Can CDM Deliver Its Emission Reduction Purpose?

A panel data analysis for developing countries.

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Degree project/Independent project • 30 credits
Swedish University of Agricultural Sciences, SLU
Faculty of Natural Resources and Agricultural Sciences / Department of Economics
Environmental Economics and Management – Master's Programme
Degree project/SLU, Department of Economics, 1451 • ISSN 1401-4084
Uppsala, 2022

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Credits:	30 credits
Level:	A2E
Course title:	Master thesis in Economics
Course code:	EX0905
Programme/education:	Environmental Economics and Management
Course coordinating dept:	Department of Economics
Place of publication:	Uppsala
Year of publication:	2022
Copyright:	All featured images are used with permission from the copyright owner.
Title of series:	Degree project/SLU, Department of Economics
Part number:	1451
ISSN:	1401-4084
Keywords:	clean development mechanism, cdm, kyoto protocol, emissions reduction, ardl, pooled mean group, pmg

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Abstract

The Clean Development Mechanism (CDM) is one of the three flexible mechanisms defined within the Kyoto Protocol. It aims to help developed countries achieve emission reduction targets with low abatement costs while providing sustainable development to developing countries. However, whether CDM has delivered this dual objective has been questionable. This study empirically examines the long-run effect of CDM projects on carbon dioxide emissions per capita for 69 eligible developing countries from 1993 to 2012 with a panel data analysis. The research mainly focuses on Pooled Mean Group (PMG) estimator that allows short-run coefficients to alter between groups but restricts long-run coefficients to be the same. The empirical results indicate a significant and positive relationship between CDM projects and carbon dioxide emissions per capita in the long run, implying that CDM did not lead to emission reductions in respective countries over 1993-2012. This result can be explained due to non-additional projects operated within the mechanism. To observe emission reductions with the implementation of CDM projects, we conclude that assessments regarding additionality and issued emission credits should be improved with better methodologies, governance and increased transparency.

Keywords: clean development mechanism, cdm, kyoto protocol, emissions reduction, ardl model, pooled mean group, pmg

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Abbreviations

ADF	Augmented Dickey-Fuller
ARDL	Autoregressive Distributed Lag
CDM	Clean Development Mechanism
CER	Certified Emission Credit
DNA	Designated National Authority
DOE	Designated Operational Entity
EKC	Environmental Kuznets Curve
ET	Emissions Trading
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GHG	Greenhouse Gas
JI	Joint Implementation
PMG	Pooled Mean Group
UNFCCC	United Nations Framework Convention on Climate Change
UNEP CCC	United Nations Environment Programme – Copenhagen Climate Centre

1. Introduction

Global efforts to decrease greenhouse gas (GHG) emissions as the main cause of anthropogenic climate change have gained significant attention over the last three decades. Although developed countries historically are accountable for the bulk of GHG emissions, developing countries will be responsible for a 70% increase in global carbon dioxide emissions from 2002 to 2030 (OECD, 2002). In addition to that, developing countries' expected per capita emissions are lower than the per capita emissions of developed countries; however, aggregate emissions of the former will be significantly higher than the latter beyond 2020 (Dagoumas et al., 2006; Banuri & Gupta, 2000).

In order to limit and reduce GHG emissions, Kyoto Protocol was adopted on 11 December 1997. The Kyoto Protocol is recognized as a milestone in global efforts to combat climate change since it is the first of its kind where governments agreed on legally-binding constraints on their emissions. It requires 37 Annex I Parties (i.e. developed countries) and the European Union to decrease their emissions on average by 5.2% compared to 1990 emissions levels over the first commitment period 2008-2012 (UNFCCC, 2022c).

