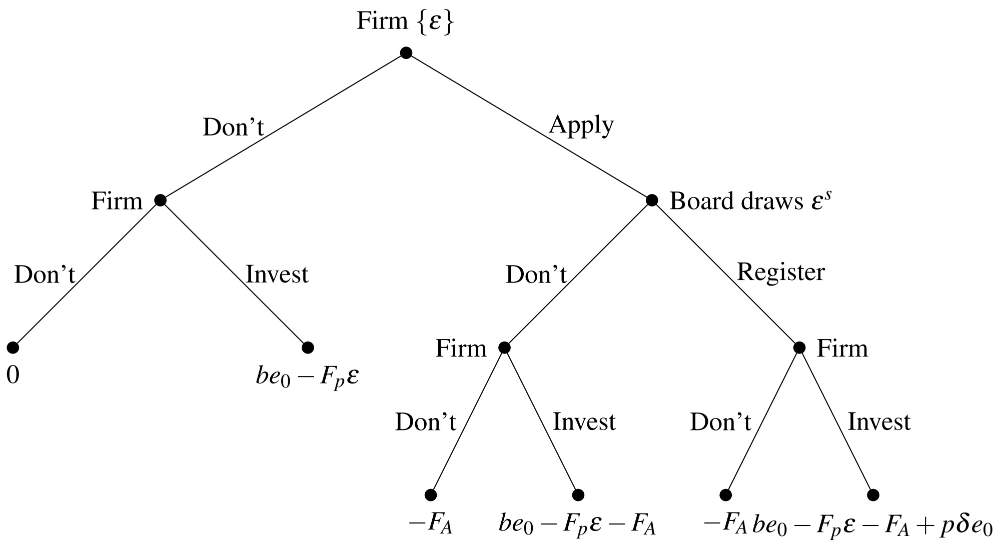
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows coefficients from the event-study specification (2) comparing CO_2 emissions and log CO_2 emissions for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (in red line) to matched 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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure 5: 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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

Figure 6: Model of the Clean Development Mechanism



Notes: 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 2). 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 7: Illustration of firm actions by firm type

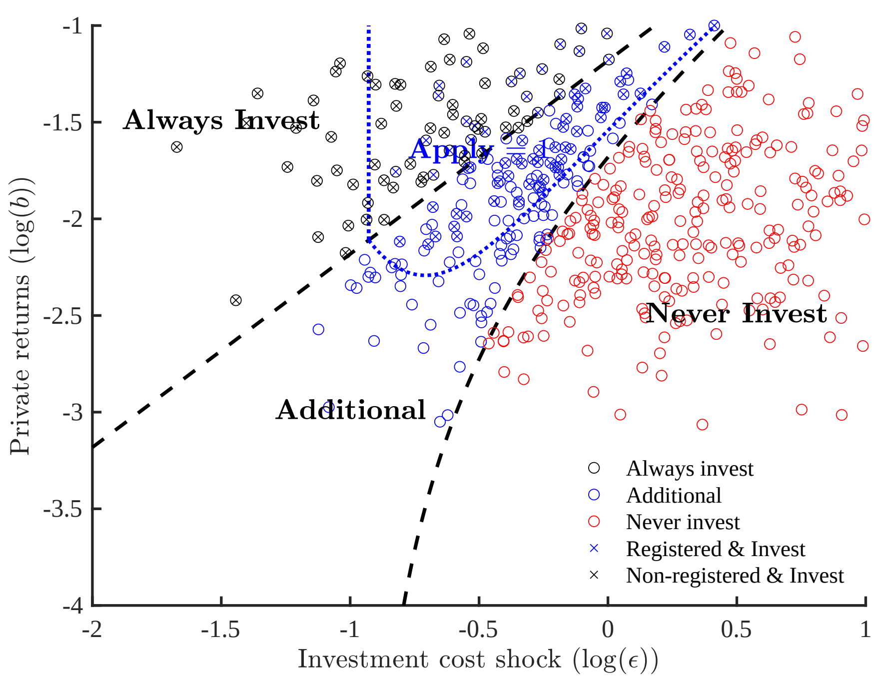
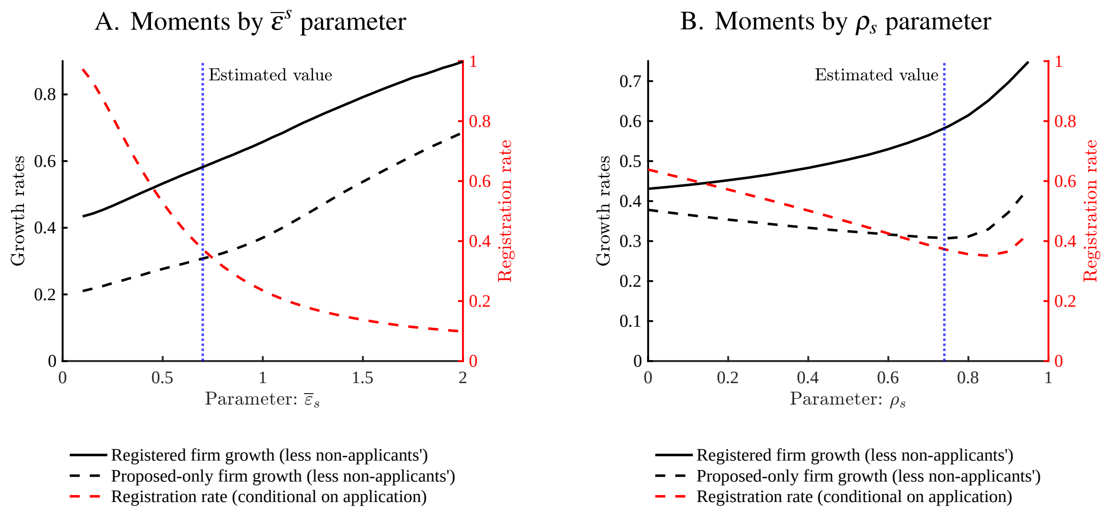


Figure 8: Illustration of Model Identification for Registration Signal and Threshold

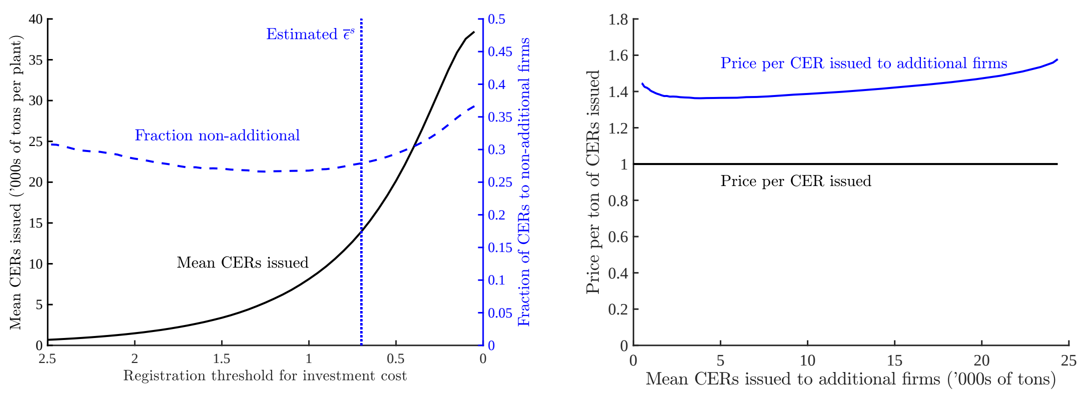


This figure illustrates how the observed data moments on firm growth rates and firm registration rates identify the parameters of the Board's registration rule. Panel A varies the value of $\overline{\varepsilon}^s$, the regulator's cut-off for the investment signal, along the horizontal axis. Moving 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 9: Additionality and Abatement under the CDM

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

B. Abatement expenditure cost curve



This figure illustrates the relationships between CER issuance its additionality and price per CER issued (See Section 6). Panel A illustrates the implications of cost threshold reductions on mean CERs issued and on the fraction of non-additional firms. Panel B illustrates the price trend additional firms face as mean CERs issued increase due to relaxed costs thresholds.

9 Tables

Table 1: 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

Notes: 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 classified as “Proposed" if there is a corresponding CDM project record in the IGES dataset, as “Applied" if the project is submitted to UNFCCC executive board for a decision.

Table 2: Estimates of the Board's Registration (Screening) Rule

	Dependent variable: Registered (=1)					
	LPM				Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Project return)	-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 3: 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	[0.002]	[0.002]	[0.002]	[0.002]
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	[0.032]	[0.174]	[0.122]	[0.104]
Firm FE		Yes	Yes	Yes
Year FE	Yes		Yes	
Industry-Year FE				Yes

Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the point estimates of firm-level 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 the 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 4: 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	[0.078]	[0.700]	[0.026]	[0.058]	[0.500]	[0.558]
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 point estimates of firm-level 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 the 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: Model parameter estimates

Parameter	Estimate	Data	Description
A. 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
B. 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
C. 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

Notes: This table gathers the model parameters which are estimated in the four parts of the model. Panel A describes the parameters relevant for the analytical computation of the production and demand functions (See Section 5.1 and Section 5.3). Panel B describes the parameters required to estimate the fixed cost of investment (See Section D.2). Panel C describes the parameters that determine the Board's registration decision (See Section 5.4 and Section D.4).

