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Is the Clean Development Mechanism Effective for Emission Reductions?

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Abstract

This research studies whether the Clean Development Mechanism (CDM) of the Kyoto Protocol achieves its objective of emission reductions in the host countries. It empirically investigates the impacts of CDM projects on CO_2 emission reductions for 60 CDM host countries over 2005-10. This research makes use of the newly-developed econometric methods for dynamic panel data models associated with X-differencing procedure. It provides evidence in support of a decline in CO_2 emissions in the CDM host countries. It has important policy implications that encourage the international community to support developing countries' efforts towards low-carbon development via CDM projects.

Keywords: clean development mechanism, emission reductions, dynamic panel data model; X-differencing

JEL classification: O19, Q54, Q56

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1 Introduction

The UNFCCC COP 17 Durban conference marks an encouraging start towards reaching an all-party-inclusive global climate agreement as successor of the Kyoto Protocol by 2015.[1] Although this Durban 'road map' is promising, given the wide divide between developed and developing nations, the international negotiation process for reaching such a deal could be the one filled with great challenges and huge difficulties. Against this background, it is, therefore, of both urgency and necessity to evaluate the effectiveness of the Kyoto market-based mechanisms such as the Clean Development Mechanism (CDM) in terms of mitigating human-induced climate change, so as to know better about how the world's collective actions against climate change should proceed after Kyoto.

Apart from setting legally binding greenhouse gas (GHG) emission reduction targets for Annex I countries,[2] one central feature and great innovation of Kyoto Protocol is that it has started the process of carbon commodification, which turns carbon dioxide emission reductions into commodities that can be market traded. Three key market-based flexibility mechanisms were set up under Kyoto Protocol: Emissions Trading (ET),[3] Joint Implementation (JI)[4] and CDM. Among others, the major purposes of the above-mentioned flexibility mechanisms are to help Annex I countries to achieve their carbon emission reduction targets in a cost-effective way, to motivate developing nations onto a GHG emission mitigation path, and to attract private capital into the global emission abatement activities.

The CDM encourages Annex I countries to invest in low-cost emission-reduction projects in developing countries in return for tradable certified emission reductions credits (CERs) to help meet their national emission mitigation targets for the Kyoto compliance.[5] According to Article 12 of the Kyoto Protocol, CDM was set up with two

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1 The Kyoto Protocol is an international treaty with legally binding effects on 37 industrialized countries plus the European Community to mitigate greenhouse gas emissions. For more information, please refer to the official website of UNFCCC at http://unfccc.int/kyoto_protocol/items/2830.php.

2 Annex I countries are mainly industrialized countries as listed in the Kyoto Protocol's Annex I. At present, there are in total 41 Annex I nations including European Community. Developing countries are referred to as non-Annex I countries, with no compulsory obligations of carbon emission reductions under the principal of 'common but differentiated responsibilities'.

3 Emission Trading allows countries with unused 'assigned amount units' (AAUs), which are emission allowances allocated to them under the Kyoto Protocol, to sell their excess capacity to other Annex I countries in the carbon market just as any other market commodity.

4 Joint Implementation enables Annex I countries to earn Emission Reduction Units (ERUs) by investing in emission abatement projects in another Annex I party, which can be used to count against their carbon emission targets or to be traded on the carbon market. This mechanism can on the one hand help Annex I parties to meet their Kyoto obligations in a cost-efficient way and on the other hand, bring benefits to the project hosting nations thanks to the direct foreign investment and potential technological diffusion.

5 By April 2012, CDM has grown into an enormous global market with more 7,000 validation projects and an expected value of 17 billion CERs (to 2040) (data provided by the UNFCCC).

intentions or dual objectives.[6] One goal is to promote the global GHG emission reductions at a low cost. The other goal is to facilitate the hosting countries' sustainable development thanks to the direct financial investment in emission reduction projects by and the potential low-carbon technological transfer from Annex I countries.

It is widely recognized that most of the low-cost emission mitigation opportunities lie in the developing countries (e.g. Olmstead and Stavins 2006). As the only mechanism formally involving developing countries in global emission reduction efforts, CDM is of special focus for both the academia and the practitioners (Paulsson 2009). However, in the literature, so far opinions have differed widely regarding the impacts of CDM on reducing hosting countries' carbon emissions, with some research arguing that CDM has failed to bring about real and additional GHG emission reductions (e.g. Rosendahl and Strand 2009; Schneider 2007) and other work lending considerable evidences to the positive impacts of CDM on emission abatement (e.g. Sutter and Parreño 2007; Huang and Barker 2011).

Huang and Barker (2011) is among the few work that carries out a cross country study to examine the effects of CDM project development on emission reductions. However, a dummy variable is used for the key regressor CDM in the regression, unable to sufficiently capture the time series variations in CDM development. Given the importance of this issue and the current controversial views on it, this paper revisits this topic by making use of actual CDM credits and actual investments of CDM projects. With the recently-developed panel data econometric method due to Han et al. (2012), it aims to contribute to the field by unveiling the myth of whether or not CDM gives rise to real, additional and measurable emission reductions in the host countries.

The remainder of the paper proceeds in Section 2 by reviewing the literature. Section 3 describes the sample and data. Section 4 outlines the methodology employed. Section 5 conducts estimation and presents the results. Section 6 concludes.

2 Literature review

The CDM is designed to embody the principle of 'common but differentiated' responsibilities by motivating developed countries to provide funds and technology to reduce GHG emissions in non-Annex I nations in return for credits to offset the carbon emissions produced in their own countries. It not only provides the industrialized countries with some flexibility in how they meet their emission abatement targets but also helps to start off the developing countries on a low-carbon development path.