Within the Protocol, three market-based mechanisms were introduced, which have created what today is known as carbon markets. These mechanisms are *Clean Development Mechanism* (CDM), *Joint Implementation* (JI) and *Emissions Trading* (ET), all of which aim to assist Annex I Parties in achieving emission reduction targets with lower abatement costs by providing flexibility. However, among the aforementioned three mechanisms, CDM is the only flexible mechanism that involves developing countries in climate mitigation and negotiations (Huang & Barker, 2012). Considering the emissions development path of developing countries and recognizing climate change as a global issue, it is clear that both developed and developing countries should take part in global climate change mitigation. However, such mitigation efforts require financial means and technology to support GHG emission reductions, which most developing countries might lack.

CDM has dual objectives: (i) to assist Annex I Parties (i.e. developed countries) in achieving emission reduction targets and (ii) to provide sustainable development for the non-Annex I Parties (i.e. developing countries). The mechanism allows Annex I Parties to invest in projects with low abatement costs in non-Annex I Parties, which leads to emission reductions. The contribution of GHG emissions to climate change is the same regardless of where the GHG emissions occur. By investing in projects in countries where abatement costs are relatively low, it is possible to promote the economic efficiency of decreasing GHG emissions (Austin & Faeth, 2000). As a return for investments, Annex I Parties receive emission credits called Certified Emission Reductions (CERs), each equivalent to one tonne of CO_2. Countries can use these emission credits to meet their emission targets under the Kyoto Protocol. In addition, these investments should support sustainable development in host countries where the CDM projects occur and increase the economic, social and environmental aspects. According to Burniaux et al. (2009), a well-functioning CDM can increase the cost-effectiveness of GHG mitigation policies in developing countries, prevent carbon leakage and decrease concerns about competitiveness by reducing the price of carbon in developed countries, and increase clean technology transfers to developing countries.

However, whether the CDM has delivered its dual objectives is highly controversial in the literature. Since there are different definitions of sustainable development and a lack of data for such indicators in developing countries, this study will only focus on the first objective of the CDM – i.e. emission reductions. So, previous studies show that researchers are divided into two groups where one group claims that CDM led to emission reductions (e.g. Huang & Barker, 2012; Banuri & Gupta, 2000; He et al., 2014), while the other group claims the opposite (e.g. Schneider, 2007; Schneider et al., 2010; Wara & Victor, 2008). Despite the controversial debate on CDM's emission reduction objective, it is crucial to evaluate the mechanism since it can provide information about how the world can cooperate in climate change mitigation after the Kyoto Protocol (He et al., 2014). In addition to that, there are currently 1243 CDM projects that will be transferred to Article 6 of the Paris Agreement (UNEP Copenhagen Climate Centre, 2022). Therefore, it is essential to understand the key learnings from CDM and improve future programs accordingly.

To investigate if CDM projects led to emission reductions, we conduct a dynamic heterogeneous panel data[1] analysis for 69 eligible developing countries from 1993 to 2012. This paper focuses on emissions from the energy sector due to oil, fuel and gas usage. The Autoregressive Distributed Lag (ARDL) model with Pooled Mean Group (PMG) estimator is adopted to investigate long-run and short-run relationships between the CDM projects and emissions. The PMG estimator allows short-run coefficients to vary across groups while constraining long-run coefficients to be the same. This study will employ a similar methodology as Huang & Barker (2012).[2] We aim to contribute to the literature by providing a panel data

[1] Dynamic heterogeneous panel data refers to when parameters in the model differ across groups (Pesaran & Smith, 1995).

[2] Huang & Barker (2012) used a private data source – i.e. Enerdata's Global Energy Market Data (2010), which requires a subscription and payment. Additionally, the authors used a binary variable for CDM projects, defined as a dummy taking a value of 1 if a project is registered before 2007 and in all years afterwards, zero otherwise. Although our methodology and the structure for the regression models are the same, we redefine the variable for CDM projects as the number of projects per capita. See Section 4. Data for more details.

analysis with open data sources since previous studies focused on panel data analysis at the aggregate level using private data sources.[3]

The remainder of this study is organized as follows. Section 2 provides an overview of the Clean Development Mechanism. Section 3 introduces the literature review. Section 4 describes data and limitations within the scope of this study. Section 5 introduces the methodology, and section 6 shares the estimations results of the analysis. Section 7 provides a discussion about the results, and finally, section 8 concludes the study and gives possible further research suggestions.