Table 6: 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

The table gives the joint probability distribution of observed firm actions (across rows) and unobserved firm types (across columns) using simulations of the model at the estimated parameters of Table 5. The firm actions are: non-application, application with registration, and application without registration (proposed-only firms). The unobserved firm types are never invest, always invest, and additional firms, as defined in equation (15).

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

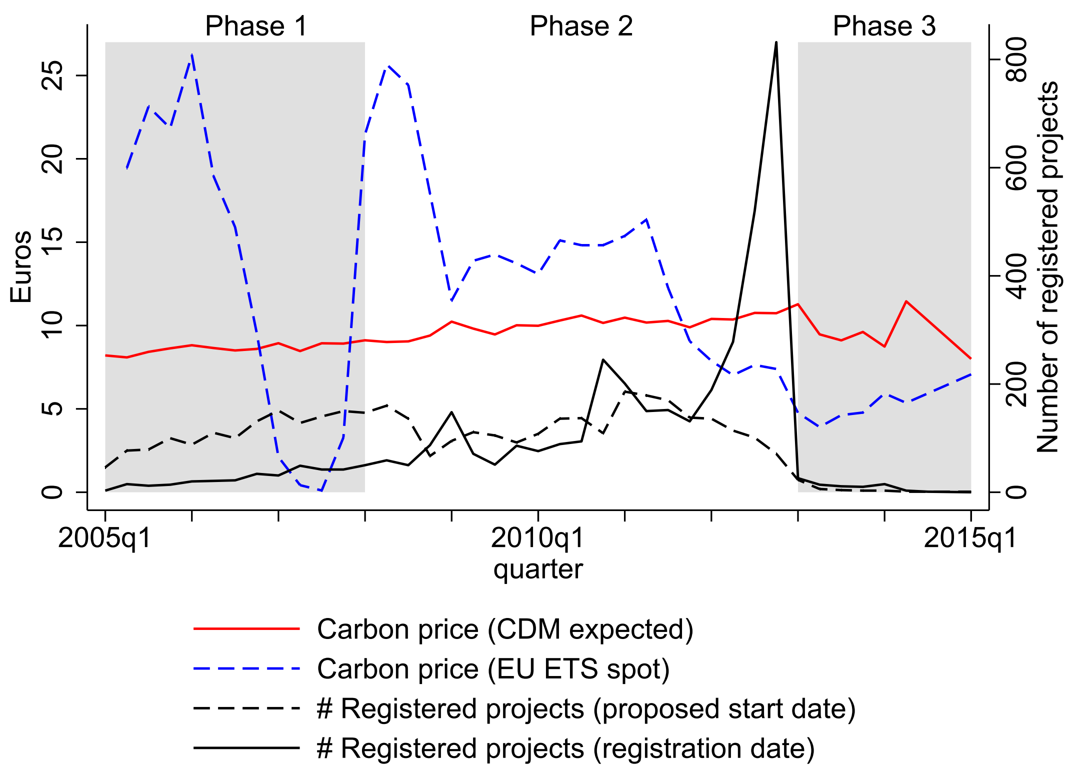
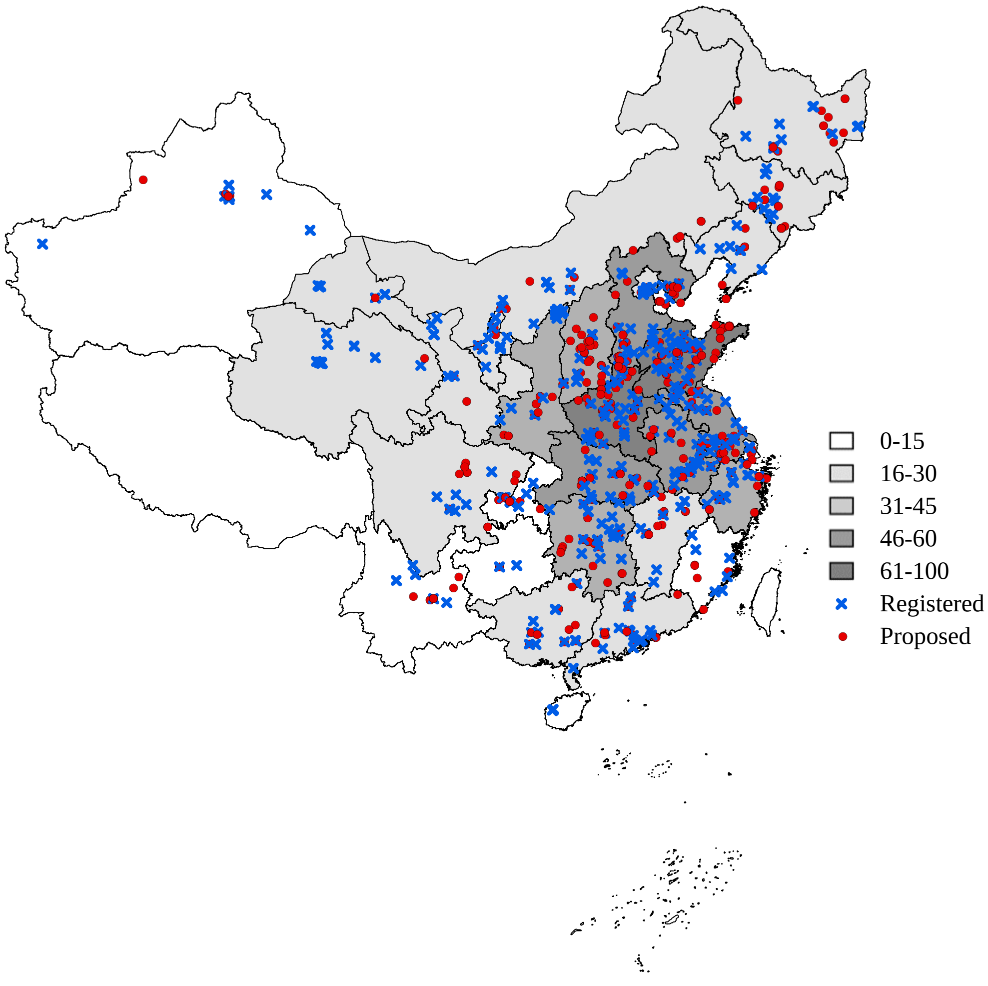


Figure A2: Map of CDM Projects Proposed in China



Notes: Authors' calculations using data from UNFCCC. This figure shows the locations of all CDM projects matched to the CESD and ASIF in China. Blue cross denotes the location of registered projects while red circle denotes the location of proposed projects. Shading represents the concentration of CDM firms within each province, a deeper shading suggests a greater mass of CDM firms.

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

(1) 2-digit industry code and name	(2) Count	(3) %	(4) % (Cum.)
44 electricity and heat production and supply	210	33.9	33.9
31 non-metallic mineral products	193	31.1	65
25 petroleum processing, coking, and nuclear fuel processing	50	8.06	73.1
32 ferrous metal smelting and rolling	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	15	2.42	91.1
13 agricultural and sideline food processing	13	2.10	93.2
33 non-ferrous metal smelting and rolling processing	10	1.61	94.8
20 wood processing, wood, bamboo, rattan, palm, and grass products	6	0.97	95.8

Notes: Authors' calculation using data from CESD, ASIF and UNFCCC. This table includes the top 10 frequent industries of the first (registered) projects by all CDM firms matched in CESD and ASIF.

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

Notes: Authors' calculation using data from UNFCCC. This table shows project types of the first (registered) projects by all CDM firms matched in CESD and ASIF.

Table A3: Project-Level Documentations

	Frequency	Percentage (%)
CDM Sample (project level)	1,259	100.00
ASIF-CDM	834	66.24
CESD-CDM	540	42.89
CDM Sample (firm level)	913	100.00
ASIF-CDM	664	72.73
CESD-CDM	430	44.91

Notes: Authors' calculation using data from UNFCCC, CESD and ASIF. This table shows the total number and percentage of CDM projects and CDM firms that can be matched in the CESD and ASIF data.