Despite its fast growth, CDM has been criticized for being ineffective in fulfilling its environmental and sustainable goals. One major concern is its additionality (e.g. Rosendahl and Strand 2009; Schneider 2007). As an offsetting mechanism, CDM projects should contribute to the global emission reductions by bringing down GHG emissions that are 'additional to any that would occur in the absence of the certified project activity' (UNFCCC 2011). That is to say, CDM projects in reality should reduce

6 Besides the two major objectives, CDM potentially has other by-product benefits for CDM hosting countries including diffusion of low-carbon technology, increased foreign direct investment (FDI), poverty reduction, and boosted economic activities (UNFCCC Report 2011).

GHG emissions to the degree that they are credited for (Paulsson 2009). However, Rosendahl and Strand (2009) state that CDM, as an offset mechanism, keeps the global carbon emission level the same by shifting the emission reduction costs from Annex I countries where emission reduction costs are higher, to non-Annex I countries where emission abatement costs are much lower if there were no flaws with CDM. The assessment of additionality in reality has never been easy, either.[7] A related concern is that the integrity of CDM might be contaminated by baseline manipulation (e.g. Rosendahl and Strand 2009).[8] People are also concerned that CDM's focus on low-cost emission reductions might to some degree compromise the host countries' sustainable development (e.g. Paulsson 2009).[9]

So far the existing research has a mix of evidences. On the one hand, there is research claiming that CDM has questionable additionality and has failed to bring about real and additional emission reductions to the hosting countries (e.g. Schneider 2007; Rosendahl and Strand 2009). An examination of 93 randomly selected CDM projects as well as interviews and literature review conducted by Scheider (2007) find that about 40 per cent of the CDM registered projects were questionable in terms of additionality, which compromises its environmental integrity. Based on a series of model analysis, Rosendahl and Strand (2009) argue that CDM projects do not imply full offset of GHG mitigation while increasing the likelihood of carbon leakage, which may result in a rise in the global carbon emissions.

On the other hand, there is empirical evidence for CDM's positive impacts on emission reductions (e.g. Lütken 2011; Sutter and Parreño 2007). By comparing the pre-CDM predictions of the mechanism's market size with the projections of current trajectory of potential mitigation entering the CDM pipeline, Rahman et al. (2010) find that, despite its limitations (unbalanced sector composition), CDM has been very successful in achieving emission reductions and is well on the way to reaching an average annual flow of 700 million CERs by 2012. The study by Lütken (2011) on the geographic distributions of CDM projects demonstrates that even the least developed countries (LDCs), especially in Africa, have enjoyed a reasonable share of the total of world's launched CDM projects and witnessed a boom of CDM projects. Based on the analysis of 16 officially registered CDM projects by employing the methodology of multi-attributive assessment, it is found that the vast majority of examined CDM projects (72 per cent) are likely to produce real and measurable emission reductions (Sutter and Parreño 2007).

The majority of existing research in this field are based on CDM projects; accordingly, the cross country evidence is lacking. Huang and Barker (2011) is an exception in that it

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7 The difficulties with the assessment of CDM's additionality or the evaluation of the actual emission reductions in host countries attributable to CDM projects include: the effects of CDM projects on the emission reductions being indirect and hard to be pinned down to certain projects; the impacts of CDM projects being long term and thus difficult to be measured within a limited crediting period; technological innovations associated with CDM projects leading to positive spill-over effects and further GHG abatement in the host countries (Schneider 2007).

8 Baseline manipulation may occur in the cases where the involving parties in CDM projects have incentives to enhance the baseline of GHG emissions so as to obtain a higher value of CERs than what should have been gained without the manipulation, which may lead to an increase of global GHG emissions (Rosendahl and Strand 2009).

9 More detailed literature review on CDM's sustainable development impacts can be found in its sister paper Huang et al. (2012).

is a cross-country study of 80 CDM host countries for the period between 1993 and 2009. It provides clear evidence for the positive effects of CDM projects on the emission reductions in the host countries. However, one limitation with that study is that due to data shortage a dummy variable is adopted to reflect the change before and after the CDM project registration, failing to sufficiently capture the rich variations in CDM development. This paper serves as a further research to Huang and Barker (2011), by using the actual numbers of CDM credits and investments with the recently developed panel data econometric method associated with X-differencing approach due to Han et al. (2012). It is of great value for this research to investigate this critical issue of whether CDM projects have led to genuine and additional emission reductions in the host countries.

3 The data

This section describes the variables used in the analysis and data sources. The dependent variable is CO_2 emissions per capita, denoted by CO_2. This analysis mainly makes use of total CO_2 emissions from fuel combustion by sectoral approach ($MtCO_2$), taken from the Enerdata's Global Energy Market Data (2012).[10] Data for total population are from the World Bank World Development Indicators Database (2012).[11]

The key independent variable is the CDM project development (CDM), which could be any of the following four indicators:[12]

(1) CDM credits per capita (CER_POP), the ratio of total CDM credits (kCERs) over total population in a given country;[13]

(2) CDM Contribution to the Economy (CER_GDP), the ratio of total CDM credits (kCERs) over total GDP.[14] It measures the economic revenue coming out of CDM projects compared to the host country's GDP. It is a direct indicator of the relative importance of CDM projects to the host country's economy or the prominence of CDM activities relative to other economic activities;

(3) CDM Actual Emissions Reductions (CER_CO_2), the ratio of total CDM credits (kCERs) over a country's actual carbon emissions.[15] It is the expected emission reductions achieved through CDM projects compared to a country's actual carbon emissions. It gives a rough idea of the domestic emission reductions

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10 According to the IPCC Tier 1 Sectoral Approach, the CO_2 emissions by sectoral approach are emissions resulted from the actual fuel combustion.

