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Co-benefits and additionality of the clean development mechanism: An empirical analysis

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ABSTRACT

The Clean Development Mechanism (CDM) allows industrialized countries to comply with the Kyoto Protocol by using carbon offsets from developing countries. There are two puzzles within this carbon market: additionality (the proposed activity would not have occurred in its absence) and co-benefits (the project has other environmental benefits besides climate mitigation). This paper proposes an econometric approach to evaluate the CDM effect on sulfur dioxide emission reductions and assess its additionality indirectly. Our empirical model is applied to China's emissions at the prefecture level. We found that the CDM does not have a statistically significant effect in lowering sulfur dioxide emissions. This result casts doubt on additionality of these CDM activities, that is, they would have happened anyway.

1. Introduction

The Clean Development Mechanism (CDM) is a project-based carbon market which enables industrialized countries to reduce costs of compliance with the Kyoto Protocol by implementing climate mitigation projects in developing countries. The CDM has been successful in mobilizing the investment of public and private sectors from both developed and developing countries for reducing greenhouse gas (GHG) emissions. By the year 2009, there were more than 4200 projects in the pipeline that are expected to reduce GHG emissions by more than 2900 million metric tons of carbon dioxide equivalent (CO_2e) by the end of 2012. The CDM emission reduction is not trivial, in that it is around 40% of the U.S. emissions in 2007.[1]

The CDM is nonetheless facing mounting criticism, in which the most serious challenge is its environmental integrity [1–3]. Since there are no emission caps for developing countries, the usefulness of the CDM hinges on whether the proposed project would have occurred in its absence. This assessment is known in the literature as additionality. Lack of rigorous criteria to establish additionality, however, may result in some projects receiving an excess of carbon credits. Even worse, some "business-as-usual" (BAU) activities might be wrongly registered as CDM projects. In this case, the credit buyers' increased emissions may not be fully offset by real emission reductions in the CDM activity. This may jeopardize on the effectiveness of the international emission trading system [4].

Another criticism is that the CDM insufficiently promotes sustainable development, although it is stipulated as one of its dual goals in the Kyoto Protocol [5,6]. The CDM is expected to improve environmental quality in host countries because

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[1] Source: The CDM project statistics are from http://cdm.unfccc.int/index.html. The U.S. emissions data are from "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2007" available at http://www.epa.gov/climatechange/emissions/usinventoryreport.html.

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GHG emission reductions may also lower emissions of other pollutants such as sulfur dioxide (SO_2). The so-called co-benefit is one of the major reasons for developing countries to be involved in climate mitigation. However, while there is a price for CO_2, the local pollutants may not be monetized. Since the carbon market is only responsive to price signals, CDM developers have limited interest in generating other benefits besides carbon credits.

Additionality and co-benefits are two puzzles within this carbon market. Little is known empirically about whether the CDM has achieved these two goals. A major barrier for empirical studies is that the GHG emission data is not reported at the subnational level in developing countries. We address this problem by exploiting the connections between GHG and its co-pollutant emission reductions. To our knowledge this is the first paper that simultaneously evaluates additionality and co-benefits. Furthermore, the proposed econometric framework is not just applicable to the CDM. It has the potential to contribute to emerging policy debates about other baseline-and-credit programs such as voluntary carbon markets and energy efficiency credits.

As for the co-benefits of the CDM, we focus on sulfur dioxide (SO_2) emission reductions because of its broad environmental and health impacts.[2] Emissions of sulfur dioxide and GHGs are closely correlated with fossil-fuel use [8]. A separate analysis of either pollutant may not be able to provide a sufficient analytical framework [9]. More importantly, since GHG data are not widely available, SO_2 abatement may be useful for inferring GHG emission reductions. The rationale is that if fossil-fuel power generation is replaced by renewable energy, both CO_2 and SO_2 emissions will be reduced. If there is no observed change in SO_2 emissions, the efficacy of the CDM to reduce CO_2 would be called into question. Note that our additionality test is conditional on non-zero co-benefits. Therefore, we are not able to assess additionality for those projects that do not reduce sulfur emissions.

The econometric framework is an extension of the literature that investigates the determinants of SO_2 emissions [10–15]. Our model is adapted from, without relying on, the environmental Kuznets curve (EKC). Realizing that the classical polynomial EKC model may be too restrictive [16], we apply a fixed-effect semiparametric model that does not specify the functional form between emissions and income.

Our model augments a typical specification of SO_2 emissions through the inclusion of a policy variable reflecting CDM activities (measured by carbon credits). Identification of the causal effect of a CDM project is achieved through the inclusion of fixed effects, as well as the fact that CDM activities are determined well in advance of current SO_2 emissions because CDM approval is a lengthy process. Project developers have to wait at least one year between public comments and registration. The fixed effects capture resource endowment and industrial base, both of which are critical in the selection of CDM projects. Because resource endowment and industrial base change slowly, they can be regarded as fixed over the sample period. Therefore, conditional on the observables and the fixed effects, the selection of CDM activities is independent of sulfur emissions.

In this paper, we estimate the effect of the CDM in reducing SO_2 emissions at China's prefecture level. China is the world's largest GHG and SO_2 emitter. It is also the dominant player on the CDM market. The prefecture is the most disaggregated administrative unit that documents SO_2 emissions consistently, and this unit of analysis provides sufficient cross-sectional and temporal variation. Our econometric model shows no empirical support that the CDM has led to lower SO_2 emissions. This finding casts doubt on additionality—specifically, that these project activities would have happened without the CDM.

2. Background and data

We first briefly discuss some key issues in the Clean Development Mechanism, including the baseline and co-benefits. We then discuss the CDM activities in China. Finally, we present the data set used in our study.

2.1. Key issues in the CDM

The Clean Development Mechanism is the only "flexible mechanism" under the Kyoto Protocol that engages developing countries in climate mitigation.[3] Because the marginal abatement costs in developing countries are lower than those of developed ones, the CDM helps the latter to reduce their costs of compliance with emission reduction commitments. Reciprocally, the host countries can benefit from financial assistance, technology transfer, and non-GHG emission reductions.

The CDM employs a baseline-and-credit program. It is distinguished from the cap-and-trade system by the fact that there are no explicit caps for carbon credit suppliers.[4] Theoretically, these two systems are numerically equivalent if the baseline implies the same level of caps. Since the baseline describes a hypothetical emission scenario that would have occurred without the project, how to construct a baseline becomes the central problem of the CDM. Project developers

[2] It is worth noting that reducing SO_2 emissions may have an unintended consequence on global warming. Its product sulfate aerosol, a major component of atmospheric brown clouds (ABCs), has a climate cooling effect by reflecting visible solar radiation [7].

[3] The other two are emission trading (ET) and joint implementation (JI) among annex I countries. The ET is an allowance-based carbon market while the CDM and the JI are project based.

[4] According to the principle of "common but differentiated responsibility", annex I countries (industrialized countries and economies in transition) are subject to quantified emission limitation and reduction commitment while developing countries have no emission caps.

have incentives to overstate BAU emissions to maximize credits. Even worse, some projects that would have occurred otherwise might enter the CDM pipeline and hence additionality requirements are violated.

In order to avoid awarding carbon credits to projects that would have happened anyway, the CDM Executive Board (EB) has set rules to determine additionality.[5] This overarching additionality framework consists of four steps: (1) identification of alternatives to the project activity, (2) investment analysis to demonstrate the proposed activity is not the most economically or financially attractive, (3) barrier analysis, and (4) common practice analysis. Although official criteria have been designed for assessment purposes, their implementation is highly subjective and often lacks documented evidence to substantiate additionality [17]. Overall, the methodology does not achieve its intended objective of establishing a valid counterfactual.

The CDM is supposed to achieve dual goals: lowering abatement costs and promoting sustainable development. As for the first objective, the certified emission reductions (CERs), being equal to one metric ton of CO_2e, consistently sell at a discount to the European Union Allowances (EUAs).[6] However, when it comes to the sustainability goal, some argue that its role is largely marginalized [5]. The carbon market cannot optimally allocate resources for non-monetized sustainability. The low-cost emission reduction projects are not necessarily aligned with the sustainability priority in the host countries. Examples include industrial gas projects such as hydrochlorofluorocarbons (HFCs) and nitrous oxide (N_2O). These projects can generate large volumes of CERs at low costs, but they have very little sustainability benefit other than climate change.