B Appendix: Supplementary results

B.1 Additional results

Table B4: 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)	73.3	1182.9	3479.5	1109.6***	2296.6***
	[634.0]	[3564.5]	[9981.2]	(246.6)	(718.4)
CO2 emissions ('000 ton)	34.8	479.9	1115.9	445.1***	636.0***
	[222.4]	[902.2]	[2934.0]	(62.1)	(207.4)
Uses coal (=1)	0.93	0.95	0.85	0.018	-0.098***
	[0.26]	[0.22]	[0.36]	(0.015)	(0.029)
Uses liquid fuel (=1)	0.048	0.16	0.15	0.11***	-0.012
	[0.21]	[0.36]	[0.35]	(0.025)	(0.035)
Uses natural gas (=1)	0.022	0.057	0.12	0.035**	0.066**
	[0.15]	[0.23]	[0.33]	(0.016)	(0.027)
Total coal consumption ('000 ton)	17.0	239.9	557.2	222.9***	317.2***
	[107.1]	[461.5]	[1517.2]	(31.8)	(107.1)
Natural gas consumption (million m3)	0.75	6.17	12.0	5.42	5.84
	[37.4]	[48.4]	[62.3]	(3.36)	(5.39)
CO2 growth	0.024	0.14	0.097	0.12**	-0.045
	[0.59]	[0.53]	[0.68]	(0.049)	(0.081)
Observations	78709	210	220	78919	430
		Panel B: ASIF variables			
Fixed assets (CNY m)	50.8	1430.9	2059.9	1380.1***	628.9
	[648.4]	[6263.1]	[10899.3]	(367.2)	(678.8)
Investment, long-term (CNY m)	5.99	82.4	291.6	76.4	209.2
	[1044.2]	[617.3]	[1768.7]	(54.4)	(167.3)
Investment, short-term (CNY m)	0.45	4.25	13.2	3.80	8.97
	[25.0]	[35.6]	[124.7]	(3.32)	(12.3)
Wage bill (CNY m)	3.64	41.4	128.9	37.8***	87.4*
	[40.3]	[105.9]	[867.8]	(6.84)	(48.4)
Revenue (CNY m)	85.5	1606.8	2607.4	1521.3***	1000.6
	[778.7]	[5263.9]	[13454.5]	(307.0)	(764.2)
Cost of product sales (CNY m)	72.8	1452.3	1773.9	1379.5***	321.6
	[704.5]	[4980.8]	[7099.0]	(291.5)	(471.8)
Employment (number)	196.6	1321.9	2577.5	1125.3***	1255.6*
	[903.9]	[3137.9]	[11483.9]	(186.9)	(645.2)
Observations	258886	293	370	259179	663

Notes: Authors' calculations using data from CESD and ASIF. This table shows the mean and standard error for main variables among firms registered under the CDM program in Column (3), firms proposed CDM projects but were not registered in Column (2), and all the other firms in the CESD data that were in the same industry and same province as the CDM registered and proposed firms but did not propose a project in Column (1). Columns (4) and (5) report the mean difference and the standard error between different groups. Variables are measured in the start year of the first (registered) CDM project for registered and proposed firms, while the year of 2005 for the other firms. If the base year data is unavailable, we impute the missing values with the most recent year for which data is available. Statistical significance at certain thresholds is indicated by * $p < 0.10$, **$P < 0.05$, ***$p < 0.01$.

Table B5: 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

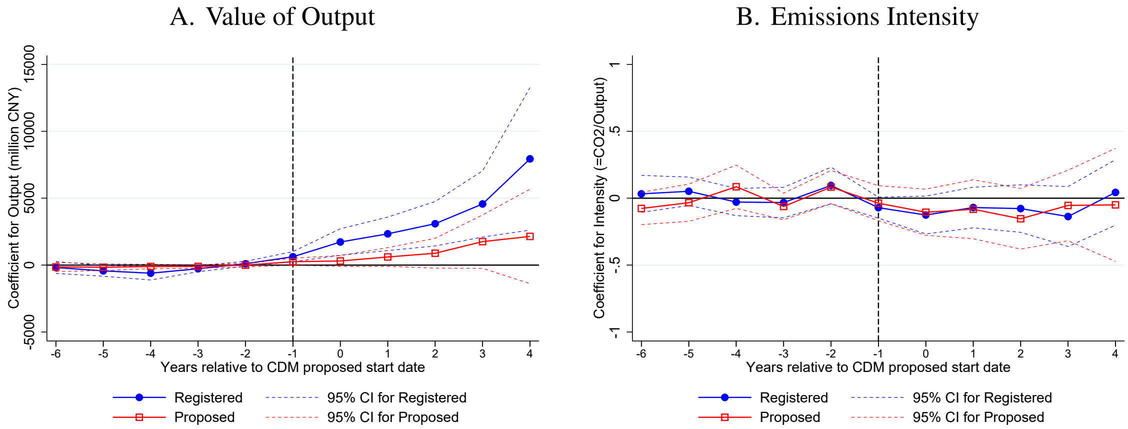
Notes: Authors' calculations using UNFCCC. This table reports point estimates from regressions of project registration on stated investment. The sample includes the first (registered) projects matched to all CDM registered or proposed firms in the CESD or ASIF. Investment is the stated amount of investment in the Project Design Documents (PDD) which is submitted as part of the CDM project proposal, with a median of 0.014, mean of 0.050 and standard deviation of 0.14. Consultant on proposal is an indicator for whether a consultant was used in CDM application or not in the PDD. Credit buyer lined up is an indicator for whether there are buyers of Certified Emissions Reduction (CER) in the PDD. Build lag measures the number of years from date of public comment of the project to proposed credit start date. All specifications include proposed credit start year, project type and deciles of proposed emission reduction fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Point Estimates for Emissions to Other Inputs Ratio

	Dependent variable: Ln of . . .		
	Emissions/ Cost of Sales (1)	Emissions/ Total Wage (2)	Emissions/ Intermediate Input (3)
Registered (=1) ×	-0.060	0.087	-0.124
Post (0-4 years)	(0.083)	(0.090)	(0.091)
Observations	2130	1848	1534
Mean dep variable	-0.235	2.809	-0.049
Proposed (=1) ×	0.058	-0.016	-0.027
Post (0-4 years)	(0.092)	(0.101)	(0.083)
Observations	2161	1872	1548
Mean dep variable	-0.080	2.930	0.123
Difference	-0.119	0.103	-0.098
P-value	[0.870]	[0.244]	[0.794]
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: Authors' calculations using data from CESD, ASIF and UNFCCC. This figure shows the point estimates of firm-level 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 the 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: Event Studies for Output and Emissions Intensity by CDM Status (In levels)

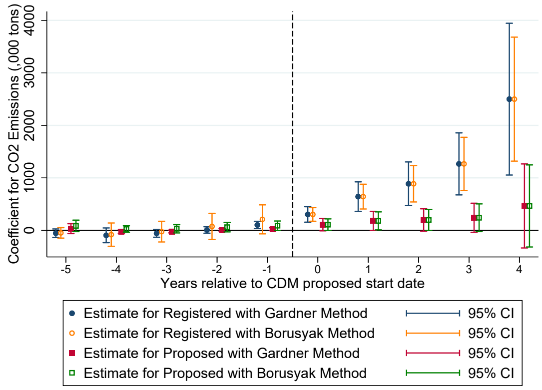


Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the coefficients from the event-study specification (2) comparing output and emissions intensity (CO_2 per unit output) for firms that *Registered* a CDM project (in blue line) and firms that only *Proposed* a CDM project (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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023).

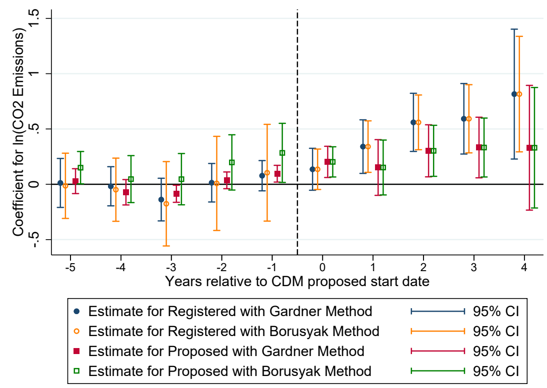
B.2 Robustness of event-study estimates to alternative specifications

Figure B4: Robustness for Different Staggered DID Estimators: CESD Data

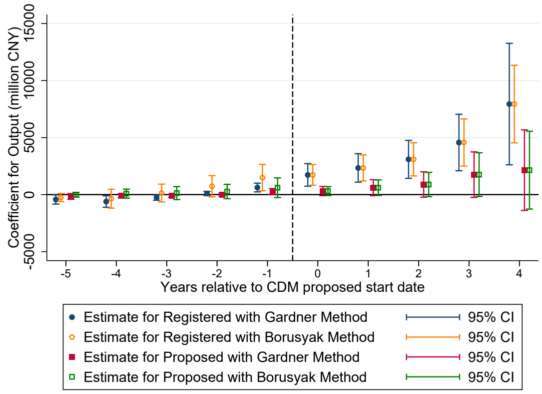
A. CO_2 Emissions



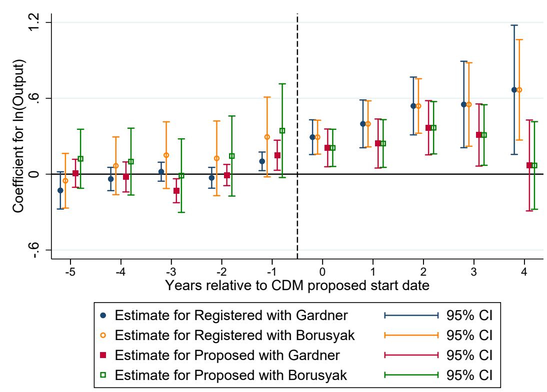
B. ln(CO_2 Emissions)