11 The analysis uses a multiplication factor of 1,000,000; so the dependent variable is tCO_2 emissions per capita.

12 Based on the total numbers of CDM projects and total CDM credits (CERs), Lütken (2011) proposes four indicators: Project Generation Ability, CDM Contribution to the Economy, Investment Capacity and Actual Emissions Reductions. Since the size of CDM projects varies considerably across countries, this analysis focuses on CDM credits (CERs) and actual investments (Million US$) instead. It gives up the indicator of Project Generation Ability and uses the ratio of investment, rather than the number of projects, over GDP for the indicator of Investment Capacity.

13 The indicator is adjusted by a multiplication factor of 1,000 so that it is CERs per capita.

14 A multiplication factor of 1,000,000 is applied, so it is CERs per 1,000 units of GDP.

15 The CERs per tCO_2 emissions (sectoral approach) is used.

efforts via CDM and how much the CDM projects can contribute to national emission reductions efforts in a given country;

(4) CDM Investment Capability (INVEST_GDP), the ratio of total investments in CDM projects over total GDP.[16] It is an immediate indicator of green FDI via CDM projects relative to GDP, capturing a country's ability to attract external financing for emission reductions.

Data on total CDM credits (kCERs to 2040) and total investments (Million US$) at project validation are provided by UNFCCC colleagues.[17] The data source for total CO_2 emissions is the Enerdata mentioned above. Data on total GDP (ppp in constant 2005 international $) and population are from the World Bank World Development Indicators Database (2012).

A number of control variables are used in this analysis, including GDP per capita (GDPPC) and its square ($GDPPC^2$), trade openness (TRADE), financial openness (KAOPEN) and World Governance Indicator (WGI). This inclusion of both GDPPC and $GDPPC^2$ in the model is to examine the so-called Environmental Kuznets Curve hypothesis. Trade openness and financial openness measure the extent of openness for external trade and financial sector in a given country. Governance indicator is to control for the level of institutional quality and government efficiency. Data on per capita GDP and trade share are from the World Bank World Development Indicators Database (2012). Data for the Chinn-Ito financial openness index, updated on 22 March 2012, are taken from Chinn and Ito (2008). The WGI measure from Kaufmann et al. (2011) is a widely-used indicator of the quality of a given government in a broader sense, derived by averaging six measures of government quality: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.

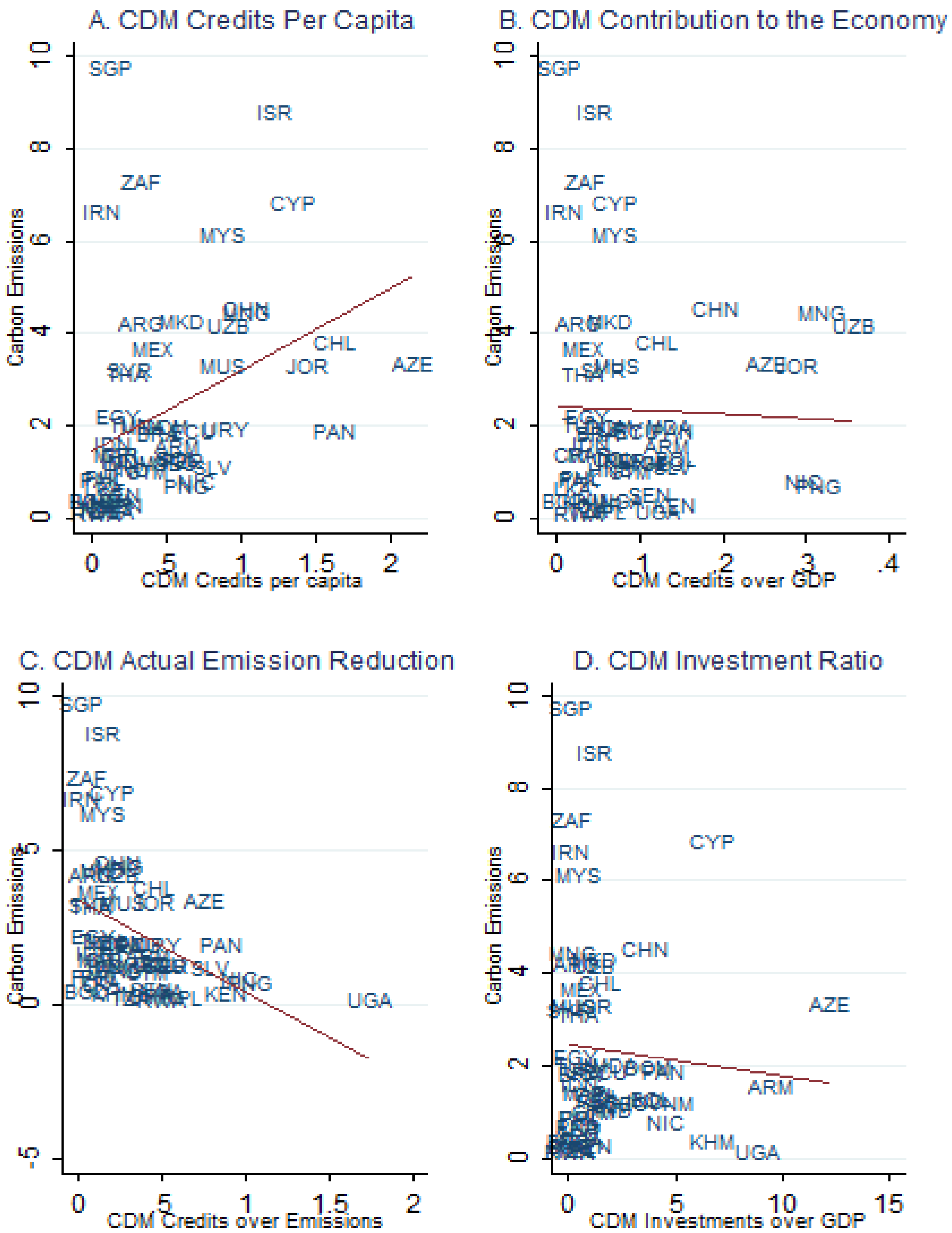
The whole sample includes 60 CDM host countries over 2005-10, as listed in the Appendix Table 1. We exclude any country which has less than 2 annual observations for dependent variable or CDM credits. Descriptive statistics of all variables can be found in Appendix Table 2 and the correlations among variables are presented in Appendix Table 3.