[3] For instance, see Huang & Barker (2012) and He et al. (2014).

2. An Overview of the Clean Development Mechanism

CDM is a flexible and project-based mechanism within the Kyoto Protocol. It aims to help Annex I Parties meet their emission reduction targets and, at the same time, provide sustainable development to non-Annex I Parties (UNFCCC, 2022b). For CDM projects to be eligible, they must fulfil two requirements: additionality and environmental integrity. Additionality means that a decrease in emissions through CDM projects should be ‘additional to any that would occur in the absence of such activities’ (UN, 1998); in other words, emissions reductions through CDM projects would not occur in a business-as-usual case. Environmental integrity refers to real and measurable projects that create long-term benefits related to climate change mitigation.

The additionality of CDM projects is vital since the mechanism is considered an offsetting mechanism. Therefore, if a project is counted as additional, but in fact, this is not the case, this situation can increase the actual GHG emissions (Schneider, 2007). Such a situation occurs since registered projects create emission credits used by developed countries, and if the credits do not reflect the represented emission reductions in real life, developed countries end up emitting more GHG than their specified Kyoto targets.

As of 1 April 2022, there are 7173 projects registered to the CDM Pipeline in various sectors such as energy, agriculture and industry (UNEP CCC, 2022). Figure 1 shows the percentage of the CDM projects in each category. More than half of the projects are made in renewable energy since moving towards fossil-free energy production plays an essential role in decarbonizing our society and economy. The second biggest share is methane (CH_4) reduction, cement and coal mine/bed. Supply and demand-side end-use energy efficiency (as shown as supply-side EE and demand-side EE in Figure 1) also have a significant share in total projects, which is quite essential since projects within EE have the potential to improve energy security and contribute to decreasing emissions in developing countries (Hinostroza et al., 2007).

Additionally, CDM has also projects to decrease hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulfur hexafluoride (SF6), which are human-generated greenhouse gases through industrial processes. However, the CDM does not include projects aiming to reduce emissions with nuclear facilities. In the first commitment period of the Kyoto Protocol 2008-2012, which is the main focus of this paper, only afforestation and reforestation projects are allowed under the category of sinks.