The controversial industrial gas projects are gradually being phased out due to the saturation of project opportunities and stringent regulations. Renewable energy and energy efficiency have become the mainstream project types. These projects have strong co-benefits beyond climate mitigation. Fig. 1 shows a breakdown of CDM projects by types. For example, renewable power replacing fossil-fuel power plants will reduce not only GHGs, but also other air pollutants such as sulfur dioxide, nitrogen oxide, and particulates. As long as the CDM activities of these types are additional, we should be able to observe associated co-benefits.

2.2. The CDM in China

China is the biggest supplier on the primary CDM market. It accounts for 35% of registered projects and 59% of expected annual reductions as of 2009. The concentration of the market is mainly due to abundant opportunities for emission reductions. China has risen to become the world's largest GHG emitter since 2007 and the momentum will likely be maintained in the future.[7] According to Auffhammer and Carson [18], the projected increase in China's emissions out to 2010 is several times larger than the amount reduced in Kyoto Protocol. In addition to total emissions and the size of industrial base, factors that attract foreign direct investment (FDI) also increase the flow of international carbon credit investment. In this regard, economies of scale and the business environment all contribute to China's market share [19].

China's preference for the CDM is aligned with its national strategy in energy and climate change [20]. According to China's National Climate Change Program, energy efficiency and renewable energy supplies are top priorities in climate mitigation [21]. Specifically, industrial and residential energy efficiency, hydro power, coal-bed/mine methane, bio-energy, wind, solar, and geothermal energy are all actively supported. These project types account for the majority of the CDM activities.

Environmental pollution is another incentive for China to be engaged in the CDM. Coal is the dominant fuel source in China's primary energy consumption. According to China's Statistical Yearbooks, its share has varied between 66% and 76% over the last two decades. Emissions of SO_2, NO_x, and particulates from coal consumption have created severe environmental and health problems. It is estimated that SO_2 caused over 213 billion Chinese Yuan (CNY) in health damage in 2003 [22].[8] Another study finds that acid rain, which is mainly caused by SO_2 emissions from fossil fuel use, causes 30 billion CNY in crop damage and 7 billion CNY in building damage [23]. The expectation that the CDM helps reduce local and regional air pollutants besides GHGs makes participation even more attractive for China.

2.3. The data

In this paper, the unit of analysis is a prefecture. A prefecture, literally translated as a region-level city, is an administrative unit ranking immediately below a province and above a county. It typically includes both urban and rural areas. A prefecture is the most disaggregated level that consistently documents economic and environmental data and information. The economic data are from China's City Statistical Yearbooks (2000–2008). China has 333 prefectures, of which 287 are covered by the Yearbooks. The prefectures that are not included are those with low economic significance. On average a prefecture had a population of 4.27 million, an area of 16,448 square kilometers, and a GDP of 112.5 billion Chinese Yuan (CNY) in 2008. Table 1 reports summary statistics for the variables used in our analysis.

[5] Source: "Tool for the demonstration and assessment of additionality" by the CDM-EB, available at http://terrapass.pbworks.com/f/Additionality_tool.pdf.

[6] The prices of CERs and EUAs are available at the European Climate Exchange http://www.ecx.eu/. The discount on the primary CDM market is greater than the secondary market. The primary market discount reflects the risks of CER issuance. The secondary market discounts may reflect that CERs are not completely fungible to EUAs.

[7] Source: "CO_2 Emissions from Fuel Combustion 2009 Highlights" by the International Energy Agency. Available at http://www.iea.org/publications/free_new_Desc.asp?PUBS_ID=2143.

[8] 1 U.S. Dollar $\approx$6.8 Chinese Yuan in 2009.

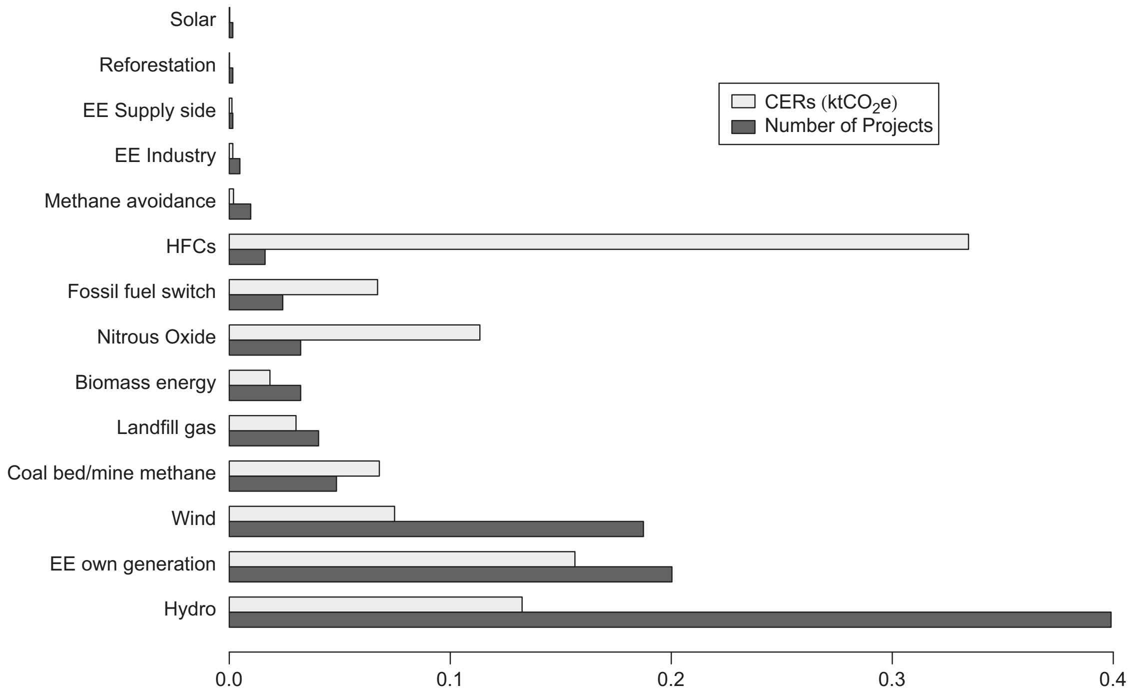

Fig. 1. Shares of CDM projects by types.

Table 1
Summary statistics.

Variable	Definitions	N	Mean	Std dev	Min	Max
SO2P	SO_2 emitted by power plants (10^5 ton)	831	0.42	0.63	0.00	4.63
SO2T	SO_2 generated by all industries (10^5 ton)	1711	1.12	1.46	0.00	13.09
SO2E	SO_2 emitted by all industries (10^5 ton)	1711	0.66	0.72	0.00	7.91
GDPPC	GDP per capita (10^5 CNY)	2239	0.17	0.22	0.02	3.42
POPDEN	Population density (10^{-1}/km^2)	2243	0.42	0.40	0.00	11.56
EE	Industrial output/electricity use (100 CNY/kWh)	2223	0.20	0.48	0.01	21.09
KL	Fixed asset investment/number of employees (10^5 CNY)	2243	0.74	0.62	0.00	7.19
ESPC	Expenditure on education and R&D per capita (10^3 CNY)	2239	0.24	0.29	0.00	4.96
FDIR	FDI as a ratio of fixed asset investment (10^{-2})	2161	0.90	1.53	0.00	32.74
CCO2	Prefecture-level CERs (10^6 ton)	2296	0.55	2.49	0.00	41.64
PCO2	Province-level CERs (10^6 ton)	2296	0.63	1.39	0.00	8.07
GCO2	Grid-level CERs (10^6 ton)	2296	0.23	0.49	0.00	2.83
HYDRO	Hydropower CERs (10^5 ton)	2296	0.09	0.62	0.00	9.07
WIND	Wind energy CERs (10^5 ton)	2296	0.08	0.67	0.00	16.66
ENERGY	Energy efficiency CERs (10^5 ton)	2296	0.20	1.66	0.00	34.95
OTHER	Other CERs (10^5 ton)	2296	0.11	1.19	0.00	41.24

Notes: All monetary values are real values.

We have two sources of data for SO_2 emissions. First, information on SO_2 emissions from power plants is provided by the Institute of Air Pollution Control at the Tsinghua University. The emission data are generated from their internal database of national power plant inventory; this detailed data set has not been used in the economics literature studying SO_2 emissions in China. Although the data are only available in 2000, 2005, and 2007, it covers a period before and after CDM activities, which enables us to identify the CDM effect in a difference-in-difference framework.