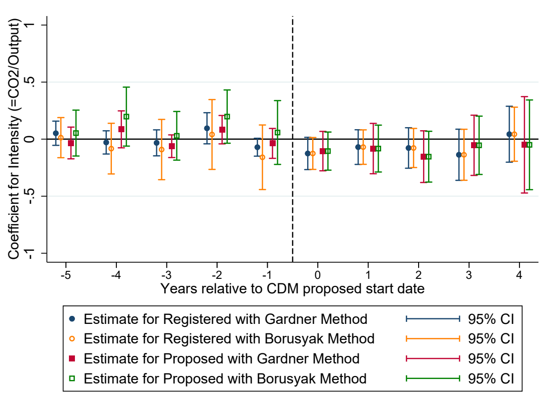
C. Output



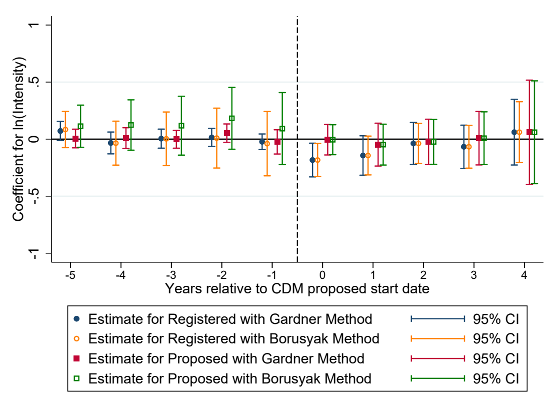
D. ln(Output)



E. Intensity

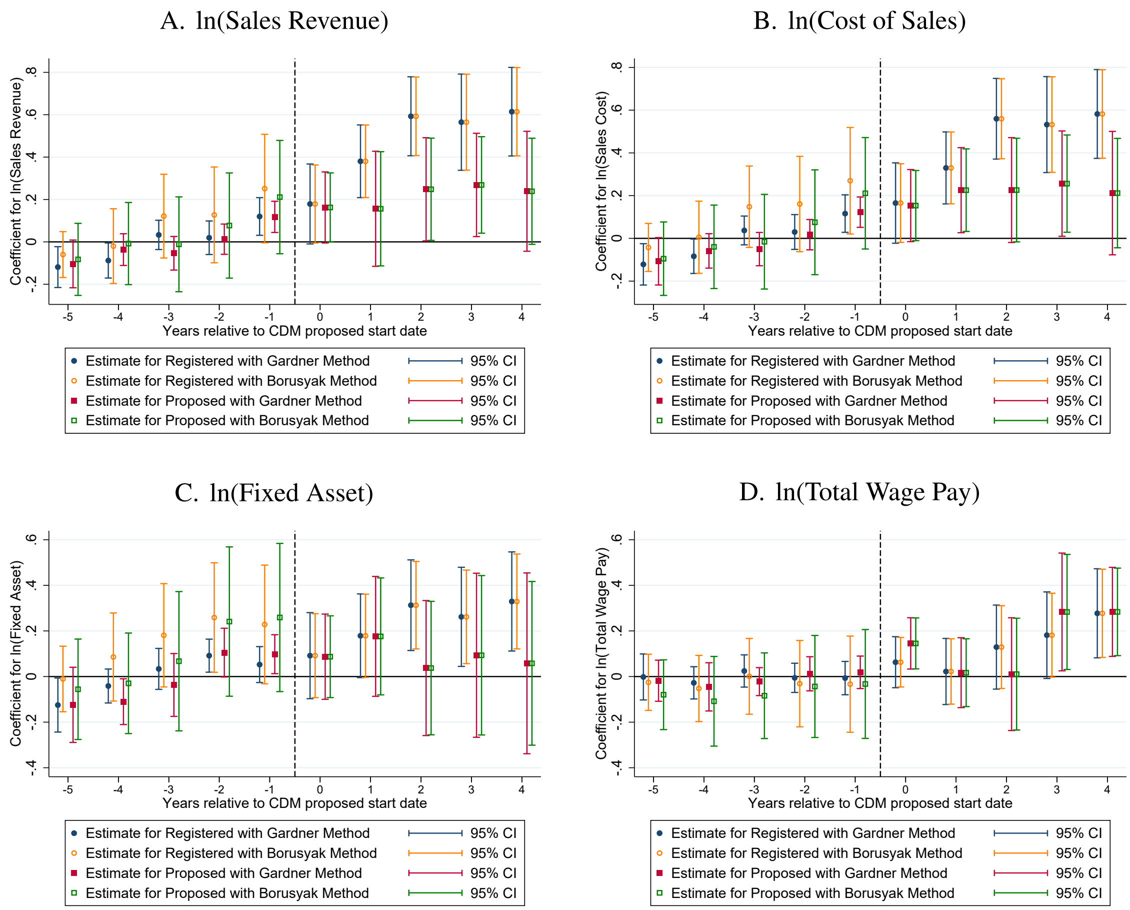


F. ln(Intensity)



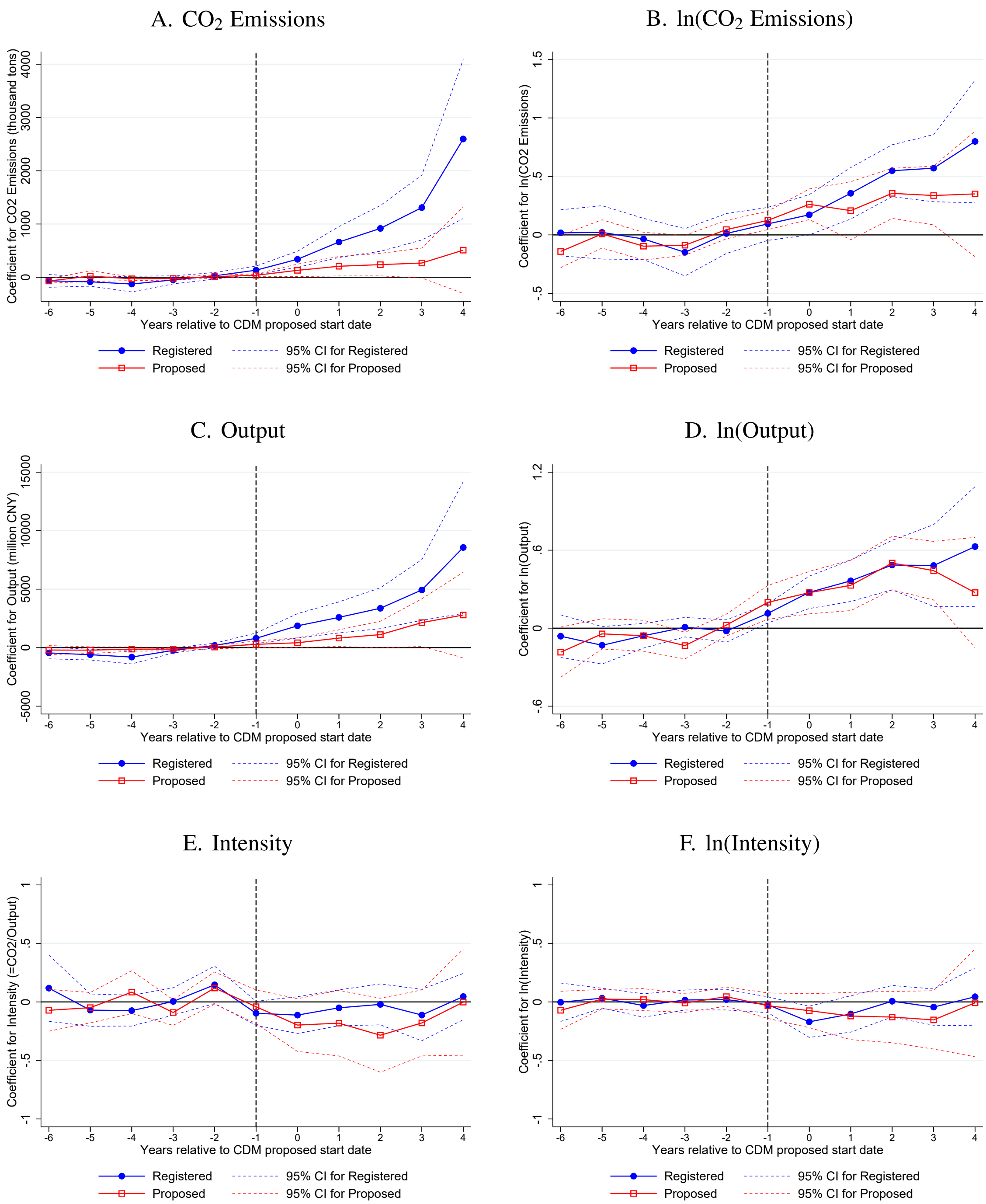
Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows event study comparisons between Gardner et al. (2023) estimator and Borusyak, Jaravel and Spiess (2021) estimator with specification (2) using our baseline sample for the CESD data. This figure corresponds to figure 4 and figure B3 in the paper while using various staggered difference-in-differences estimators.