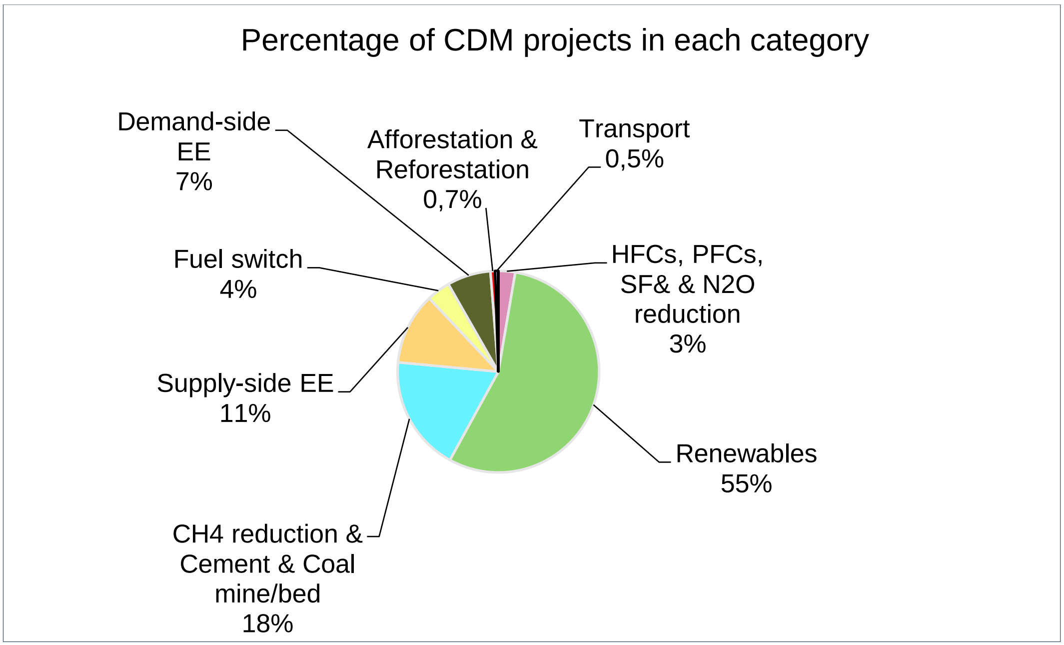

Figure 1. Percentage share of CDM projects in each category.
Source: UNEP Copenhagen Climate Centre (CCC) (2022)

Any project that can produce Certified Emission Credits (CERs) according to the rules defined by the CDM is required to fulfil the exact requirements and follow the same steps. This process is called the CDM project cycle (UNDP, 2003). Seven steps of the CDM project cycle are provided in Figure 2.

The first step is the *project design*, where project participants prepare project design documents and identify the potential projects which must satisfy the environmental integrity and additionality requirements. In order to assess these requirements, emissions produced by the projects are compared to a baseline scenario. Baseline scenarios can be created using UNFCCC's methodologies on a project basis. Project participants should also create a monitoring plan at this stage to gather precise data if the projects leads to emission reductions and if the emission reductions are in line with the scenarios. The second stage is *national approval*, where Designated National Authorities (DNAs) assess the projects and approve them according to both criteria set by UNFCCC and their countries. With these criteria, DNAs are responsible for evaluating if the projects support sustainable development in their country.

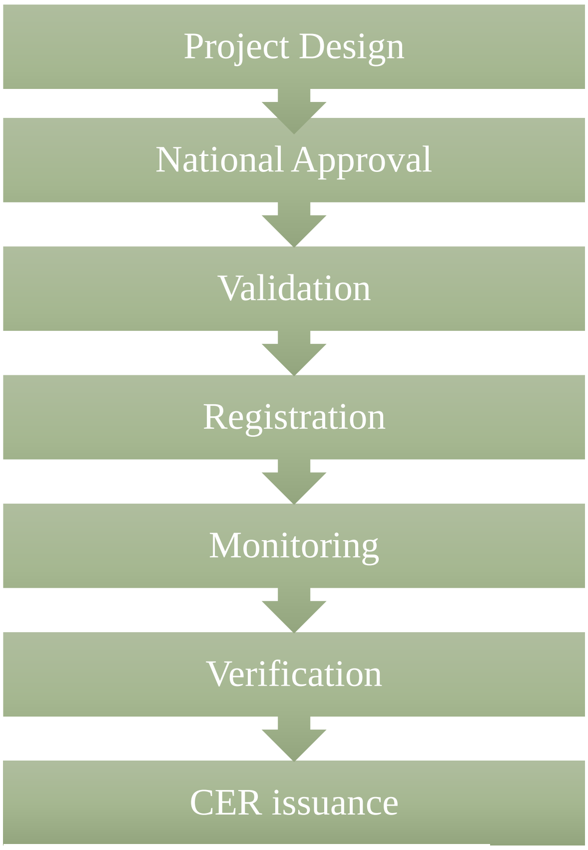

Figure 2. CDM project cycle.
Source: UNFCCC (2022a)

The following steps are the *validation* and *registration*, where the projects are assessed by a Designated Operational Entity (DOE) to validate the project. DOEs can be private companies operating in audit or consultancy that can evaluate emission reductions independently. If DOEs give a green light for the projects and validates them, the projects are sent to the CDM Executive Board for the *registration* process. The next step is *monitoring*, where the project participant is pledged to monitor actual emissions by taking into account the approved methodology. For that purpose, they prepare a monitoring report that evaluates CERs produced. Then, this report is submitted to the DOEs for the next step, i.e. *verification*. At the verification stage, an independent assessment is done by DOEs to control whether CERs are produced according to the guidelines and if the project achieves emission reductions for the mentioned period. If so, as a next and last step, DOEs submit a verification report to the CDM Executive Board for *CER issuance*.