Second, the Yearbooks have documented SO_2 emissions from all industries during 2003–2008. Although SO_2 emissions before 2003 were also reported, their measurement was inconsistent with those after 2003 so they are not used. The power and heating industry accounts for about 60% of total emissions. Two industrial SO_2 variables are used in the analysis: the amount of SO_2 generated and the amount of SO_2 released into the atmosphere. The two variables are related by the following equation:

$$SO_2 \text{ emitted} = SO_2 \text{ generated} - SO_2 \text{ removed}.$$

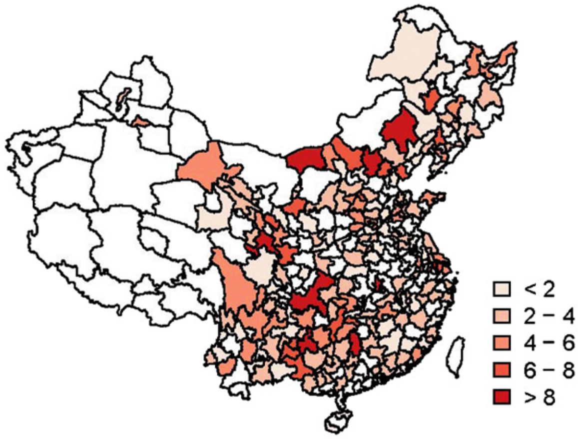

Fig. 2. CDM activities in China by the number of projects.

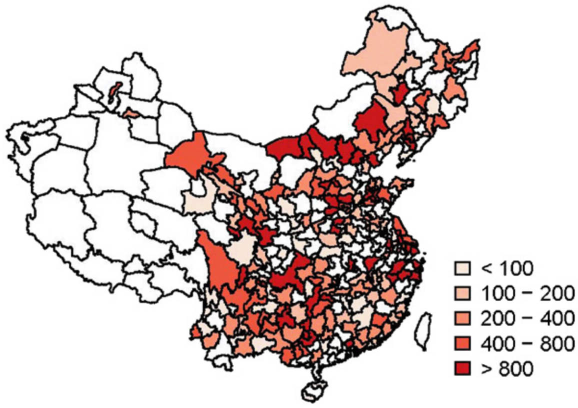

Fig. 3. CDM activities in China by CERs (10^3 ton).

We analyze industrial emissions because the CDM also affects non-power SO_2 emissions, which is the so-called "leakage effect." Although a CDM project can reduce emissions within the boundary (power sector), it may cause additional emissions elsewhere. For example, the construction and operation of CDM projects may boost local economic activities and increase emissions out of the boundary.

The CDM data are from the United Nations Framework Conference on Climate Change (UNFCCC), which maintains a database that includes project design documents (PDDs) for every registered project. Only the projects in China that were registered before 2008 are used because of the constraint posed by the economic and emission data. The United Nations Environmental Program (UNEP) Risoe Center provides a compiled list of all CDM projects.[9] The first CDM project in China was a wind farm in the Liaoning Province which started in 2003. The credit start date is used to match the economic data because this is the time when the project starts emission reductions. As of 2008, 191 prefectures in all provinces except Tibet had CDM activities. The locational distributions of the CDM projects are depicted in Figs. 2 and 3.

3. Empirical strategy

The emission reduction of a CDM project is measured by the difference between the baseline emissions and the project's real emissions. A baseline is a scenario that represents GHG emissions in the absence of the CDM. Let t index time and k index pollutant. Let y denote the project emission, y^* denote the baseline emission, and r denote the emission reduction. A project's emission reduction is

$$r_{kt} = y^*_{kt} - y_{kt}. \tag{1}$$

Note that the emission reduction is positive only if its emission level is below the baseline. While it is straightforward to monitor a project's real emissions, it is tricky to determine what the emissions would otherwise be. Different baselines

[9] Source: http://www.cdmpipeline.org/.

may imply significantly different amounts of emission reductions. In this section, we present two approaches that can be used to construct emission baselines.

3.1. Engineering model

Most CDM activities replace fossil-fuel power generations by delivering electricity generated from renewable energy sources. Hence the emissions reduction attributed to a CDM project is the avoided emissions of the displaced power plants/units. Instead of identifying the exact source of displaced generations, a grid-level emission baseline can be used to quantify the emission reduction

$$r_{kt} = e_t f_{kt}^{\text{grid}} - l_{kt}. \tag{2}$$

In this form, e is the net electricity supply by the CDM project (MWh), f^{grid} is a grid-level emission factor (ton/MWh), and l is the leakage. The leakage is the increased emissions attributable to CDM activities that occur outside the project boundary. For renewable energy projects, there are no emissions and leakage is often treated as zero.

One method to calculate the emission factor is the operating margin (OM). The OM assumes that it is the electricity from marginal power plants that is displaced. A marginal plant is defined as the power plant on the top of the grid system dispatch order without CDM activities. It is apparent that the OM measures the short-run effect of CDM activities. The CDM Executive Board suggests the operating margin emission factor can be calculated by generation-weighted emissions from all grid-tied power plants excluding low-cost and base-load plants/units.[10]

Another method is to use the build margin (BM) emission factor. It assumes that CDM activities delay or cancel the construction of new power plants/units. The BM can be calculated in the same ways as the OM, except that a different sample of power plants is used. In general, the newly built plants are equipped with better technology and thus emit fewer pollutants than existing plants. This implies that the build margin is normally smaller than the operating margin.

In this section, we outline an engineering model that can be used to compute emission factors. This model is based on the simple OM method since it is widely used in CDM project designs. The grid-level emission factor is calculated by

$$f_{kt}^{\text{grid}} = \frac{\sum_{\text{plant}} e_t^{\text{plant}} f_{kt}^{\text{plant}}}{\sum_{\text{plant}} e_t^{\text{plant}}}, \tag{3}$$

where f^{plant} is a plant-level emission factor. It is worth noting that not all power plants/units in the grid are included in the calculation. The project developers, following guidelines in host countries, propose how to select the sample. The proposed baseline needs to be validated by independent audits.

If multiple fuels are involved, the plant-level emission factor is then

$$f_{kt}^{\text{plant}} = \frac{\sum_{\text{fuel}} c_t^{\text{fuel}} v_t^{\text{fuel}} f_{kt}^{\text{fuel}} (1-\lambda_{kt})}{e_t^{\text{plant}}}. \tag{4}$$

In this form, c is the amount of fuel consumed (mass or volume unit), v is the energy content (GJ/mass or volume unit), and λ is the fraction of pollutants removed. Carbon capture and storage (CCS) can remove CO_2 but it is not yet commercialized, so that $\lambda_{CO_2} = 0$. As for SO_2 emissions, all new and existing coal-fired power plants in China are required to install flue gas desulfurization (FGD) equipment. The average removal rate in 2008 is around 78.7%.[11]

In calculating emission factors, either the *ex ante* or *ex post* approach is allowed. All CDM projects in China employ *ex ante* information to establish the baseline because it reduces the risks of carbon credit generation. The most recent available information of already built power plants/units is included in the sample group (three years before the submission of PDDs). In addition, the emission factor is generally fixed or adjusted according to a predetermined rate during the project crediting period.

According to Eqs. (2)–(4), it is apparent that there is a connection between CO_2 and SO_2 emission reductions. To simplify this illustration, suppose that a renewable energy project with zero leakage delivers electricity to a grid. The grid's baseline emissions can be characterized by average emission factors f_{SO_2} and f_{CO_2}, as well as average the SO_2 removal rate λ_{SO_2}. The ratio of emission reductions for these two pollutants is then

$$\frac{r_{SO_2}}{r_{CO_2}} = \frac{f_{SO_2}(1-\lambda_{SO_2})}{f_{CO_2}}. \tag{5}$$

In this form, if all parameters are known, we can use CO_2 emission reductions to estimate the abatement of SO_2 emissions.

Note that Eq. (5) is greatly simplified. When the engineering approach is used to estimate SO_2 emission reductions, the emission factors take into account multiple plants and multiple fuels. The emission factors of China's power industry are adapted from Cao and Wang [24] and are reported in Table 2. In this table, the combined margin (CM) is just a simple average of the operating margin and the build margin.

[10] Source: "Tool to calculate the emission factor for an electricity system (October 2009)". Available at http://cdm.unfccc.int/methodologies/PAmethodologiesapproved.html.

[11] Source: "Emission Reductions of Power Plants in 2008" by the State Electricity Regulatory Commission. Available at www.serc.gov.cn/ywdd/200911/W020091102328545684394.doc.

Table 2
Emission factors for China's power industry.