In four separate charts, Figure 1 presents the scatter plots of CO_2 against four CDM indicators mentioned above, respectively. Apart from CDM credits per capita, CO_2 is negatively associated with the other three CDM indicators. Due to the existence of outliers, this evidence alone is not very convincing. Robust evidence will be generated from a detailed panel data econometric analysis of the relationship between CDM and CO_2 emissions in Section 5.

16 It is adjusted by a multiplication factor of 1,000,000,000 so that it is investment per 1,000 units of GDP.

17 Grant A. Kirkman and Mathew Wilkins at UNFCCC have generously shared the data with us.

Figure 1: Scatter plots of CO_2 and CDM indicators



Note: 60 countries, 2005-2010. Variables and data are described in text.

Source: Authors' calculations.

4 Methodology

This section outlines the bias-corrected estimation methods developed for a dynamic panel data model with fixed effects. This research basically applies the Panel Fully Aggregated Estimator (PFAE) using X-differencing due to Han et al. (2012), against the conventional Least Square Dummy Variables (LSDV) estimator and the bias-corrected Least Square Dummy Variables (LSDVC) estimator due to Kiviet (1995), Bun and Kiviet (2003) and Bruno (2005).

To assess the impacts of CDM projects on the reductions of CO_2 emissions in the host countries, the following model is estimated in this case:

$$y_{it} = \eta_i + \alpha y_{i,t-1} + x_{it}^{'}\delta + v_{it} \qquad (1)$$
i = 1, 2,..., 60; t = 2,...6

where η_i is an unobserved time-invariant country-specific effect and can be regarded as capturing the combined effects of all the omitted variables. y_{it} is the dependent variable CO_2, $x_{it}$is a vector of explanatory variables including CDM_{it}, $GDPPC_{it}$, $GDPPC_{it}^2$, $TRADE_{it}$, $KAOPEN_{it}$, and WGI_{it}. α is the autoregressive coefficient, assumed to lie inside the unit circle, |α|<1, to ensure the model stability. δ is a parameter vector, e.g. $(\delta_1, .. \delta_6)'$. v_{it} is the unobserved transitory disturbance term, assumed to be independently distributed with zero mean and finite variance, and uncorrelated with individual effects.

Since we expect that reverse effects going from CO_2 emissions to some macroeconomic variables such as GDP per capital, trade openness, and governance level take considerable time, it is reasonable to assume that CDM_{it}, $GDPPC_{it}$, $GDPPC_{it}^2$, $TRADE_{it}$, $KAOPEN_{it}$, and WGI_{it} are strictly exogenous with respect to v_{it} in the sense that these variables are uncorrelated with the earlier, current and subsequent shocks. This assumption rules out the possibility of feedbacks from the past, current and future shocks onto x_{it}.

For a dynamic panel data model like this, the within-group transformation and first-differencing are common approaches used to eliminate any omitted variable bias created by the unobserved individual effects. Since the lagged values of $y_{it}$are positively correlated with the omitted fixed effects, as shown by Nickell (1981), the Least Square Dummy Variable (LSDV) estimator in the autoregressive panel models is not consistent and can be badly downwards biased for short time dimension (fixed T), even as cross section dimension N goes to infinity. Starting from Kiviet (1995), a number of bias-correction methods of LSDV for finite samples have been developed.[18]

Kiviet (1995) derives an approach to approximating the small sample bias of the LSDV estimator and suggests that the bias approximation can be evaluated at the estimates from some consistent estimates rather than the unobserved true parameter values, which makes bias correction operationally feasible. The Monte Carlo evidence from Kiviet (1995) and Bun and Kiviet (2003) suggest that the bias-corrected LSDV estimator (LSDVC) is more efficient than LSDV, first-differenced 2SLS due to Anderson and

18 Hahn and Kuersteiner (2002) study the bias-correction LSDV estimator when both N and T are large.

Hsiao (1982), first-differenced GMM due to Arellano and Bond (1991) and system GMM due to Blundell and Bond (1998) in terms of bias and root mean squared error (RMSE) for small or moderately large samples.