CERs, each equivalent to one ton of carbon dioxide, can be seen as commodities bought and sold on the global carbon markets. As Parties can trade their emission permits as commodities, they acquire the flexibility to meet their targets defined under the Kyoto Protocol. Moreover, although the Protocol does not put any direct legally binding responsibility on non-Annex I Parties, the channel created by the CDM aims to encourage voluntary actions to fulfil the dual objectives of the mechanism (Banuri & Gupta, 2000). Furthermore, CERs issued for respective categories are shown in Figure 3. According to Article 12 of the Kyoto Protocol, CERs are produced once the projects start to operate. Therefore, those produced CERs can be used at any time by the developed countries as long as they ratify the Kyoto Protocol.

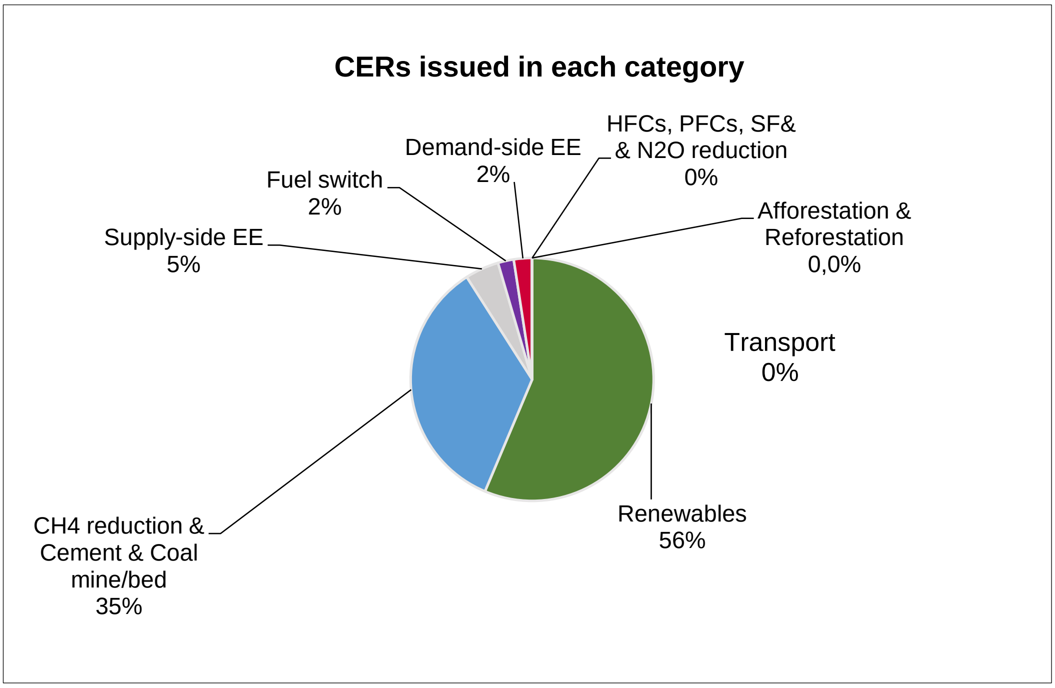

Figure 3. CERs issued in each category.
Source: UNEP Copenhagen Climate Centre (CCC) (2022)

In addition to CDM's emission reduction and sustainable development goals, the mechanism was also designed to assist developing countries in adaptation to climate change effects. For that purpose, UNFCCC has established the Adaptation Fund to create financial means for adaptation projects and help vulnerable countries. As a result, 2% of the revenues created by CERs have been transferred to the Adaptation Fund. During the first commitment period of the Kyoto Protocol, CDM was the only fund source. However, after 2012, the other two mechanisms of the Protocol (emissions trading and joint implementation) were also included as a financial source to the Adaptation Fund with a contribution of a 2% share of the proceeds (UNFCCC, 2022c).