Grid	CO_2			SO_2		
	OM	BM	CM	OM	BM	CM
North	1.007	0.780	0.894	0.009	0.002	0.006
Northeast	1.129	0.724	0.927	0.007	0.002	0.004
East	0.882	0.683	0.783	0.007	0.002	0.005
Central	1.126	0.580	0.853	0.013	0.002	0.008
Northwest	1.025	0.643	0.834	0.010	0.002	0.006
South	0.999	0.577	0.788	0.009	0.002	0.005
Hainan	0.815	0.730	0.773	0.007	0.002	0.005

Notes: Unit: ton/MWh. The CO_2 emission factors are from "Emission Factors of China's Regional Electricity Grid 2009" published by China's National Development and Reform Commission. Available at http://qhs.ndrc.gov.cn/qjfzjz/t20090703_289357.htm. The SO_2 emission factors are from Cao and Wang [24].

3.2. Econometric identification

The engineering approach can be used to quantify co-benefits if CO_2 emission reductions are real (or additional). However, if we only observe carbon credits instead of real emission reductions, this approach is correct only if the carbon credits are issued based on an appropriate baseline. An exaggerated baseline results in overallocated carbon credits and exaggerated co-benefits. To estimate co-benefits without assuming that carbon credits reflect real emission reductions, we propose an econometric approach in this section.

An alternative treatment of Eq. (5) is to regard the emission ratio as a parameter. If CO_2 and SO_2 emission reductions are known, this parameter can be estimated by regression analysis. Let $\sigma \equiv f_{SO_2}(1-\lambda_{SO_2})/f_{CO_2}$, then Eq. (5) is rewritten as

$$r_{SO_2} = \sigma r_{CO_2}. \tag{6}$$

However, this model is not estimable because emission reductions in CO_2 and SO_2 are not directly observable.

Suppose that a CDM project receives a credit of c_{CO_2}, while the real emission reduction is $r_{CO_2} = \rho c_{CO_2}$, where ρ is an unknown parameter. If the project is awarded more than what it actually reduces, then $\rho < 1$. If $\rho = 1$, then the carbon credit issuance is fair. If $\rho > 1$, it means that the emission baseline is too conservative. According to Eq. (6), the reduction in SO_2 emissions is $\sigma\rho c_{CO_2}$. The relationship between SO_2 emission reductions and carbon credits is

$$r_{SO_2} = \sigma\rho c_{CO_2}. \tag{7}$$

In this form, the empirical challenge is that the SO_2 emission reductions attributed to the CDM activities are not directly observable. According to Eq. (1), SO_2 emission reductions are estimated by the difference between baseline and real emissions. Combining Eqs. (1) and (7) and denoting $\gamma \equiv -\sigma\rho$, we obtain

$$y_{SO_2} = y^*_{SO_2} + \gamma c_{CO_2}. \tag{8}$$

Eq. (8) can be used to evaluate the effectiveness of the CDM on SO_2 emission reductions. It also provides an indirect test for additionality. Based on the engineering model, σ can be estimated and used as the prior information. If $-\gamma < \sigma$ or equivalently $\rho < 1$, it suggests that there is an over-issuance of the carbon credits. Even worse, if $\gamma = 0$, it implies that the CDM activities may not be additional at all. Note that our argument is based on the assertion that $\sigma \neq 0$. Since we have excluded all industrial gas projects that have zero co-benefits, the assumption is true for all other projects. The argument is supported by the environmental engineering studies, for example Aunan et al. [8].

Let i index prefecture ($i = 1 \ldots n$) and t index year ($t = 1 \ldots T$). The baseline emission $y^*_{SO_2}$ is modeled as

$$E(y^*_{it}|w_{it}, x_{it}, u_i, v_t) = m(w_{it}) + x'_{it}\beta + u_i + v_t.$$

The pollutant subscripts are ignored to reduce notational clutter. According to Eq. (8), the CDM effect is additive and proportional to the project scale, which implies that

$$E(y_{it}|w_{it}, x_{it}, c_{it}, u_i, v_t) = m(w_{it}) + x'_{it}\beta + \gamma c_{it} + u_i + v_t. \tag{9}$$

In this form, w_{it} is income measured by real GDP per capita (GDPPC), $m(\ )$ is a flexible function that we define below, and x_{it} includes prefecture- and time-variant control variables other than income. The prefecture fixed effects u_i controls for time invariant unobservables such as resource endowment, industrial base, and institutional capacity. The time effect v_t controls for unobserved trends such as national emission regulations and technological progress as well as year-specific shocks to emissions.

The causality of the regression follows that if the CDM decreases fossil fuel consumption, SO_2 emissions will also be reduced since sulfur emissions result from energy use. A CDM project is determined before the current SO_2 emissions because its approval is a lengthy process. Project developers have to wait at least one year from public comments to registration. In addition, the selection of the CDM projects hinges on resource endowment and industrial base. Hydro, wind, solar, coal-bed methane, and biomass projects depend on the abundance of their respective natural resources. The remaining energy efficiency projects depend on the industrial base and the energy intensity of the economy. Because resource endowment and the industrial base change slowly, they can be regarded as the fixed effects. Energy intensity can also be controlled for. Therefore, conditional on the observables and the fixed effects, the selection of CDM activities is independent of sulfur emissions.

The included explanatory variables are widely used in the empirical studies that investigate the determinants of SO_2 emissions (see [13] for a review). The causal relationship of income and pollution is a concern [15]. The argument that income causes emissions is fully discussed in Antweiler et al. [11]; changes in real income have contemporaneous effect on pollution, but environmental policies that determine pollution level respond to income levels slowly. To further address this issue, we use lagged income to replace current income in the robustness checks as is suggested by the growth literature.

In the set of control variables x_{it}, population density (POPDEN) is a measure of land area per capita. This demographic is a determinant of pollution but it responds to pollution slowly because migration takes time to realize. In addition, residential migration is constrained by the family register system (*hukou*) in China. Energy efficiency (EE) is a measure of real industrial output per kilowatt of electricity use. Pollution is a consequence of energy use and so it hinges on the energy intensity. The capital-to-labor ratio (KL) is defined as a ratio of fixed asset investment to number of employees. The inclusion of KL controls for the factor endowment effect. Both EE and KL enter the model with a quadratic term to account for nonlinearity. Expenditure on education and R&D per capita (ESPC) controls for the knowledge and technology effect. The empirical decomposition of pollution into scale, composition, and technique effects is attributed to Antweiler et al. [11].

We also include FDIR, which a ratio of foreign direct investment (FDI) as a share of fixed asset investment. The endogeneity of this trade variable might be a concern. According to Frankel and Rose [14], geographical variables can be used as instruments for endogenous trade based on trade theory. However, this approach is not applicable to panel data, because these instruments are time invariant. In any case this particular instrumental variable approach is not superior to a panel method that uses individual fixed effects to control for geographical attributes. In addition to the prefecture effects, we use subnational time dummies to control for time-variant unobservables that may be correlated with both FDI and emissions.[12]

3.3. *Specification and estimation*

The classical environmental Kuznets curve (EKC) model posits an inverted-U relationship between income and pollution [10]. It claims that emissions increase with income at an early development period and then decrease after passing some income thresholds. Although the EKC model has many limitations [12,13,15], it provides a basic structure to predict pollution at the aggregate level. Although our approach does not rely on the EKC framework, it motivates us to specify a nonlinear income–emission relationship.

A prefecture is the unit of analysis in this paper, but the CDM activity does not necessarily replace carbon-intensive generators in the same prefecture. It may replace generators in the same province or even in the same grid. It is therefore important to incorporate the spillover effect in a spatially explicit model. Following the approach proposed by Duflo and Pande [25], we incorporate the effects of the CDM activities in adjacent areas.