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



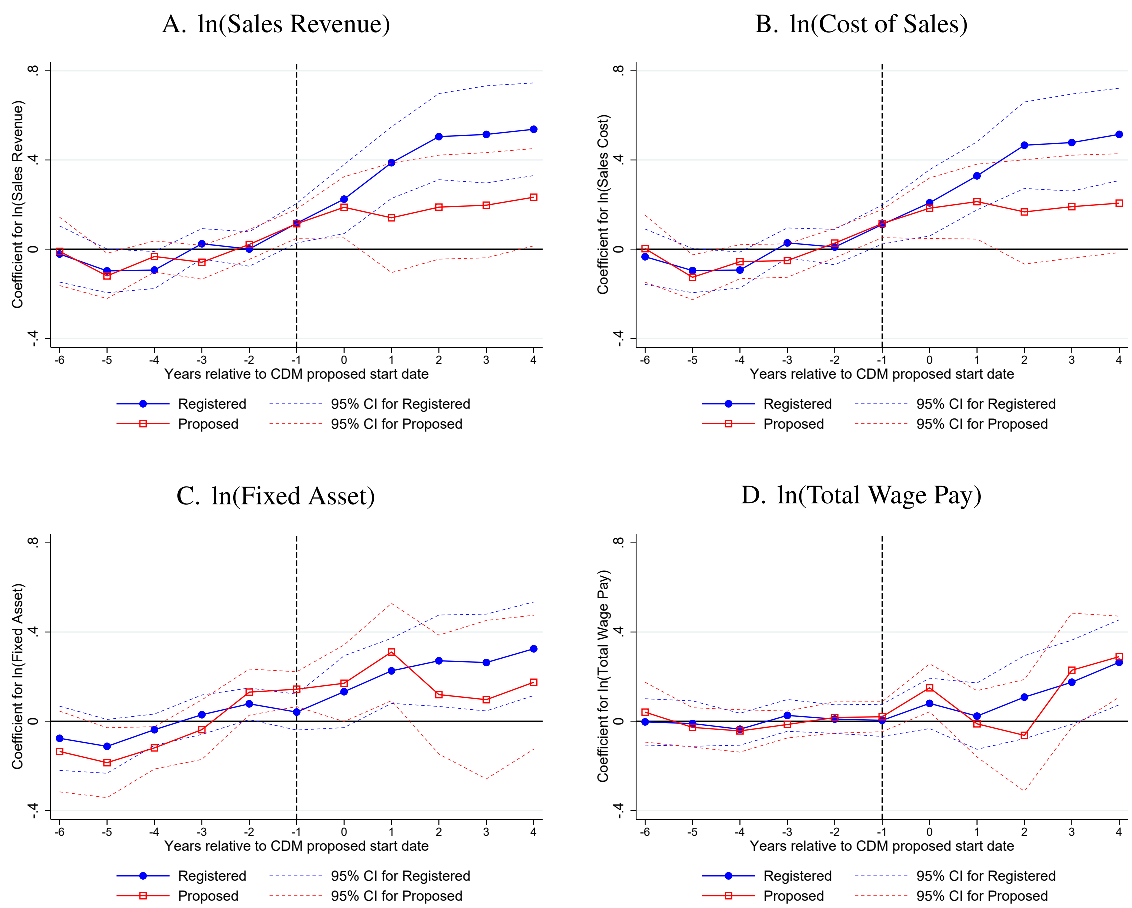
Notes: Authors' calculations using data from AISF and UNFCCC. This figure shows event study comparisons between Gardner et al. (2023) estimator and Borusyak, Jaravel and Spiess (2021) estimator with specification (2) using our baseline sample for the ASIF data. This figure corresponds to figure 5 in the paper while using various staggered difference-in-differences estimators.

Figure B6: Robustness for 1:10 Matching: CESD Data



Notes: Authors' calculations using data from CESD and UNFCCC. This 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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). This figure corresponds to figure 4 and figure B3 in the paper while enlarging the control samples.

Figure B7: 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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). This figure corresponds to figure 5 in the paper while enlarging the control samples.

Table B7: Robustness for Borusyak Estimator: CESD Data

	CO_2 (1)	ln(CO_2) (2)	ln(Output) (3)	ln(Intensity) (4)
Registered (=1) ×	945.6***	0.398***	0.422***	-0.092
Post (0-4 years)	(173.6)	(0.111)	(0.091)	(0.072)
Observations	3594	3490	3560	3190
Mean dep variable	1008.5	5.299	5.543	-0.340
Proposed (=1) ×	199.9*	0.215**	0.238***	-0.013
Post (0-4 years)	(121.2)	(0.097)	(0.083)	(0.081)
Observations	3656	3548	3616	3242
Mean dep variable	314.5	4.801	4.960	-0.203
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows the point estimates of firm-level 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 the difference-in-differences estimates use the staggered estimator of (Borusyak, Jaravel and Spiess, 2021). This table corresponds to the table 3 and table 4 while using various staggered difference-in-differences estimator. 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 (1)	$\ln(CO_2)$ (2)	ln(Output) (3)	ln(Intensity) (4)
Registered (=1) ×	985.2***	0.405***	0.386***	-0.070
Post (0-4 years)	(246.9)	(0.104)	(0.086)	(0.059)
Observations	9875	9629	9773	8764
Mean dep variable	618.3	5.063	5.191	-0.190
Proposed (=1) ×	230.7*	0.272***	0.353***	-0.112
Post (0-4 years)	(128.7)	(0.093)	(0.084)	(0.090)
Observations	9998	9658	9880	8869
Mean dep variable	210.2	4.469	4.597	-0.212
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Authors' calculations using data from CESD and UNFCCC. This figure shows point estimates of firm-level 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 the difference-in-differences estimates use the staggered estimator of (Gardner et al., 2023). This table corresponds to the table 3 and table 4 while enlarging the samples. 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	Cost of Sales	Wage bill	Fixed assets
	(1)	(2)	(3)	(4)
Registered (=1) × Post (0-4 years)	0.391***	0.358***	0.164**	0.125*
	(0.089)	(0.087)	(0.080)	(0.069)
Observations	16934	16920	16905	15489
Mean dep variable	6.204	6.017	5.111	2.719
Proposed (=1) × Post (0-4 years)	0.196***	0.192***	0.217**	0.131*
	(0.076)	(0.074)	(0.094)	(0.071)
Observations	15637	15625	15636	14248
Mean dep variable	5.607	5.420	4.435	2.204
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 point estimates of firm-level 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). This table corresponds to the table 4 while enlarging the samples. 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

This section of the Appendix includes derivations for the model omitted from the main text.

C.1 Derivation of firm outputs and emissions

We start from the production function (6). 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

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

With the assumed inverse demand curve $p = y^{-\frac{1}{\eta}}$, profit maximization then gives

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

Solving this expression yields the optimal output

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

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 (19) of a project with cost shock ε as P_ε.

Firms with sufficiently low cost shocks will never apply to the CDM because it is unlikely they will be registered. If $p\delta_e < \frac{(A/\tilde{T})}{P_\varepsilon}$, then the expected benefit from the CDM is lower than the application cost for all firms, even those with non-additional projects. The probability P_ε is increasing in ε. As a result, we can define

$$P_{\tilde{\varepsilon}}\, p\delta_e \tilde{T} = A \tag{26}$$

such that no firms with $\varepsilon < \tilde{\varepsilon}$ will choose to apply. For what follows, we condition on a value of $\varepsilon > \tilde{\varepsilon}$ such that some firms may apply to the CDM if their benefits from doing so are high enough.

Firm decisions as to whether to apply and invest are defined by a series of threshold values for the private benefits of investment. These thresholds are defined by

$$\log b \quad < b_0(\varepsilon) = \log((\gamma\varepsilon/\tilde{T} - p)\delta_e) \qquad \text{Never invest and not apply} \tag{27}$$

$$b_0(\varepsilon) \leq \quad \log b \quad < b_1(\varepsilon) = \log((\gamma\varepsilon/\tilde{T} - p)\delta_e + (A/\tilde{T})/P_{\bar{\varepsilon}})) \qquad \text{Additional but not apply} \tag{28}$$

$$b_1(\varepsilon) \leq \quad \log b \quad < b_2(\varepsilon) = \log((\gamma\varepsilon/\tilde{T})\delta_e) \qquad \text{Additional and apply} \tag{29}$$

$$b_2(\varepsilon) \leq \quad \log b \qquad \text{Non-additional and apply.} \tag{30}$$

Using these cut-offs, the fraction of firms of each type can be calculated as

$$\omega^{NI}(\varepsilon) = \int_0^{b_0(\varepsilon)} dF_{\log b} \quad \text{Never invest and not apply} \tag{31}$$

$$\omega_0^A(\varepsilon) = \int_{b_0(\varepsilon)}^{b_1(\varepsilon)} dF_{\log b} \quad \text{Additional but not apply} \tag{32}$$

$$\omega_1^A(\varepsilon) = \int_{b_1(\varepsilon)}^{b_2(\varepsilon)} dF_{\log b} \quad \text{Additional and apply} \tag{33}$$

$$\omega^A(\varepsilon) = \omega_0^A(\varepsilon) + \omega_1^A(\varepsilon) \quad \text{Additional} \tag{34}$$

$$\omega^{NA}(\varepsilon) = \int_{b_2(\varepsilon)} dF_{\log b} \quad \text{Non-additional and apply.} \tag{35}$$

The threshold rules for application induce selection on growth at the application stage. Firms that expect to have higher productivity growth Δ_z, and thus higher private returns b, choose to apply to 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.