Han et al. (2012) introduce a new estimation method for linear dynamic panel data models with fixed effects, AR (p) idiosyncratic errors and exogenous variables. First, they propose a novel form of systematic differencing, called X-differencing, which has the advantage of removing fixed effects while retaining information and signal strength in cases of persistent or near unit root dynamics.[19] They then suggest using the least square regression method to estimate the stacked and pooled system of X-differenced equations, leading to the PFAE.

More specifically, the implied forward looking regression equation of Equation (1) can be written as:

$$y_{is} = \eta_i + \alpha y_{i,s+1} + x'_{is}\delta + v^*_{is} \tag{2}$$

where $v^*_{is} = v_{it} - \alpha(y_{i,s+1} - y_{i,t-1})$

Subtracting Equation (2) from Equation (1), we have:

$$y_{it} - y_{is} = \alpha(y_{i,t-1} - y_{i,s+1}) + (x'_{it} - x'_{is})\delta + (v_{it} - v^*_{is}) \tag{3}$$

Since the regressor $(y_{i,t-1} - y_{i,s+1})$ are uncorrelated with the error $(v_{it} - v^*_{is})$ as long as *s*<*t-1* and |α|<1, the following orthogonality condition hold:

$$E(y_{i,t-1} - y_{i,s+1})(v_{it} - v^*_{is}) = 0 \text{ for all } s < t\text{-}1 \text{ and } |\alpha|<1 \tag{4}$$

Also, because the previous assumption about $\mathrm{CDM_{it}}$, $\mathrm{GDPPC_{it}}$, $\mathrm{GDPPC^2_{it}}$, $\mathrm{TRADE_{it}}$, $\mathrm{KAOPEN_{it}}$, and $\mathrm{WGI_{it}}$being strictly exogenous variables implies that those variables are uncorrelated with $y_{i,s+1}$ and $y_{i,t-1}$, we have good reasons to believe that the regressors $(x'_{it} - x'_{is})$ are uncorrelated with the error $(v_{it} - v^*_{is})$ as well as long as s<t-1 and |α|<1.

$$E(x'_{it} - x'_{is})(v_{it} - v^*_{is}) = 0 \text{ for all } s < t\text{-}1 \text{ and } |\alpha|<1 \tag{5}$$

Han et al. (2012) suggest making full use of all information by stacking the regression equations for all possible values of *s*. Given these orthogonality conditions, they then suggest to apply the least squares regression to estimate the full system of X-differenced equations for *s*=1, 2,...*t-3*.

Han et al. (2012) show that the PFAE estimator is consistent for all parameter values, and has strong asymptotic and finite sample properties that dominate other estimation methods such as LSDVC. There is no need of bias correction for this estimator. In the unit root case, it has higher asymptotic efficiency than LSDVC, while both PFAE and

[19] After eliminating the individual effects, X-differencing procedure makes the transformed regressor uncorrelated with the transformed error while the conventional procedures such as within-group transformation and first differencing cause the transformed regressor to be correlated with the transformed error.

LSDVC are large-T efficient for the stationary case. The asymptotic properties of this estimator hold for short or long panels as well as narrow and wide panels.

5 Econometric evidence

This section presents the empirical evidence for the effectiveness of CDM project development in terms of emission reductions in 60 CDM host countries over 2005-10. Four CDM indicators explained in Section 3 are examined, with the results reported in Tables 1 to 4, respectively.

Each table compares the LSDV estimates, LSDVC estimates and PFAE estimates. The conventional LSDV estimates are the OLS estimates of coefficients of a panel data regression model after removing the fixed effects via within transformation. The bias-corrected LSDV estimates and LSDVC estimates are generated using the approach due to Bruno (2005) for the dynamic unbalanced panels with a strictly exogenous selection rule.[20] The PFAE estimator uses X-differencing approach to remove the fixed effects and applies the least squares regression to estimate the full system of X-differenced equations for s=1,2,3. For each model, the point estimate of the long-run effect of respective CDM variable is calculated with its standard error being approximated by using the delta method (for example, Papke and Wooldridge 2005).

Table 1 reports the results when the indicator of CDM credits per capita is considered. All of the LSDV, LSDVC and PFAE estimates suggest that the lagged dependent variable, Lag $\mathrm{CO_2}$ Emissions, is significantly positive. The LSDVC estimate of Lag $\mathrm{CO_2}$ Emissions is close to the unit circle. Having higher asymptotic efficiency than LSDVC, the PFAE estimate of Lag $\mathrm{CO_2}$ Emissions is much smaller.

The key regressor, CDM credits per capita, has been found negative in the model in which PFAE estimate suggests a significantly negative effect on $\mathrm{CO_2}$ emissions, not only in the short run but also in the long run.[21] This evidence clearly supports that more credits generated from CDM projects over total population in a given CDM host country are associated with more emission reductions.

For the control variables, GDP per capita ($\mathrm{GDPPC_{it}}$) and Squared GDP per capita ($\mathrm{GDPPC_{it}^2}$), both LSDV and LSDVC estimates imply a positive impact for both of them, although they are almost significant using the LSDV approach while insignificant using the LSDVC approach. The PFAE estimates clearly indicate that $\mathrm{GDPPC_{it}}$ has a significantly positive impact on $\mathrm{CO_2}$ emissions while $\mathrm{GDPPC_{it}^2}$, a negative impact on $\mathrm{CO_2}$ emissions (significant at 16 per cent level). The evidence is in support of the

20 Bruno (2005) derives a bias approximation of various orders in dynamic unbalanced panels with a strictly exogenous selection rule. Essentially, Bruno (2005) adjusts the within operator to include an exogenous selection rule which only selects the observations with observable current and one-time lagged values, by which missing observations for some individuals are allowed. We use the system-GMM estimator as the initial estimator for the LSDVC since it is believed to be a more reliable estimator than the first-differenced 2SLS and first-differenced GMM estimators.