With the above two assumptions, our parametric regression is specified as

$$y_{it} = \alpha_1 w_{it} + \alpha_2 w_{it}^2 + \alpha_3 w_{it}^3 + x_{it}'\beta + \gamma_1 c_{it}^c + \gamma_2 c_{it}^p + \gamma_3 c_{it}^g + u_i + v_t + \varepsilon_{it}. \tag{10}$$

In this form, c_{it}^c designates prefecture-level carbon credits generated from the CDM activities. c_{it}^p designates carbon credits in the same province excluding c_{it}^c. c_{it}^g designates carbon credits in the same grid excluding c_{it}^p, and α, β, and γ are parameters to be estimated. ε_{it} is an error term which captures deviations between actual and estimated baselines emissions. Under the assumption of strict exogeneity, its mean is zero conditional on the observables and the fixed effects.[13]

Although a cubic term is included to accommodate more curvatures in Eq. (10), the polynomial specification is still very restrictive. Millimet et al. [16] suggest that a semiparametric model is more appropriate because the parametric model is rejected by their specification test. We generalize their model to accommodate CDM activities and other variables. Specifically, we propose a semiparametric partially linear model, in which the conditional mean of SO_2 emissions has an unknown relationship in income and is linear in other variables. The semiparametric model is then

$$y_{it} = m(w_{it}) + x_{it}'\beta + \gamma_1 c_{it}^c + \gamma_2 c_{it}^p + \gamma_3 c_{it}^g + u_i + v_t + \varepsilon_{it}, \tag{11}$$

where $m(w_{it})$ is a smooth function that is unknown to the researcher. For simplification, the above model can be written as

$$y_{it} = m(w_{it}) + z_{it}'\pi + u_i + \varepsilon_{it}, \tag{12}$$

where z_{it} includes all time-variant explanatory variables other than income w_{it}. The time effects are lumped into z_{it} as dummy variables. To estimate the above model, we can use the first difference or de-meaning to cancel out fixed effects.

[12] To further address the concern of endogenous FID, we have estimated all models without FDI. These additional robustness checks do not change our results.

[13] Our identification strategy rests on the timing of the CDM application process in light of the strict exogeneity requirement. If CDM is related to past unobserved determinants of baseline emissions, the results will be biased.

A first difference of Eq. (12) leads to

$$\Delta y_{it} = \Delta m(w_{it}) + \Delta z'_{it}\pi + \Delta\varepsilon_{it}. \tag{13}$$

The profile-kernel method proposed by Henderson et al. [26] is employed to estimate the differenced partially linear panel data model. This approach shows that a consistent estimator of π is given by

$$\hat{\pi} = \left(\sum_{i=1}^{n} \Delta\ddot{z}_{i\cdot}\Omega^{-1}\Delta\ddot{z}_{i\cdot}\right)^{-1}\left(\sum_{i=1}^{n} \Delta\ddot{z}_{i\cdot}{}'\Omega^{-1}\Delta\ddot{y}_{i\cdot}\right). \tag{14}$$

In this form, $\Omega = \text{cov}(\Delta\varepsilon_{it})$, $\Delta\ddot{z}_{it} = \Delta z_{it} - (\hat{m}_z(w_{it}) - \hat{m}_z(w_{it-1}))$ and $\Delta\ddot{y}_{it} = \Delta y_{it} - (\hat{m}_y(w_{it}) - \hat{m}_y(w_{it-1}))$. $m_z(w)$ (or $m_y(w)$) represents estimates from a nonparametric regression of z (or y) on w alone. This estimator in (14) is $\sqrt{n}$-consistent, and the asymptotic variance can be estimated by

$$\hat{\text{Avar}}(\hat{\pi}) = \frac{1}{n}\sum_{i=1}^{n} \Delta\ddot{z}_{i\cdot}\hat{\Omega}^{-1}\Delta\ddot{z}_{i\cdot}.$$

A consistent estimator of the variance–covariance matrix Ω is

$$\hat{\Omega} = \hat{\sigma}_v^2(I_{T-1} - e_{T-1}e'_{T-1}).$$

In this form, I is an identity matrix, e is a vector of ones, and σ_v^2 is estimated by

$$\hat{\sigma}_v^2 = \frac{1}{2n(T-1)}\sum_{i=1}^{n}\sum_{t=2}^{T}(\Delta\ddot{y}_{i\cdot} - \Delta\ddot{z}_{i\cdot}\hat{\pi})^2.$$

With a consistent estimate of π, let $\hat{y}_{it} = y_{it} - z_{it}{}'\hat{\pi}$. With this model (12) can be converted to a nonparametric fixed effect regression

$$\hat{y}_{it} = m(w_{it}) + u_i + \varepsilon_{it}. \tag{15}$$

Multiple methods are available to estimate this model including the series method and the profile-kernel method [27,28]. We utilize the nonparametric iterative kernel estimator proposed by Henderson et al. [26] because it accounts for the variance structure and semiparametric efficiency. The estimation is implemented in Matlab. The code is available upon request.

4. Results and discussion

4.1. Engineering results

First, we estimate the effect of CDM activities in reducing SO_2 emissions by means of the engineering approach. The grid-specific combined margin emission factors are used, which is a simple average of the operating margin and the build margin. The combined margin is shown in Table 2. We report the resulting grid-level emission reductions from the CDM activities in Table 3. The emission data are for 2005, which is the most recent available information. The CO_2 data are also included for comparison. The figures show that the CDM activities are expected to reduce 35.8 million tons of CO_2 annually, which is about 1.6% of total emissions from all grids in 2005. In terms of SO_2 emissions, they are expected to reduce 0.27 million tons annually, or 1.4% of 2005 emissions from all grids. According to the national data, σ is estimated to be 0.0076 ton-SO2/ton-CO2, which implies that one ton of CO_2 emission reduction will lower SO_2 emissions by 0.0076 ton at the grid level.

Table 3
Annual emission reductions by hydro and wind CDM activities.

Grid	CO_2		SO_2	
	Emissions	Reductions	Emission	Reductions
North	651.753	6.820	5.812	0.039
Northeast	207.338	3.100	1.089	0.012
East	499.415	2.002	4.037	0.011
Central	360.321	7.655	3.938	0.087
Northwest	147.440	7.131	1.365	0.067
South	310.883	9.077	2.543	0.055
Hainan	5.999	0.021	0.048	0.000
All	2183.877	35.805	18.848	0.272

Notes: Unit: million tons/year. The emissions data are for 2005. The reductions data are based on CDM projects registered before 2008. Only small hydro and wind power projects are included.

It is worth noting the engineering estimate does not have an associated standard error. The parameters that we are using, mostly from the literature and official documents, only report the mean values instead of confidence intervals. Another important point is that only small hydro power and wind power projects are included in the analysis, because they have zero emissions. These two project types account for 59% of total registered projects as of 2008. CDM activities other than industrial gas projects can also reduce SO_2 emissions. However, their own emissions need to be taken into account. If other project types are included, the estimated coefficient would be smaller than the current estimate.

The engineering approach assumes that the BAU emissions can be extrapolated from the *ex ante* information. Specifically, the baseline is calculated by using present and past emission factors of existing power plants. This approach reduces risks for project developers because the expected carbon credits are known in the future. However, uncertainties arise in the environmental integrity because the static baseline does not make adjustment for future changes. Most CDM projects use static baselines. Even if a "dynamic" baseline is used, the adjustment is linear and the slope is predetermined [29,30]. In a fast changing economy, this methodology does not perform well. For example, if renewable energy increases exponentially as is observed in some developing countries, the engineering baseline would set the BAU emissions too high and lead to an inflation of carbon credits.

4.2. Econometric results

In this section, we present the results for the econometric models that use *ex post* information to evaluate the CDM's co-benefits on sulfur emissions. We estimate the parametric model (10) and the semiparametric model (11) using the prefecture-level data in China. The CDM effect on power generation is the focus of this study, which determines if the CDM has co-benefits and additionality within the power sector. The semiparametric model is our preferred specification because of its flexibility, while the parametric model is used for comparison purpose. The estimates of central interest are the coefficients for carbon credits at the prefecture level (CCO2), province level (PCO2), and grid level (GCO2). The estimation results are reported in Table 4. A Wald test of model 1.2.1 for the joint significance of the CDM effect results in a p-value at 0.99, which rejects the null hypothesis that the CDM reduces SO_2 emissions. A joint test of the parametric model 1.1.1 leads to the same conclusion.

It is interesting to test the econometric estimate against the engineering estimate. If the CDM activities receive a fair amount of carbon credits, both estimates should be close. Since the econometric models are estimated using the prefecture-level data, the CDM effect needs to be aggregated to the grid level to be compared with that of the engineering model.[14] The test results show that we fail to reject the null hypothesis that engineering and econometric estimates are being equal. The fact that we are not able to rule out co-benefits and additionality is at odds with the previous result. This is likely because the data do not provide precise enough estimates to distinguish between two vastly different hypotheses.