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".

$$E[\log(g_e)|\text{proposed, not registered}, \varepsilon] =$$

$$\left[\underbrace{\int_{b_2(\varepsilon)} (\eta-1)\log\Delta_e + \log b(\Delta_z) dF_{\log b}}_{\text{Non-additional}} + \underbrace{\int_{b_1(\varepsilon)}^{b_2(\varepsilon)} \log b(\Delta_z) dF_{\log b}}_{\text{Additional}}\right] / (\omega^{NA}(\varepsilon) + \omega_1^A(\varepsilon)) - \log \bar{b}$$

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

These expressions can be used to produce the model analogs of the difference-in-difference of emissions growth rates from our event-study regressions, as reported in Table 3. The difference in growth rates between registered and non-applicant firms is

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

The first term is the scale effect of investment by registered firms increasing productivity and therefore scale and emissions. The second term, in parentheses, is the selection effect of the difference in growth rates between firms that apply ($\log b > b_1(\varepsilon)$) and those that do not.

The difference in growth rates between registered firms and proposed firms that are not registered is

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

The fraction at right is the share of additional firms ($\omega_1^A(\varepsilon)$) in the mix of applicants. The difference in emissions growth rates is increasing in the share of additional firms because, if most firms applying are not additional, then they will implement their projects even if they are rejected by the CDM.

C.3 Alternative Production Function with Emission

In our baseline specification, we assumed a Cobb-Douglas production function of value-added and emissions. We now extend our modeling framework to allow for a non-unitary elasticity of substitution between variable inputs and emissions. Specifically, consider a CES (Constant Elasticity of Substitution) production function:

$$y = z[(1-\alpha_e)(v)^{\frac{\gamma-1}{\gamma}} + \alpha_e(z_e e)^{\frac{\gamma-1}{\gamma}}]^{\frac{\gamma}{\gamma-1}}$$

where γ is the elasticity of substitution across composite inputs v and emission e. As $\gamma \to 1$, the function converges to our baseline Cobb-Douglas model.

Cost minimization gives the first order condition of optimal input mix

$$\frac{v}{e} = \left[\frac{\alpha_e z_e^{\frac{\gamma-1}{\gamma}}}{(1-\alpha_e)}\frac{w}{t_e}\right]^{-\gamma} = \left[\frac{\alpha_e}{(1-\alpha_e)}\frac{w}{t_e}\right]^{-\gamma} z_e^{1-\gamma}$$

Unlike the Cobb-Douglas model, the improvement in energy efficiency z_e has an impact on emission-to-variable cost ratio such that

$$d\ln\left(\frac{e}{wv}\right) = (\gamma-1)d\ln z_e$$

With a conventional value of $\gamma < 1$, the firm will substitute away from emissions following a CDM investment project.

The overall impact of a CDM project on a firm's emissions is more nuanced. To understand this, note that cost minimization yields the cost function $C(y;z,z_e) = C_w\left(\frac{y}{z}\right)$, where

$$C_w = \left[(1-\alpha_e)(\frac{w}{(1-\alpha_e)})^{1-\gamma} + \alpha_e(\frac{t_e}{\alpha_e z_e})^{1-\gamma}\right]^{\frac{1}{1-\gamma}}$$

Profit maximization gives the optimal level of emissions as:

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

We can show that

$$d\ln e = [\underbrace{(\gamma-1)}_{\text{substitution}} + \underbrace{(\eta-\gamma)s_e}_{\text{scale}}]d\ln z_e$$

, where the cost share

$$s_e = \frac{\alpha_e(\frac{t_e}{\alpha_e z_e})^{1-\gamma}}{\left[(1-\alpha_e)(\frac{w}{(1-\alpha_e)})^{1-\gamma} + \alpha_e(\frac{t_e}{\alpha_e z_e})^{1-\gamma}\right]}$$

In general, $\gamma < 1 < \eta$, there is a negative substitution effect and a positive scale effect. When the substitution elasticity across firms is substantially larger than that across inputs, the scale effect still dominates. However, this outcome also depends on the relative importance of emissions in the cost share.

C.4 Equilibrium implications of CDM offsets

To assess the general equilibrium implications of the CDM program, we embed our model of CDM firms into a nested CES structure. We now suppose that manufacturing is comprised of an emissions-intensive industry (sector 1), to which all of the sectors of CDM firms belong, and all other clean manufacturing sectors (sector 0). For simplicity, we fix total manufacturing expenditure at I and normalize the clean manufacturing sector price $P_0 = 1$.

We assume a nested CES production structure. Output in the emissions-intensive sector is

$$Y_1 = \left[\int_i y_i^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}. \tag{36}$$

This aggregator assumes that the composite emissions-intensive good is produced with a CES technology across producer varieties i. The CES form is consistent with the residual demand curve $y_i = \frac{1}{P_1^{-\eta}} (p_i)^{-\eta}$ we imposed in calculating CDM firms' optimal output. The equilibrium price index for emissions-intensive output is defined as $P_1 = \left[\int_i p_i^{1-\eta} \right]^{\frac{1}{1-\eta}}$. Aggregate manufacturing output is given by

$$Y = \left[Y_0^{\frac{\theta-1}{\theta}} + Y_1^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{37}$$

with elasticity of substitution θ between emissions-intensive and non-emissions-intensive output.

We wish to calculate the effect of efficiency improvements in sector 1 on aggregate emissions in this framework. Since firms' output choices depend only on their $\tilde{z}$, the industry aggregate emissions can be expressed as

$$E = \tilde{\eta}(\eta-1)\frac{\alpha_e}{t_e}\left(\frac{C_w}{P_1}\right)^{1-\eta} \left[\int (\tilde{z})^{\eta-1} dF_{\tilde{z}} \right]. \tag{38}$$

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

$$P_1^{1-\eta} = (C_w)^{1-\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta} \left[\int (\tilde{z})^{\eta-1} dF_{\tilde{z}} \right] \tag{39}$$

As a result, similar to Shapiro and Walker (2018), the industry-level emissions intensity is proportional to the price index

$$\frac{E}{Y_1} \equiv E \times P_1 = C_w \left(\frac{\alpha_e}{t_e}\right) (\tilde{Z})^{-1} \tag{40}$$

where $\tilde{Z} = \left[\int (\tilde{z})^{\eta-1} dF_{\tilde{z}} \right]^{\frac{1}{\eta-1}}$. The CDM, then, acts on emissions by increasing efficiency and productivity, which brings down the price index in the emissions-intensive sector and expands output.

How much a lower price index expands output depends on the elasticity of substitution between the output of the emissions-intensive sector and other sectors. Emissions are proportional to the expenditure share of the emission-intensive sector

$$E \propto s_1 \equiv \frac{P_1 Y_1}{I} = \frac{P_1^{1-\theta}}{(1+P_1^{1-\theta})}. \tag{41}$$

For small changes in efficiency, then, the change in aggregate emissions will be

$$d \ln E = (1-\theta)(1-s_1) d \ln P_1, \tag{42}$$

where s_1 is the initial emissions-intensive sector's share of sales *absent* the CDM program and θ is the elasticity of substitution between sectors. Our empirical results on the share of additional firms and the efficiency gains from the CDM imply that the emissions-intensive price index declines by $d \ln \tilde{Z} \equiv -d \ln P_1 = 0.098 \times d \ln \Delta_e = 0.12\%$. If we take a value of $\theta = 2$ and an emissions-intensive share of 0.20, then the implied change in emissions is

$$d \ln E = (1-2)(1-0.2)(-0.12\%) = 0.1\%. \tag{43}$$

We conclude that the existence of the CDM program induced aggregate carbon emissions in Chinese manufacturing to increase by on the order of one part in one thousand. Chinese manufacturing emissions are roughly 2000 MT CO_2e (Guan et al., 2021), so this would imply that the CDM program increased emissions by 2 MT CO_2e.

D Appendix: Model estimation

D.1 Production function

We parameterize the composite input function v and the productivity process z to estimate the firm production function. The firm production function is Cobb-Douglas in value added and emissions according to (6). We additionally assume a Cobb-Douglas production function for the value-added input

$$v_{it} = l_{it}^{\alpha_l} k_{it}^{\alpha_k}. \tag{44}$$

The firm's log output is then

$$\log y_{it} = \log z_i^e + (1-\alpha_e)[\log z_{it} + \alpha_l \log l_{it} + \alpha_k \log k_{it}] + \alpha_e \log e_{it} \tag{45}$$

Using the relationship that $\log r_{it} = (1-1/\eta)\log y_{it}$, the firm's revenue production function is

$$\log r_{it} = \alpha_l^* \log l_{it} + \alpha_k^* \log k_{it} + \alpha_e^* \log e_{it} + \log z_i^{e*} + \log z_{it}^* + \varepsilon_{it}^m \tag{46}$$

with coefficients and productivity of

$$\alpha_l^* = (1-1/\eta)(1-\alpha_e)\alpha_l \tag{47}$$

$$\alpha_k^* = (1-1/\eta)(1-\alpha_e)\alpha_k \tag{48}$$

$$\alpha_e^* = (1-1/\eta)\alpha_e \tag{49}$$

$$\log z_i^{e*} = (1-1/\eta)\log z_i^e \tag{50}$$

$$\log z_{it}^* = (1-1/\eta)(1-\alpha_e)\log z_{it} \tag{51}$$

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 estimate this function using proxy control methods to account for the endogeneity of inputs. In particular, 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 use this equation to estimate the α^* coefficients in revenue production and then our calibrated value of η to recover the α coefficients of the physical production function.