21 Both LSDV estimate and LSDVC estimate suggest a negative effect on $\mathrm{CO_2}$ emissions at 13 per cent and 24 per cent level, respectively.

Table 1: The effectiveness of CDM for carbon emission reductions – (CDM credits per capita)

Estimator	LSDV Estimator	LSDVC Estimator	PFAE Estimator
Data Transformation	**Within Transformation**	**Within Transformation**	**X-differencing**
Lag CO_2 Emissions	0.510***	0.745***	0.147*
	(0.000)	(0.000)	(0.096)
CDM Credits Per Capita	-0.037	-0.034	-0.037*
	(0.130)	(0.242)	(0.078)
GDP Per Capita	0.099*	0.076	0.283***
	(0.076)	(0.315)	(0.000)
Squared GDP Per Capita	0.001	0.001	-0.002
	(0.153)	(0.622)	(0.162)
Trade Openness	0.268	0.258	0.351***
	(0.126)	(0.185)	(0.008)
Financial Openness	0.022	0.034	0.033
	(0.587)	(0.578)	(0.288)
World Governance	0.025	0.031	-0.028
	(0.520)	(0.581)	(0.211)
Long-run Effect	-0.076	-0.134	-0.044*
Standard Error	[0.05]	[0.14]	[0.03]
Number of Countries	58	58	58
Observations	204	204	401

Note: The dependent variable is CO_2 emissions by sectoral approach for 60 CDM host countries over 2005-2010. This table focuses on the CDM credits per capita. Variables and data sources are described in the text. This table presents the Least Square Dummy Variables estimates (LSDV), Bias-corrected LSDV estimates (LSDVC) and Panel Fully Aggregated estimates (PFAE), respectively. Both LSDV and LSDVC approaches use within transformation to remove the fixed effects while PFAE approach removes fixed effects via X-differencing. LSDVC uses the Arellano and Bond estimator as the initial estimator and calculates a bootstrap variance-covariance matrix using 50 repetitions. P-values are reported in the parentheses. All equations include year dummies. *, **, *** significant at 10%, 5%, 1%.

Source: Authors' calculations.

hypothesis of Environmental Kuznets Curve in the sense that CO_2 emissions increase when the level of per capita income goes up; however, when the income reaches a certain level, CO_2 emissions decline.

For the control variables of openness, trade openness (TRADE) and financial openness (KAOPEN), both LSDV and LSDVC estimates find a positive but insignificant impact for both of them, although TRADE is more likely to have significant impacts on CO_2 emissions. Using the PFAE approach, both TRADE and KAOPEN positively enter the model in which TRADE is significant at 1 per cent level. The observed positive effects of trade openness and financial openness on CO_2 emissions are in line with the existing literature such as Frankel and Rose (2005) that it is likely that more open policies will contribute to increased CO_2 emissions.

Regarding the control variable of institutional quality, World Governance Indicator (WGI), no significant evidence has been generated using three estimation approaches. Both LSDV and LSDVC estimates suggest a positive impact while the PFAE estimate suggests a negative impact, but the latter is more plausible and consistent with the literature. Good governance can facilitate market activities, minimize environmental degradation, and enhance the emission control procedure, etc. (see Gani (2012) for a detailed review).

Table 2 examines the impacts on CO_2 emissions of CDM Contribution to the Economy (CER_GDP), the ratio of CDM credits over total GDP. All of the LSDV, LSDVC and PFAE estimates indicate a negative, but insignificant, impact of CER_GDP on CO_2

emissions. This shows that the more importance of CDM projects for the economy is not necessarily leading to more CO_2 emission reductions. For the control variables, the pattern of the results is quite similar to those in Table 1. WGI has been found negatively associated with CO_2 emissions at 12.5 per cent significance level, as suggested by the PFAE estimate.

Table 2: The effectiveness of CDM for carbon emission reductions – (CDM contribution to the economy)

Estimator	LSDV Estimator	LSDVC Estimator	PFAE Estimator
Data Transformation	Within Transformation	Within Transformation	X-differencing
Lag CO_2 Emissions	0.519***	0.757***	0.147*
	(0.000)	(0.000)	(0.098)
CDM Contribution to the Economy	-0.114	-0.118	-0.004
	(0.459)	(0.489)	(0.961)
GDP Per Capita	0.088	0.066	0.275***
	(0.115)	(0.386)	(0.000)
Squared GDP Per Capita	0.001	0.001	-0.002
	(0.130)	(0.596)	(0.183)
Trade Openness	0.291	0.282	0.367***
	(0.100)	(0.147)	(0.006)
Financial Openness	0.020	0.032	0.023
	(0.627)	(0.610)	(0.470)
World Governance	0.020	0.027	-0.034
	(0.605)	(0.633)	(0.125)
Long-run Effect	-0.237	-0.484	-0.004
Standard Error	[0.32]	[0.78]	[0.09]
Number of Countries	58	58	58
Observations	204	204	401

Note: This table focuses on the indicator of CDM Contribution to the Economy, the ratio of CDM credits over total GDP. See Table 1 for more notes

Source: Authors' calculations.