Although the treatment effect is insignificant, the sign of the estimate is still interesting. If CDM activities have lowered sulfur dioxide emissions, the coefficients of carbon credits should be negative. However, the estimates for provincial and grid CERs are positive. This may be explained by the fact that fossil-fuel power plants are built to match with renewable power generation. For example, wind power is highly variable in electricity output at different time scales. Additional power plants are needed to stabilize intermittent power supply and safeguard against blackouts. The coal-fired power is often used as a backup because of its availability and reliability. It is possible that the CDM helps ramp up thermal power capacity as it promotes wind farms. In this case, the effect of the CDM activity – a combination of wind and coal-fired power – hinges on the baseline scenario. If the baseline is coal-fired power, the CDM reduces emissions unambiguously. If the baseline is renewable power, the CDM actually increases emissions. If the baseline is a wind–coal combination, the CDM has no effect at all. In all other cases, the CDM has an uncertain effect in emission reductions. Table 7 summarizes the hypothetical effect of the CDM activity under different baseline scenarios.

The econometric results suggest that the CDM activities in China are not effective at reducing SO_2 emissions, and therefore cast doubt on additionality. That is, without the compensation of carbon credits, these projects may still have occurred. There is some evidence to support this hypothesis. As of 2008, the cumulative installed capacity of wind power in China was 12,152.79 MW, of which 11,389.58 MW was installed during 2005–2008.[15] In the same period, the CDM wind farms generated a total capacity of 5154.92 MW. This suggests that about 55% of wind power projects have been built without the assistance of the CDM. During a recent CDM-EB meeting in December 2009, 10 of China's wind power CDM projects were not approved. The decision was made on the grounds that these projects do not meet the additionality requirement.

This is not to say that project developers intentionally manipulate additionality requirements. Rather, it is the current CDM baseline methodology that fails to predict future emissions in a fast changing economy. China's central planners made the same mistake as they set a 2010 wind power target of 5000 MW in the Renewable Energy Planning Report of 2007. In fact, in the same year that the Plan was published, China's total capacity reached 5906 MW. The rapid growth of

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[14] The null hypothesis $\gamma_1+\gamma_2+\gamma_3=\sigma$ is tested. The engineering estimate is the grid level reduction in SO_2 from a carbon credit unit. So, we need the econometric estimate of a grid level reduction. If a carbon credit is issued in prefecture i, then CCO2 goes up by one unit and SO_2 changes in i by γ_1. But, then SO_2 changes in each other prefecture in the same province by γ_2, and in each other prefecture in the grid, but outside the province, by γ_3.

[15] Source: "China Wind Power Installed Capacity Statistics 2008" by the China wind power Association. Available at www.cwea.org.cn/upload/20090305.pdf.

Table 4
Regression results: dependent variable-SO_2 emitted by power plants.

	Parametric models			Semiparametric models		
	1.1.1	1.1.2	1.1.3	1.2.1	1.2.2	1.2.3
GDPPC	2.995***	2.270***	1.424***			
	(0.741)	(0.760)	(0.763)			
$GDPPC^2$	−2.910***	−2.305***	−1.785***			
	(0.825)	(0.849)	(0.828)			
$GDPPC^3$	0.740***	0.593***	0.491***			
	(0.233)	(0.239)	(0.232)			
POPDEN	0.139	0.148	0.181	0.178	0.165	0.278**
	(0.125)	(0.143)	(0.136)	(0.128)	(0.121)	(0.118)
EE	0.625***	0.528***	0.350***	0.618**	0.536**	0.526**
	(0.237)	(0.233)	(0.222)	(0.265)	(0.252)	(0.258)
EE^2	−0.384**	−0.371**	−0.230**	−0.340*	−0.324*	−0.325*
	(0.167)	(0.165)	(0.157)	(0.187)	(0.179)	(0.180)
K/L	0.281**	0.164**	0.007**	0.394***	0.251*	0.642***
	(0.136)	(0.136)	(0.150)	(0.097)	(0.132)	(0.127)
$(K/L)^2$	−0.107*	−0.063*	−0.015*	−0.126***	−0.088	−0.232***
	(0.057)	(0.058)	(0.059)	(0.046)	(0.054)	(0.051)
ESPC	−0.084	−0.091	−0.064	−0.019	−0.063	0.070
	(0.111)	(0.109)	(0.113)	(0.079)	(0.082)	(0.081)
FDIR	0.001	−0.005	−0.010	0.003	−0.006	−0.007
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
CCO_2	0.007	0.014	−0.051	−0.000	0.025	−0.021
	(0.064)	(0.062)	(0.057)	(0.072)	(0.067)	(0.063)
PCO_2	0.005	0.007		0.002	−0.013	
	(0.020)	(0.027)		(0.023)	(0.030)	
GCO_2	−0.001			0.002		
	(0.009)			(0.010)		
Time effects	YES			YES		
Prefecture effects	YES	YES	YES	YES	YES	YES
Grid-time effects		YES			YES	
Province-time effects			YES			YES

Notes: Number of observations 758. The SO_2 emission data for power plants are only available for 2000, 2005, and 2007. Block bootstrapping standard errors in parenthesis. Significance level: *10%, **5% and ***1%.

wind power is partially explained by the favorable on-grid power tariff. It also reflects the fact that state-owned power companies have attempted to grab market share without cost considerations [31]. If this is true, it shows that wind power projects are still not the most economically or financially attractive. Under the current additionality criteria, wind projects should still qualify as CDM activities.

Our model sheds some insight on the environmental Kuznets curve. The estimated coefficient is highly significant for all parametric models. The result supports a nonlinear relationship between SO_2 emissions and income. However, the relationship is not an exact inverted U-shape because the coefficient for the cubic term is significantly different from zero. Instead, the pollution–income relationship is better described by an N-shape curve. The semiparametric model does not specify the functional form. The nonparametric estimate of the relationship is depicted in Fig. 4. The solid line is $\hat{m}(w)$ estimated by the iterative kernel method. Two dashed lines outline a 95% confidence interval for each point estimate.

A visual inspection of Fig. 4 shows that there are multiple maxima and minima in the environmental Kuznets curve. This implies that the parametric model is misspecified because the cubic model only has one local maximum and one local minimum. A formal specification test is needed to show that the semiparametric model performs better. This can be implemented by the bootstrapping method proposed by Henderson [26]. However, since different specifications produce the same qualitative results for the policy variables, we leave this specification test for future research.

The econometric model also yields reasonable estimates for other parameters. The coefficient for population density (POPDEN) is positive but it is not statistically significant. It may be a net effect of: (1) fossil-fuel power generation is located close to demand factors such as population centers and (2) pollution is more regulated in population centers because of public health concerns. Energy efficiency (EE) has a significant nonlinear effect on power SO_2 emissions. At first, as the industrial output per kilowatt increases, demand for electricity as well as emissions climb. After some threshold, improving energy efficiency will lower the demand for electricity and hence SO_2 emissions. The capital-to-labor ratio (KL) has a significant nonlinear effect as well. If the capital endowment is low, increasing capital can cause more constructions of power plants and induce more SO_2 emissions. However, if the capital endowment is large enough, an increasing capital-to-labor ratio leads to lower emissions because of investment in capital-intensive cleaner industry or pollution abatement. The investment in education and R&D per capita (ESPC) reduces SO_2 emissions but the effect is not significant. The level of foreign direct investment (FDIR), which is measured as a ratio of FDI to fixed asset investment, has an ambiguous effect on

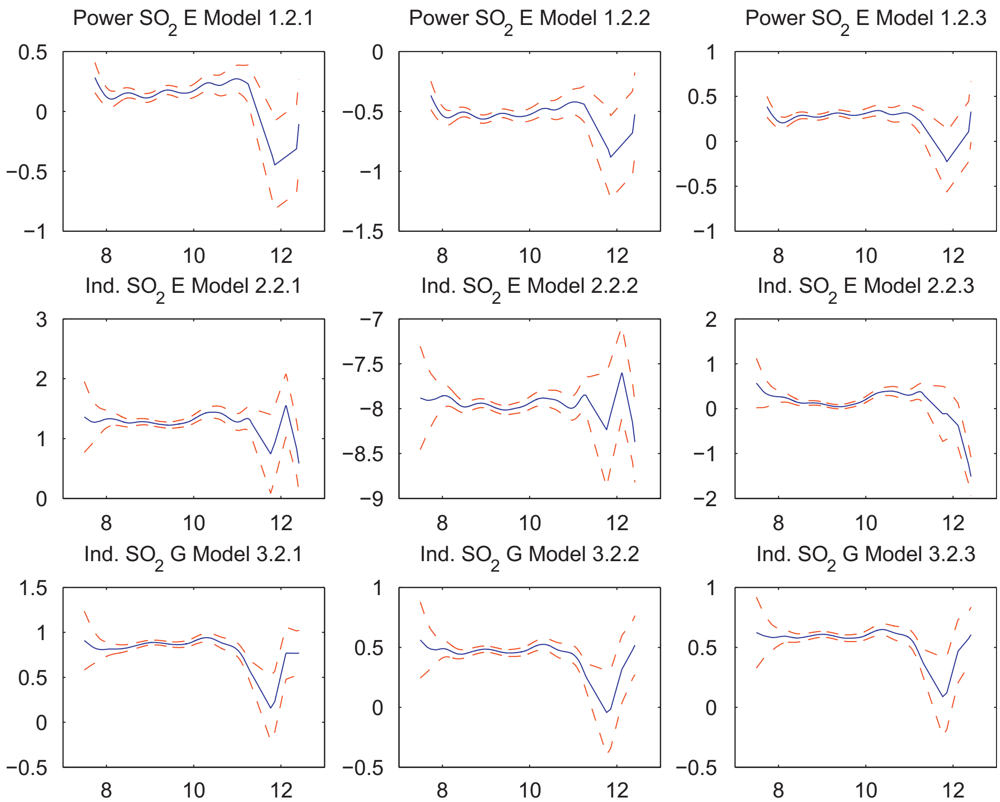

Fig. 4. Nonparametric estimate of the pollution–income relationship $m(w)$.