D.2 Fixed cost of investment

In the model, we assume that the fixed cost of investment is linear in the proposed certified emissions reductions (CERs) such that $F_p = \gamma_0(\delta_e e_0)^{\gamma_1} = \gamma_0(\delta_e e_0)$. Here we test this hypothesis with a regression of log (investment) on log(CER):

$$\log(F_p) = \log(\gamma_0) + \gamma_1 \log(\delta_e e_0) + \varepsilon$$

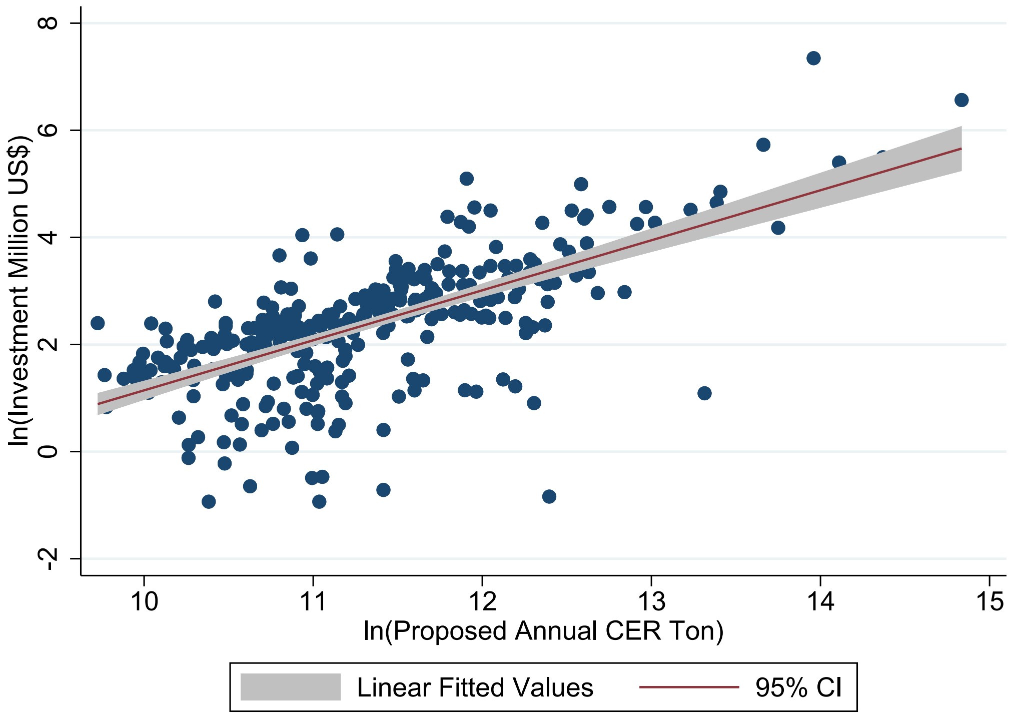
Table D10 shows the results of the regression and a test of the null hypothesis that $\gamma_1 \neq 1$. For specifications with start year effects, we fail to reject the null hypothesis, which supports our model assumption that $F_p = \gamma(\delta_e e_0)$.

Table D10: Regression of log(investment) on log(CER) for CDM firms

	Dependent variable: log(investment)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(proposed CER)	0.934***	0.892***	0.892***	0.877***	0.917***	0.904***
	(0.0586)	(0.0479)	(0.0579)	(0.0626)	(0.0666)	(0.0696)
Project Type		Yes	Yes	Yes	Yes	Yes
Indsutry			Yes	Yes	Yes	Yes
Province				Yes	Yes	Yes
Start Year					Yes	Yes
log(CO2)						Yes
$\log(\gamma)$	-8.20					
RMSE	0.89	0.70	0.64	0.63	0.63	0.63
R^2	0.44	0.67	0.76	0.80	0.80	0.81
p-value $H_0 : \beta_1 \neq 1$	0.26	0.024	0.063	0.051	0.21	0.17
firms	324	324	324	324	324	324

Notes: Authors' calculation using data from UNFCCC and CESD. This table reports results from regressions of the log firm stated investment on log proposed CER. The sample includes all CDM registered and proposed firms that matched to CESD 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 0.63.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure D8: Scatter plot of log(investment) on log(CER)



Notes: Authors' calculation using data from UNFCCC and CESD. This figure shows the relationship between log firm stated investment and log firm proposed CER. The sample includes all CDM registered and proposed firms that matched to CESD and has emissions record before the proposed CDM start year. The fitted line has a slope close to 1, which supports our assumption that the fixed cost of investment is linear in proposed CER.

D.3 Improvement in emissions productivity

Table D11: Estimation for δ_e

	Original Value			*Winsor Value*		
	All	Waste	Others	All	Waste	Others
	(1)	(2)	(3)	(4)	(5)	(6)
CER	36.48	27.57	8.90	31.13	25.38	5.75
	(3.36)	(3.13)	(0.79)	(3.26)	(3.12)	(0.57)
Initial CO2	233.7	219.2	14.4	233.7	219.2	14.4
	(36.51)	(32.55)	(2.01)	(36.51)	(32.55)	(2.01)
δ_e=CER/Initial CO2	0.156	0.126	0.617	0.133	0.116	0.399
	(0.021)	(0.018)	(0.101)	(0.017)	(0.016)	(0.048)
$\Delta_e = (1-\delta_e)^{-\alpha_e}$	1.037	1.029	1.229	1.031	1.027	1.116
	(0.006)	(0.005)	(0.113)	(0.004)	(0.004)	(0.020)
Observation	319	233	86	319	233	86

Notes: Authors' calculation using data from UNFCCC and CESD. This table shows estimation for Δ_e. The sample includes all CDM registered and proposed firms that matched to CESD and has emissions record before the proposed CDM start year. Column (1) and (4) show results for all project types, column (2) and (5) for project type of waste gas and heat utilization, and column (3) and (6) for all other project types except waste gas and heat utilization. Since a few CDM firms may report larger CERs than their initial CO_2 emissions, we winsor these CER values to their initial $CO2_2$ emissions in column (4)- (6). Standard errors are calculated with 500 times bootstrap.

D.4 Board's signal and registration threshold and firm growth

The final part of the estimation, which is the most novel to our model, is to recover the parameters $\theta_e = \{\mu_{\Delta_Z}, \sigma_{\Delta_Z}, \rho, \overline{\varepsilon}^s\}$ by matching moments for firm registration and emissions growth rates. This part describes how we derive these moments within the model and match them to their empirical counterparts.

Distributional assumptions.—For estimation we assume that all of ε, ε_s and Δ_z are log-normally distributed. We specify ε and ε_s as jointly log-normal, with

$$\log\left(\begin{bmatrix}\varepsilon\\ \varepsilon^s\end{bmatrix}\right) \sim \mathcal{N}\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_\varepsilon^2 & \rho\sigma_\varepsilon\\ \rho\sigma_\varepsilon & 1\end{bmatrix}\right). \tag{52}$$

We normalize the variance of the Board's signal to one. This normalization is without loss because the Board's registration threshold $\overline{\varepsilon}_s$ is a free parameter. 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 about ε. We additionally assume that firm growth $\log\Delta_z \sim \mathcal{N}(0, \sigma_z^2)$ is log-normal and independent of the investment cost shocks.

Application probability.—Firm application decisions depend on their benefits from investment. Equation (12) gives the firm's benefit of adoption as a function of its exogenous growth and endogenous investment in emissions productivity. From this equation,

$$b(\Delta_e, \Delta_z) = \frac{1}{\eta - 1}\frac{t_e}{\alpha_e}(\Delta_e^{\eta-1} - 1)(\Delta_z)^{(1-\alpha_e)(\eta-1)} e_0 \tag{53}$$

$$\log b = (1-\alpha_e)(\eta-1)\log\Delta_z + \underbrace{\log\left(\frac{1}{\eta-1}\frac{t_e}{\alpha_e}(\Delta_e^{\eta-1}-1)e_0\right)}_{\log\bar{b}}. \tag{54}$$

Therefore our distributional assumption on Δ_z implies that $\log b \sim \mathcal{N}\left(\log(\bar{b}), \sigma_b^2\right)$ for $\sigma_b^2 = [(1-\alpha_e)(\eta-1)\sigma_z]^2$.