3. Literature Review

Whether the CDM has contributed to emission reductions or not is controversial among previous studies. For instance, Huang & Barker (2012) conducted a dynamic heterogeneous panel data analysis on 80 CDM host countries from 1993 to 2009 to examine the relationship between the CDM projects and carbon dioxide emission reductions. The authors employed a pooled mean group estimator that allows for heterogeneous dynamic adjustments towards a common long-run equilibrium. Their result yielded a significant effect of CDM projects on emission reductions – i.e. in the long run, it is anticipated that the existence of CDM projects in host countries led to emission reductions.

Moreover, He et al. (2014) extended Huang & Barker's (2012) study and focused on 60 CDM host countries from 2005 to 2010. The authors employed a dynamic panel data model with an X-differencing procedure[4] and found a significant impact of CDM projects on emission reductions. They conclude that the international community must continue to support CDM projects for low carbon development in developing countries. Additionally, Banuri & Gupta (2000) studied the conceptual frameworks to define issues about the CDM, focusing primarily on sustainable development. The authors concluded that developing countries could adopt less GHG-intensive technologies through CDM projects, which would reduce emissions.

Furthermore, the mechanism has also the potential to prevent carbon leakage that might decrease the environmental effectiveness of international climate agreements. Kallbekken et al. (2007) studied how CDM can decrease carbon leakage by adopting a computable general equilibrium model and investigated the effect of three different baseline approaches.[5] Their result showed that realizing the potential of such leakage depends on how the CDM baseline approach explains this impact. Still, the authors concluded that under the realistic assumptions on the level of CDM activity, CDM has the potential to decrease carbon leakage regardless of which baseline approach is adopted.

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[4] The X-differencing procedure is a panel data econometric model, which uses systematic differencing by eliminating fixed effects and keeping the information and signal strength in situations where there is a unit root or a root near unity. The "panel fully aggregated" estimator (PFAE) is created through pooled least squares on X-differencing equations. For more details, see Han et al. (2013).

[5] Three scenarios were described by Kallbekken et al. (2007) as follows. Scenario 1 – No Kyoto (i.e. what the emissions would be without the implementation of the Kyoto Protocol). Scenario 2 – No CDM (i.e. To find the weight of carbon leakage with the implementation of the Kyoto Protocol, with IET and JI but without any CDM projects). Scenario 3 – CDM scenario.

On the other hand, Schneider (2007) focused on assessing the environmental integrity and sustainable development objectives of the CDM by using 93 registered CDM projects, including interviews and a literature survey. The selection of the projects was made randomly out of 768 projects registered between 2004 and 2007. The author ranked the projects according to the date of the registration request and then picked every eighth project. The results yielded that CDM had not successfully achieved its emission reduction objective. Schenider (2007) concluded that CDM had successfully created a market for greenhouse gas emissions; however, it did not delivered a high level of environmental integrity and sustainable development. The author also emphasized that there is room for developing the mechanism.

In another context, Schneider et al. (2010) focused on adipic acid projects within the CDM and investigated if these projects carry any risk against environmental integrity. Their result showed that CDM seemed to cause carbon leakage in 2008 and 2009 during the economic downturn when adipic acid production shifted from non-CDM plants to CDM plants. Such a shift probably happened from plants that emitted NO_2 or functioned in other countries with a cap under the Kyoto Protocol due to revenues provided by the CDM. The authors highlighted that the magnitude of such a carbon leakage was not specific but considering the CDM plants in the absence of CDM operated at the average global plant utilization rate, this shift increased GHG emissions by around 6.3 $MtCO_2$ in 2008 and 7.2 $MtCO_2$ in 2009. In terms of percentage perspective, these numbers correspond to 17% - 22% of CERs produced from this project type did not represent the actual emission reduction. Schneider et al. (2010) suggest that in order to prevent such a situation, the current baseline and monitoring methodology can be improved; one example can be implementing an ambitious baseline emission benchmark.