emissions. Its estimate is statistically insignificant. The insignificant effect of FDI might be due to a complex interaction between the "pollution haven" effect and the "gain from trade" effect [11,32,33].

5. Robustness checks

The first robustness check is concerned with the dependent variable. Besides power generation, we also evaluate the CDM effect on SO_2 emitted (SO2E) and generated (SO2T) by all industries. The CDM effect on all industries is not necessarily the same as that of the power sector because of the spillover or leakage effect. Estimation results for industrial SO_2 emissions are reported in Table 5. The semiparametric specification is still preferred because of its flexibility. For the main specification 2.2.1, the p-value of the Wald test for the joint significance of the CDM effect is 0.21, so that we cannot reject the null hypothesis of no effect at the 90% confidence level. The empirical results do not support the notion that CDM activities reduce total industrial SO_2 emissions.

As for SO_2 generated from all industries, the coefficients for CCO2, PCO2, and GCO2 are positive as is shown in Table 6. The Wald test for model 3.2.1 has a p-value less than 0.01, which means that the null hypothesis of no effect is rejected at the 99% confidence level. This result suggests that the CDM has increased SO_2 generated by all industries. This can be explained by the leakage effect. An increase in pollution induced by CDM activities outside the project boundary could fully offset the effect within the boundary. The magnitude of the CDM effect is the greatest at the prefecture level and the weakest at the grid level. This is sensible, because the leakage effect comes from project construction and operation, and thus the prefecture that hosts the projects undergoes the major impact.

To address the concern that locational and time-varying unobservables may affect CDM projects and SO_2 emissions simultaneously, we include province-by-time and grid-by-time dummies. When subnational time dummies are included, the time effects are not necessary because of multicollinearity. It is also worth noting that provincial CERs are almost absorbed by the province-by-time dummies. Note that PCO2 is defined as the difference between provincial and prefecture CERs. Because provincial CERs are much larger than prefecture CERs, prefectures within the same province have very little variation in PCO2. Including both PCO2 and province-by-time dummies causes the data matrix to be close to singularity. This is also true for the grid-by-time dummies. Therefore, when the grid-by-time dummies are present, the grid CERs are removed for identification purpose; when the province-by-time dummies are present, both grid and provincial CERs have to be removed.

Our empirical results are robust to the inclusion of the subnational time effects. For the emissions from power plants, the CDM effect is still insignificant with additional dummies. Other parameters yield the same qualitative results. A notable

Table 5
Regression results: dependent variable-SO_2 emitted by all industries.

	Parametric models			Semiparametric models		
	2.1.1	2.1.2	2.1.3	2.2.1	2.2.2	2.2.3
GDPPC	0.933	0.960	1.133			
	(0.803)	(0.849)	(0.824)			
$GDPPC^2$	−1.359*	−1.397*	−1.492*			
	(0.764)	(0.801)	(0.753)			
$GDPPC^3$	0.368*	0.380*	0.402*			
	(0.199)	(0.206)	(0.191)			
POPDEN	−0.167	−0.160	−0.091	−0.009	−0.009	−0.016
	(0.199)	(0.201)	(0.182)	(0.156)	(0.151)	(0.142)
EE	0.075	0.044	−0.049	0.083	0.008	−0.060
	(0.233)	(0.236)	(0.223)	(0.205)	(0.206)	(0.206)
EE^2	−0.213	−0.176	−0.149	−0.204	−0.152	−0.144
	(0.163)	(0.165)	(0.152)	(0.145)	(0.143)	(0.140)
K/L	0.316***	0.290***	0.292***	0.460***	0.342***	0.275***
	(0.093)	(0.095)	(0.104)	(0.065)	(0.080)	(0.087)
$(K/L)^2$	−0.098***	−0.094***	−0.093***	−0.132***	−0.109***	−0.097***
	(0.025)	(0.026)	(0.025)	(0.019)	(0.021)	(0.021)
ESPC	−0.051	−0.072	−0.122	−0.054	−0.108	−0.176***
	(0.104)	(0.106)	(0.104)	(0.070)	(0.072)	(0.068)
FDIR	−0.035	−0.049	−0.007	−0.047**	−0.038**	−0.026
	(0.022)	(0.023)	(0.025)	(0.019)	(0.019)	(0.022)
CCO_2	−0.032	−0.035	−0.022	−0.028	−0.031	−0.046
	(0.038)	(0.038)	(0.036)	(0.034)	(0.033)	(0.031)
PCO_2	0.009	0.010		0.007	0.009	
	(0.012)	(0.014)		(0.009)	(0.012)	
GCO_2	−0.006			−0.007		
	(0.004)			(0.004)		
Time effects	YES			YES		
Prefecture effects	YES	YES	YES	YES	YES	YES
Grid-time effects		YES			YES	
Province-time effects			YES			YES

Notes: Number of observations 1608. Time period 2004–2008. Block bootstrapping standard errors in parenthesis. Significance level: *10%, **5% and ***1%.

difference is that the coefficient for population density is now significantly positive. For SO_2 emitted by all industries, there is no significant CDM effect either. However, including provincial time dummies makes the parameter for FDI insignificantly negative and that for ESPC significantly negative. Subnational time dummies do not change the qualitative results for SO_2 generated by all industries. Similar to the previous case, the significance of the FDI effect disappears with subnational dummies, which suggests that locational differences that affect FDI may be time variant [33].

The causality of the pollution–income relationship is another concern. According to the growth theory, lagged income can be used as an instrument for current income [14]. Because the income parameters are not our focus, we adopt the reduced form strategy and use lagged GDP per capita as a regressor. Since the model yields very similar results to the one that uses current income, we do not report the full estimation results here, but they are available upon request.

The last robustness check is to separate out the treatment effect by project types. The CDM is divided into four categories: hydropower (HYDRO), wind energy (WIND), energy efficiency (ENERGY), and other activities (OTHER). Table 1 reports the summary statistics for these variables. Our specification includes province-by-time dummies. The estimation results support our main conclusion. For power plants, none of the parameters for CERs yields significant results. The CDM effect on industrial SO_2 emissions is also insignificant. As for SO_2 generated by all industries, the only significant effect is that the energy efficiency projects increase SO_2 generation. Results for these regressions are also available upon request.

6. Conclusion

Utilizing the relationship that CO_2 and SO_2 are co-pollutants of fossil-fuel combustion, we propose an econometric approach to evaluate the co-benefits of the Clean Development Mechanism and indirectly assess its additionality. Using China's prefecture-level economic and emission data, we find that the CDM does not have a statistically significant effect on SO_2 emissions. Our empirical findings contradict the results predicted by the engineering model. It thus casts doubt on the additionality assumption on which the engineering model is based. These results lend support to the previous conjectures that some CDM activities would have happened anyway.

Nevertheless, our paper is limited by the available data. We only include the registered CDM projects, while there are many more in the pipeline. If all these projects are eventually approved and implemented, it is possible that some non-negligible co-benefits will be observed. At present, the number of projects is relatively small, and the time period is

Table 6
Regression results: dependent variable-SO_2 generated by all industries.