Table 3 examines whether the higher probabilities of CDM actual emission reductions (CER_CO_2) could result in more CO_2 emissions in the host countries. All of the LSDV, LSDVC and PFAE estimates indicate a negative impact of CER_GDP on CO_2 emissions, in which the significance suggested by the PFAE is close to the valid significance level. We still do not have sufficient evidence to support that more domestic emission reduction efforts such as CDM project development in a given country will lead to more emission reductions. For the control variables, the pattern of the results is quite similar to those in Table 2.

Table 4 focuses on the amount of investments put into the CDM projects (INV_GDP), rather than the CDM credits generated. It presents evidence on whether more investment in CDM projects is associated with more CO_2 emissions in the host countries. All of the LSDV, LSDVC and PFAE estimates exhibit a negative impact of INV_GDP on CO_2 emissions, in which the significant evidence has been suggested by PFAE, but not necessarily by LSDV and LSDVC. The PFAE estimate also indicates that this negative impact is likely to persist into the long run. This finding has an immediate policy implication that the more investments put into the environmentally-friendly CDM projects or the more foreign investments or green FDI a host country could attract from Annex I countries, the more emission reductions can be expected in the host countries. For the control variable, PFAE estimates have also provided

Table 3: The effectiveness of CDM for carbon emission reductions – (CDM actual emission reductions)

Estimator	LSDV Estimator	LSDVC Estimator	PFAE Estimator
Data Transformation	Within Transformation	Within Transformation	X-differencing
Lag CO_2 Emissions	0.519***	0.759***	0.147*
	(0.000)	(0.000)	(0.098)
CDM Actual Emission Reductions	-0.013	-0.014	-0.012
	(0.511)	(0.545)	(0.188)
GDP Per Capita	0.088	0.066	0.275***
	(0.116)	(0.385)	(0.000)
Squared GDP Per Capita	0.001	0.001	-0.002
	(0.131)	(0.597)	(0.184)
Trade Openness	0.290	0.281	0.374***
	(0.102)	(0.151)	(0.006)
Financial Openness	0.018	0.030	0.024
	(0.656)	(0.623)	(0.441)
World Governance	0.019	0.026	-0.032
	(0.626)	(0.649)	(0.142)
Long-run Effect	-0.028	-0.058	-0.014
Standard Error	[0.04]	[0.10]	[0.01]
Number of Countries	58	58	58
Observations	204	204	401

Note: This table focuses on the indicator of CDM Actual Emission Reductions, the ratio of CDM credits over total emissions. See Table 1 for more notes.

Source: Authors' calculations.

Table 4: The effectiveness of CDM for carbon emission reductions – (CDM investment capability)

Estimator	LSDV Estimator	LSDVC Estimator	PFAE Estimator
Data Transformation	Within Transformation	Within Transformation	X-differencing
Lag CO_2 Emissions	0.542***	0.774***	0.255***
	(0.000)	(0.000)	(0.008)
CDM Investment Capability	-0.002	-0.003	-0.006*
	(0.629)	(0.581)	(0.051)
GDP Per Capita	0.133**	0.090	0.250***
	(0.047)	(0.346)	(0.000)
Squared GDP Per Capita	0.000	0.000	-0.001
	(0.809)	(0.781)	(0.181)
Trade Openness	0.283	0.291	0.195
	(0.198)	(0.256)	(0.168)
Financial Openness	0.013	0.013	0.063*
	(0.790)	(0.822)	(0.051)
World Governance	0.029	0.037	-0.045**
	(0.533)	(0.508)	(0.031)
Long-run Effect	-0.004	-0.012	-0.009*
Standard Error	[0.01]	[0.02]	[0.00]
Number of Countries	57	57	57
Observations	178	178	375

Note: This table focuses on the indicator of CDM investment capability, the ratio of CDM investment over total GDP. See Table 1 for more notes.

Source: authors' own calculations.

significant evidence for a positive impact of KAOPEN while a negative impact of WGI on CO_2 emissions.

In sum, by using different CDM indicators, this research produces significant evidence that CDM project development can contribute to CO_2 emission reductions in a given host country. It finds that higher CDM credits per capita and higher investment ratios are linked to more CO_2 emission reductions in both the short run and long run, but not necessarily the case with higher ratios of CDM credits over both total GDP and total CO_2 emissions. It also reveals significant evidence in support of the Environmental Kuznets Curve hypothesis, as well as trade openness and financial openness being the driving factors for CO_2 emissions and governance level being the limiting factor for CO_2 emissions. The findings of CDM being effective for emission reductions in the host countries have important policy implications. Developing countries and the international community should encourage more CDM projects to be established in developing countries and more investments from Annex I countries to be put into the CDM projects, which will be conducive to the global low-carbon development cause. The results are not due to unobserved heterogeneity, and in general robust to the use of different CDM indicators, which measure different dimensions of CDM project development in a given country.

6 Conclusion

This paper focuses on the effectiveness of the CDM in achieving carbon emission reductions in the host countries. It demonstrates that CDM projects as a whole have brought 'real' and 'additional' emission reductions to the host developing countries. The results imply that the criticisms against CDM's additionality and the raised issue of the manipulations of and even corruptions surrounding CDM projects (e.g. baseline manipulation), are at least overstated in most cases. The results also indicate that, despite its limitations, the Kyoto Protocol has been very successful in not only setting legally binding emission abatement targets but also offering the means to help to achieve the end.