We previously defined the fraction of applicants at each ε above by (33) and (35). Using the assumed distribution of benefits, the fraction of firms that do not apply to the CDM, conditional on ε, is

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

The probability of application conditional on ε is

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

The unconditional probability of application is

$$Pr(Apply) = \int_{\tilde{\varepsilon}} \omega_1^A(\varepsilon) + \omega^{NA}(\varepsilon)\, dF_\varepsilon \tag{55}$$

$$= \int_{\tilde{\varepsilon}} 1 - \Phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right) dF_\varepsilon. \tag{56}$$

Registration probability.—Under the distributional assumption (52), the registration probability can be written

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

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

The unconditional probability of registration, among the population of firms, is

$$Pr(Registered) = \int_{\tilde{\varepsilon}} Pr(Registered|\varepsilon)\, dF_\varepsilon, \tag{57}$$

where $\tilde{\varepsilon}$ is the threshold investment cost defined in (26). The probability of registration conditional on application is the ratio $Pr(Registered)/Pr(Apply)$.

Firm emissions growth.—Using the application and registration probabilities we can calculate expected values of firm emissions growth for all non-applicants, proposed but rejected firms and registered firms.

Non-applicant firm growth. A non-applicant firm may or may not invest in the project. If the non-applicant firm has $\varepsilon < \tilde{\varepsilon}$ it will invest if it is non-additional and has very high returns to the project. The firm then has expected growth

$$E[\log(g_e)|\text{not apply}, \varepsilon < \tilde{\varepsilon}] - \log \bar{b} = (\eta - 1)\log \Delta_e \left(1 - \Phi\left(\frac{b_2(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)\right). \tag{58}$$

If the non-applicant firm has $\varepsilon > \tilde{\varepsilon}$ it will never invest. If the firm had high investment costs and a high enough benefit to invest, it would have applied and would not be a non-applicant. Hence the non-applicant is negatively selected and has expected growth

$$E[\log(g_e)|\text{not apply}, \varepsilon > \tilde{\varepsilon}] - \log \bar{b} = E[\log b | \log b < b_1(\varepsilon)] - \log \bar{b} \tag{59}$$

$$= -\sigma_b \frac{\phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}{\Phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}. \tag{60}$$

The unconditional growth rate of non-applicant firms is therefore a weighted average

$$E[\log(g_e)|\text{not apply}] = (1 - \Phi(\tilde{\varepsilon}/\sigma_\varepsilon))\, E[\log(g_e)|\text{not apply}, \varepsilon < \tilde{\varepsilon}] + \tag{61}$$

$$\Phi(\tilde{\varepsilon}/\sigma_\varepsilon)\, \frac{\int_{\tilde{\varepsilon}} (1 - Pr(Apply|\varepsilon)) E[\log(g_e)|\text{not apply}, \varepsilon > \tilde{\varepsilon}] dF_\varepsilon}{\int_{\tilde{\varepsilon}} (1 - Pr(Apply|\varepsilon)) dF_\varepsilon}. \tag{62}$$

Proposed-only firm growth. For firms that proposed it must be the case that $\varepsilon > \tilde{\varepsilon}$. Proposed firms that are not registered are doubly-selected: positively selected on application growth rates and positively selected on investment costs, since high-cost applicants are more likely to be registered. Proposed-only firms have expected growth

$$\begin{aligned} E[\log(g_e)|\text{proposed only}, \varepsilon] - \log \bar{b} &= E[\log b | \log b > b_1(\varepsilon)] + (\eta - 1)\log \Delta_e \frac{1 - \Phi\left(\frac{b_2(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}{1 - \Phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)} \\ &= \sigma_b \frac{\phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}{1 - \Phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)} + (\eta - 1)\log \Delta_e \frac{1 - \Phi\left(\frac{b_2(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}{1 - \Phi\left(\frac{b_1(\varepsilon) - \log(\bar{b})}{\sigma_b}\right)}. \end{aligned}$$

The first term is the growth adjustment due to selection on application and the second term is growth due to investment in the project from firms that are rejected but have high enough returns to be non-additional. The unconditional growth rate among proposed-only firms is then

$$E[\log(g_e)|\text{proposed only}] - \log(\bar{b}) = \frac{\int_{\tilde{\varepsilon}} (Pr(Apply|\varepsilon) - Pr(Register|\varepsilon))\, E[\log(g_e)|\text{proposed only}, \varepsilon] dF_\varepsilon}{\int_{\tilde{\varepsilon}} (Pr(Apply|\varepsilon) - Pr(Register|\varepsilon))\, dF_\varepsilon}.$$

Registered firm growth. All registered firms invest, because a firm would not bother to apply if it did not plan to invest if it succeeded in being registered. The expected growth of registered firms is therefore

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

The first term is the growth adjustment due to selection on application and the second term is endogenous growth due to universal investment in the project under the CDM.

The unconditional growth rate among registered firms is then

$$E[\log(g_e)|\text{registered}] - \log \bar{b} = \frac{\int_{\tilde{\varepsilon}} Pr(\text{Apply}|\varepsilon) Pr(\text{Registered}|\varepsilon) E[\log(g_e)|\text{registered}, \varepsilon]\, dF_\varepsilon}{\int_{\tilde{\varepsilon}} Pr(\text{Apply}|\varepsilon) Pr(\text{Registered}|\varepsilon)\, dF_\varepsilon}.$$

Estimation moments.—With the firm growth rates above we can form moments in the model to match to the data. We now augment our notation to acknowledge that the model moments are all conditioned on a parameter vector θ_e. Let the model moment functions for $J = 4$ moments be given by:

$$h(\theta_e) = \begin{bmatrix} h_1(\theta_e) \\ h_2(\theta_e) \\ h_3(\theta_e) \\ h_4(\theta_e) \end{bmatrix} = \begin{bmatrix} Pr(\text{Registered}|\theta_e)/Pr(\text{Apply}|\theta_e) \\ E[\log(g_e)|\text{not apply}, \theta_e] \\ E[\log(g_e)|\text{proposed only}, \theta_e] \\ E[\log(g_e)|\text{registered}, \theta_e] \end{bmatrix}$$

We estimate growth rates in the data using a staggered difference-in-difference estimator (Gardner et al., 2023). The first stage of this estimator residualizes log emissions on firm and industry × year fixed effects using only non-treated observations. The second stage of this estimator regresses residualized log emissions on interactions for treatment status and post-CDM start indicators:

$$\begin{aligned} \log e_{ijt} &= \beta_1 Post_{ijt} + \beta_2 Post_{ijt} \times Proposed_i + \beta_3 Post_{ijt} \times Registered_i + \nu_{ijt} \\ &= [Post_{ijt}\ \ Post_{ijt} \times Proposed_i\ \ Post_{ijt} \times Registered_i]\beta + \nu_{ijt} \\ &= X_{ijt}\beta + \nu_{ijt}. \end{aligned}$$

The first-order conditions for this OLS regression can be used to form moments.

$$\begin{aligned} g_{5it}(\beta) &= Post_{ijt}\left(\log e_{ijt} - \beta_1 Post_{ijt} - \beta_2 Post_{ijt} Proposed_i - \beta_3 Post_{ijt} Registered_i\right) \\ g_{6it}(\beta) &= Post_{ijt} Proposed_i \left(\log e_{ijt} - \beta_1 Post_{ijt} - \beta_2 Post_{ijt} Proposed_i - \beta_3 Post_{ijt} Registered_i\right) \\ g_{7it}(\beta) &= Post_{ijt} Registered_i \left(\log e_{ijt} - \beta_1 Post_{ijt} - \beta_2 Post_{ijt} Proposed_i - \beta_3 Post_{ijt} Registered_i\right). \end{aligned}$$

Finally, we form a moment to capture the registration rate conditional on proposal

$$g_{8it}(\beta) = StartYear_{ijt} Proposed_i \left(Registered_i - \beta_4 Proposed_i\right),$$

where $StartYear_{ijt}$ is a dummy variable equal to one in the year firm i proposed to start a project, in order to create a cross-sectional moment within the firm-year panel data set.

Stacking the moments from both the model-generated difference-in-differences and the regression first-order conditions yields the vector of moment functions

$$g_{it}(\theta_e, \beta) = \begin{bmatrix} \beta_4 - h_1(\theta_e) \\ \beta_1 - h_2(\theta_e) \\ \beta_2 - h_3(\theta_e) \\ \beta_3 - h_4(\theta_e) \\ g_{5it}(\beta) \\ g_{6it}(\beta) \\ g_{7it}(\beta) \\ g_{8it}(\beta) \end{bmatrix}.$$

We form sample averages of the moments as $\hat{g}(\theta_e, \beta) = \sum_{it} g_{it}(\theta_e, \beta)/N$ and then solve for the GMM estimator

$$\hat{\theta}_e, \hat{\beta} = \arg\min_{\theta_e, \beta} \hat{g}(\theta_e, \beta)' \hat{g}(\theta_e, \beta).$$

We omit a weighting matrix as the parameters are just-identified. This joint estimation both illustrates the connection of the difference-in-difference estimates of Table 3 to the model and allows for inference on model parameters accounting for the uncertainty in estimates of $\hat{\beta}$.