	Parametric models			Semiparametric models		
	3.1.1	3.1.2	3.1.3	3.2.1	3.2.2	3.2.3
GDPPC	5.921***	5.758***	6.367***			
	(1.300)	(1.362)	(1.436)			
$GDPPC^2$	−3.128**	−3.087**	−3.443**			
	(1.231)	(1.280)	(1.311)			
$GDPPC^3$	0.493	0.496	0.563			
	(0.320)	(0.329)	(0.332)			
POPDEN	0.574*	0.522*	0.619*	−0.045	−0.135	−0.016
	(0.318)	(0.319)	(0.315)	(0.301)	(0.289)	(0.283)
EE	0.010	−0.057	0.024	0.112	−0.172	0.141
	(0.376)	(0.380)	(0.390)	(0.402)	(0.400)	(0.414)
EE^2	−0.054	−0.012	−0.051	−0.029	0.072	−0.112
	(0.262)	(0.264)	(0.264)	(0.282)	(0.276)	(0.280)
K/L	0.265*	0.309*	0.091*	0.476***	0.282*	0.280
	(0.155)	(0.157)	(0.187)	(0.129)	(0.161)	(0.182)
$(K/L)^2$	−0.191***	−0.203***	−0.181***	−0.173***	−0.145***	−0.159***
	(0.042)	(0.042)	(0.045)	(0.037)	(0.041)	(0.043)
ESPC	0.114	0.085	0.095	0.488***	0.340**	0.460***
	(0.166)	(0.169)	(0.179)	(0.135)	(0.140)	(0.137)
FDIR	−0.009	−0.009	−0.021	−0.077**	−0.028	−0.031
	(0.038)	(0.039)	(0.046)	(0.039)	(0.040)	(0.049)
CCO_2	0.187***	0.185***	0.134***	0.202***	0.188***	0.190***
	(0.061)	(0.061)	(0.063)	(0.066)	(0.064)	(0.062)
PCO_2	0.043**	0.022**		0.033*	0.023	
	(0.019)	(0.023)		(0.018)	(0.024)	
GCO_2	0.015**			0.004		
	(0.006)			(0.005)		
Time effects	YES			YES		
Prefecture effects	YES	YES	YES	YES	YES	YES
Grid-time effects		YES			YES	
Province-time effects			YES			YES

Notes: Number of observations 1557. Time period 2004–2008. Block bootstrapping standard errors in parenthesis. Significance level: *10%, **5% and ***1%.

Table 7
Hypothetical effect of the CDM activity under different baseline scenarios.

Baseline scenario	Effect of the CDM activity (wind+coal)	
	SO_2 emitted	SO_2 generated
Wind/other renewable energy	+	+
Wind+coal	0	0
Natural Gas	±	±
Coal	−	−
Other combinations	±	±

Notes: The CDM activity is building a wind farm. A companion coal-fired power plant is built for backup supply. Each baseline scenario generates the same electricity output.

relatively short for the CDM to make a difference. Methodologically, our micro-econometric approach is appealing for further tests of additionality, since project-level information is also available. We leave this for future research.

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References

[1] M. Wara, Is the global carbon market working? Nature 445 (7128) (2007) 595–596.
[2] D.G. Victor, Climate accession deals: new strategies for taming growth of greenhouse gases in developing countries, in: J. Aldy, R. Stavins (Eds.), Post-Kyoto International Climate Policy: Implementing Architectures for Agreement, Cambridge University Press, Cambridge, 2009.
[3] J. Jaffe, M. Ranson, R.N. Stavins, Linking tradable permit systems: a key element of emerging international climate policy architecture, Ecology Law Quarterly 36 (2010) 789–808.
[4] C. Fischer, Project-based mechanisms for emissions reductions: balancing trade-offs with baselines, Energy Policy 33 (14) (2005) 1807–1823.
[5] K.H. Olsen, The clean development mechanism's contribution to sustainable development: a review of the literature, Climatic Change 84 (1) (2007) 59–73.
[6] C. Sutter, J.C. Parreno, Does the current clean development mechanism (CDM) deliver its sustainable development claim? An analysis of officially registered CDM projects, Climatic Change 84 (1) (2007) 75–90.
[7] V. Ramanathan, Y. Feng, On avoiding dangerous anthropogenic interference with the climate system: formidable challenges ahead, Proceedings of the National Academy of Sciences of the United States of America 105 (38) (2008) 14245–14250.
[8] K. Aunan, J.H. Fang, T. Hu, H.M. Seip, H. Vennemo, Climate change and air quality—measures with co-benefits in China, Environmental Science & Technology 40 (16) (2006) 4822–4829.
[9] E.C.D. Silva, X. Zhu, Emissions trading of global and local pollutants, pollution havens and free riding, Journal of Environmental Economics and Management 58 (2) (2009) 169–182.
[10] G.M. Grossman, A.B. Krueger, Economic-growth and the environment, Quarterly Journal of Economics 110 (2) (1995) 353–377.
[11] W. Antweiler, B.R. Copeland, M.S. Taylor, Is free trade good for the environment? American Economic Review 91 (4) (2001) 877–908.
[12] S. Dasgupta, B. Laplante, H. Wang, D. Wheeler, Confronting the environmental Kuznets curve, Journal of Economic Perspectives 16 (1) (2002) 147–168.
[13] D.I. Stern, The rise and fall of the environmental Kuznets curve, World Development 32 (8) (2004) 1419–1439.
[14] J.A. Frankel, A.K. Rose, Is trade good or bad for the environment? Sorting out the causality, The Review of Economics and Statistics 87 (1) (2005) 85–91.
[15] R.T. Carson, The environmental Kuznets curve: seeking empirical regularity and theoretical structure, Review of Environmental Economics and Policy 4 (1) (2010) 3–23.
[16] D.L. Millimet, J.A. List, T. Stengos, The environmental Kuznets curve: real progress or misspecified models? Review of Economics and Statistics 85 (4) (2003) 1038–1047.
[17] L. Schneider, Assessing the additionality of CDM projects: practical experiences and lessons learned, Climate Policy 9 (3) (2009) 242–254.
[18] M. Auffhammer, R.T. Carson, Forecasting the path of China's CO_2 emissions using province-level information, Journal of Environmental Economics and Management 55 (3) (2008) 229–247.
[19] K. Capoor, P. Ambrosi, State and trends of the carbon market 2008, World Bank Technical Report, 2008.
[20] The World Bank, Chinese Ministry of Science and Technology, The Deutsche Gesellschaft für Technische Zusammenarbeit, German Federal Ministry of Economic Cooperation and Development, and Swiss State Secretariat for Economic Affairs, Clean Development Mechanism in China: Taking a Proactive and Sustainable Approach, second ed., The World Bank, Washington, D.C., 2004.
[21] National Development and Reform Commission, China's National Climate Change Programme, 2007 ⟨http://en.ndrc.gov.cn/⟩.
[22] J. Cao, M.S. Ho, D.W. Jorgenson, The local and global benefits of green tax policies in China, Review of Environmental Economics and Policy 3 (2) (2009) 189–208.
[23] World Bank, Cost of Pollution in China, World Bank, East Asia and Pacific Region, Available at ⟨http://www.worldbank.org/⟩, 2007.
[24] L. Cao, C. Wang, Calculation of SO_2 and NO_x emission factors of China's national power grids, China Environmental Science 30 (1) (2010) 7–11.
[25] E. Duflo, R. Pande, Dams, Quarterly Journal of Economics 122 (2) (2007) 601–646.
[26] D.J. Henderson, R.J. Carroll, Q. Li, Nonparametric estimation and testing of fixed effects panel data models, Journal of Econometrics 144 (1) (2008) 257–275.
[27] D.Y. Lin, Z. Ying, Semiparametric and nonparametric regression analysis of longitudinal data (with comment), Journal of the American Statistical Association 96 (453) (2001) 103–113.
[28] L.J. Su, A. Ullah, Profile likelihood estimation of partially linear panel data models with fixed effects, Economics Letters 92 (1) (2006) 75–81.
[29] J. Zhang, J. Zou, J. Chen, On the dynamic CO_2 emission baselines in the thermal power sector, in: X. Lu (Ed.), Studies on Climate Change: Progress and Outlook, China Meteorological Press, Beijing, 2003.
[30] M. Lee, Baseline Methodologies for Clean Development Mechanism Projects: A Guidebook, UNEP Risoe Center, Denmark, 2005.
[31] J. Li, H. Gao, China Wind Power Report 2007, China Environmental Science Press, Beijing, 2008.
[32] T. Jeppesen, J.A. List, H. Folmer, Environmental regulations and new plant location decisions: evidence from a meta-analysis, Journal of Regional Science 42 (1) (2002) 19–49.
[33] J.E. Dean, M.E. Lovely, H. Wang, Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China, Journal of Development Economics 90 (1) (2009) 1–13.