According to the IPCC report (2001), developing countries are going to overtake developed countries in terms of GHG emissions between 2010 and 2020. At the same time, it is important to note that the developing nations are still struggling to cope with the immediate development concerns. This reality means that on the one hand, the positive involvement of developing nations in the global efforts of GHG emission reductions is a necessity for the world's climate change combat to be successful, and on the other hand, to get the developing countries on board in the global emission abatement campaign, more emphasis is needed to enhance the financial and technological transfers into developing countries, for which CDM is an ideal channel.

This once again highlights that the importance of CDM's role in facilitating the Annex I countries to achieve the targeted emission reductions as set by the Kyoto should not be overlooked. By making it easier for Annex I countries to meet their emission targets, CDM along with the other two flexibility mechanisms, helps to ensure the lasting success of the Kyoto and its renewal into the next commitment period. Although improvements are required, CDM is one of such essential means that a future global climate regime cannot afford to be without.

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Appendix Table 1: The List of Sample Countries (60)

Country Code	Country Name	Country Code	Country Name
ALB	Albania	LKA	Sri Lanka
ARE	United Arab Emirates	MAR	Morocco
ARG	Argentina	MDA	Moldova
ARM	Armenia	MEX	Mexico
AZE	Azerbaijan	MKD	Macedonia, FYR
BGD	Bangladesh	MNG	Mongolia
BOL	Bolivia	MUS	Mauritius
BRA	Brazil	MYS	Malaysia
BTN	Bhutan	NGA	Nigeria
CHL	Chile	NIC	Nicaragua
CHN	China	NPL	Nepal
CMR	Cameroon	PAK	Pakistan
COL	Colombia	PAN	Panama
CRI	Costa Rica	PER	Peru
CUB	Cuba	PHL	Philippines
CYP	Cyprus	PNG	Papua New Guinea
DOM	Dominican Republic	QAT	Qatar
ECU	Ecuador	RWA	Rwanda
EGY	Egypt, Arab Rep.	SEN	Senegal
FJI	Fiji	SGP	Singapore
GEO	Georgia	SLV	El Salvador
GTM	Guatemala	SYR	Syrian Arab Republic
HND	Honduras	THA	Thailand
IDN	Indonesia	TUN	Tunisia
IND	India	TZA	Tanzania
IRN	Iran, Islamic Rep.	UGA	Uganda
ISR	Israel	URY	Uruguay
JOR	Jordan	UZB	Uzbekistan
KEN	Kenya	VNM	Vietnam
KHM	Cambodia	ZAF	South Africa

Note: This table lists the country codes and country names for 60 CDM host countries.

Source: Authors' calculations.

Appendix Table 2: Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
CO_2(sectoral)	overall	3.243	5.918	0.045	45.717	N = 360
	between		5.923	0.053	39.859	n = 60
	within		0.658	-2.926	9.101	T = 6
CER_POP	overall	1.043	5.447	0.001	63.025	N = 246
	between		6.117	0.013	39.307	n = 60
	within		3.350	-27.020	29.107	T-bar = 4.1
CER_GDP	overall	0.158	0.879	0.000	13.186	N = 242
	between		1.087	0.003	8.399	n = 59
	within		0.443	-4.629	4.944	T-bar = 4.10169
CER_CO_2	overall	1.086	10.031	0.001	154.407	N = 246
	between		11.956	0.010	92.922	n = 60
	within		5.579	-60.400	62.571	T-bar = 4.1
INV_GDP	overall	2.610	7.889	0.004	74.890	N = 209
	between		12.620	0.034	74.890	n = 58
	within		3.510	-19.533	24.753	T-bar = 3.60345
GDPPC	overall	8.639	12.373	0.840	77.108	N = 352
	between		12.813	0.948	72.363	n = 59
	within		1.361	-3.508	20.996	T = 5.9661
$GDPPC^2$	overall	227.283	794.267	0.706	5945.678	N = 352
	between		829.412	0.903	5244.678	n = 59
	within		142.797	-1031.785	1644.144	T = 5.9661
TRADE	overall	0.880	0.563	0.223	4.459	N = 354
	between		0.557	0.251	4.152	n = 60
	within		0.087	0.490	1.188	T = 5.9
KAOPEN	overall	0.507	1.500	-1.856	2.456	N = 354
	between		1.488	-1.856	2.456	n = 59
	within		0.260	-0.989	1.715	T = 6
WGI	overall	-1.650	3.480	-9.258	9.186	N = 360
	between		3.473	-8.094	8.824	n = 60
	within		0.469	-4.191	0.386	T = 6

Note: See text for the description of each variable.

Source: Authors' calculations.

Appendix Table 3: Correlations among Variables

	CO_2	CER_POP	CER_GDP	CER_CO_2	INV_GDP	GDPPC	GDPPC²	TRADE	KAOPEN	WGI
CO_2	1.000									
CER_POP	0.383	1.000								
CER_GDP	-0.013	0.786	1.000							
CER_CO_2	-0.045	0.754	0.992	1.000						
INV_GDP	-0.100	0.067	0.034	0.046	1.000					
GDPPC	0.906	0.301	-0.021	-0.031	-0.062	1.000				
GDPPC²	0.930	0.426	0.003	-0.020	-0.052	0.948	1.000			
TRADE	0.228	0.035	0.034	0.007	0.065	0.417	0.340	1.000		
KAOPEN	0.277	0.018	-0.076	-0.076	-0.060	0.406	0.316	0.189	1.000	
WGI	0.407	0.123	0.041	0.045	0.019	0.616	0.435	0.458	0.463	1.000

Note: See text for the description of each variable.

Source: Authors' calculations.