Moreover, Shi et al. (2021) focused on China as the biggest emitter of carbon dioxide and investigated if CDM projects have contributed to emission reduction in the country. The authors carried out panel data analysis at the provincial level from 2000 to 2017. In their analysis, provincial carbon dioxide was taken as the dependent variable while the number of CDM projects was taken as an independent variable, including a control variable for the selected series, the city fixed effect, and the year fixed effect. Since the government lacked data related to carbon emissions, the authors used a method to calculate carbon emissions by referring to previous studies.[6] They extended the regression model in the next step and took CDM project type as a dependent variable instead in order to capture the effect of projects that are cooperative and non-cooperative. The authors found that CDM

[6] The authors calculated the carbon emissions as follows: *Carbon emissions = Energy consumption × Carbon emission coefficient,* where energy consumption represents the energy usage mostly from coal, oil and gas; the carbon emission coefficient refers to a sensitivity coefficient of carbon emissions of various types of energies. The average value of such coefficient is calculated primarily according to the carbon emission coefficients published by the United States Department of Energy, the Japan Institute of Energy Economics, the Climate Change Projects of the National Science and Technology Commission, and the Energy Research Institute of National Development and Reform Commission.

projects significantly contributed to a decrease in carbon dioxide emissions per unit of GDP and the growth rate of carbon dioxide emissions. This empirical analysis also showed that the effect of cooperative projects on carbon emissions is more significant than that of non-cooperative ones. Their study also proved that the implementations of CDM projects in China supported the substitution of fossil usage in the energy sector and developed energy-utilization efficiency.

In a Latin American context, Watts et al. (2015) studied the dynamics of the global distribution of CDM projects. Their analysis focused more closely on Chile since it is one of the most active countries within CDM projects and has the most registered CERs among small countries. For that purpose, they conducted a case study with 180 renewable energy projects to understand the factors that affected the inclusion of projects to the CDM program and the additionality of the projects. Their results showed that additionality assessment under CDM is too subjective, preventing the projects' validation and transparency.

Moreover, another aspect that has been analysed in the literature is the uneven distribution of the CDM projects. Some countries are over-dominating other countries regarding the number of CDM projects (e.g. China, India or Brazil). Li & Lin (2021) studied the factors that affected the distribution of CDM projects with negative binomial regression and conducted a panel data analysis for 107 host countries. The authors created sub-groups for the host countries according to their number of operating CDM projects a year. They found that experience in advanced international trading, increasing demand for energy in the host countries, and the affluence of a host country positively affect the successful registration of the CDM projects. On the other hand, the cost of carbon emission reduction can prevent a successful registration. However, Li & Lin (2021) emphasized that in the case of host countries with fewer CDM projects, their result showed no significant effect between the industrial level, national carbon emission, and CDM projects' distribution.

The mentioned studies highlight that the debate about the CDM's impact on emission reductions is highly controversial and that results and interpretations change significantly according to used methodologies or included regions and countries. Nevertheless, it is essential to examine this issue to understand whether CDM can deliver its emission reduction purpose and, if not, how the mechanism can be improved to achieve its objective.

4. Data

This section describes the variables included in the analysis, data sources and how the process is handled. Afterwards, we end the section by presenting data limitations. However, before we move on to the next section, it is essential to highlight some points. First, the focus of this study is on the first commitment period of the Kyoto Protocol, i.e. 2008-2012. To examine the emission developments of countries, it is essential to include years before 2008. However, most developing countries lacked data prior to 1993; therefore, this paper considers the time period from 1993 to 2012. Second, the list of the countries is shaped after going through the CDM projects registered during the first commitment period related to the energy sector. Third, we eliminated any country with less than 17 observations for variables included in the regression. More details related to this process are provided under Section 4.2, Data Handling.

4.1 Data Sources

To investigate the impact of CDM projects on emissions for 69 countries from 1993 to 2012, we include the following variables in our regression model: carbon dioxide emissions per capita from the energy sector, the number of CDM projects per capita, gross domestic product per capita, square of gross domestic product per capita and a proxy variable representing the level of democracy. Summary of the variable names, descriptions and data sources are given in Table 1.

Our dependent variable is carbon dioxide emissions per capita, denoted as CO_2 and taken in logarithm. As shown in Section 2, energy-related projects have the most significant share of overall CDM projects. Additionally, as stated in the OECD Environmental Outlook Report for 2050 (2012), global GHG emissions could increase by 50% by 2050, 70% of which would occur due to energy consumption based on fossil fuels. Therefore, this paper focuses on emissions from the energy sector due to coal, oil, and gas usage. Data for CO_2 emissions is taken from Our World in Data (2022), which is updated regularly and contains information related to annual, per capita, cumulative and consumption-based carbon dioxide emissions. Their CO_2 emission is sourced from the Global Carbon Project.

The primary independent variable is the number of CDM projects per capita, denoted as CDM. Here we observe that CDM projects increase if a country is highly populated (e.g. China and India). In addition, main regressors are taken from a per capita perspective; therefore, the CDM variable is also considered as the number of projects per capita for respective countries. Data related to CDM projects are taken from UNEP Copenhagen Climate Centre (CCC) (2022). There are different stages for CDM projects. This paper considers the projects with status as *validation, de-registered, registered, registration request,* and *request review*. Dataset related to population (i.e. POP variable) is taken from World Development Indicators (WDI) provided by the World Bank (2022b).

The other independent variable is the gross domestic product per capita, denoted as GDP and taken in logarithm. Data related to GDP is taken from World Bank (2022a) for 1993-2012 and in current US dollars. Given dollar figures for GDP values are calculated from domestic currencies by using single year official exchange rates. The squared version of the GDP variable is also included as another independent variable, denoted as GDP^2.

Table 1. Summary of the variables and data sources.

Variable description	Symbols	Data sources
Carbon dioxide emissions per capita from the energy sector due to oil, gas and fuel usage. In logarithm.	$\mathbf{CO_2}$	Our World in Data (2022)
The number of CDM projects per capita.	**CDM**	UNEP Copenhagen Climate Centre – CDM/JI Pipeline Analysis and Database (2022)
Gross domestic product per capita. In logarithm.	**GDP**	World Bank (2022a)
Square of log of gross domestic product per capita.	$\mathbf{GDP^2}$	World Bank (2022a)
A proxy that represents the democracy level.	**DEMOC**	Polity5 database – Marshall & Gurr (2020)
Population (all residents regardless of legal status or citizenship)	**POP**	WDI, World Bank (2022b)

For a robustness check, a variable representing the level of democracy is also included in our regression, denoted by DEMOC. As a proxy for the DEMOC variable, we use the Polity indicator ("polity2") from the Polity5 Database due to Marshall and Gurr (2020).[7] The polity indicator shows scores ranging from -10 to +10, representing autocracies and democracies. This indicator is commonly used to analyse institutional quality derived from factors such as freedom of suffrage, operational constraints and respect for fundamental political rights. Such factors might affect how the host countries can operate within the CDM and the number of projects they host since developed countries could consider these factors as

[7] Polity5 database can be downloaded from: http://www.systemicpeace.org/inscrdata.html

stability, creating a tendency to make more investments in those developing countries. Additionally, previous studies show that the democracy level is positively or negatively related to emissions; or does not have any relationship (e.g. Chou et al., 2019; Lægreid, 2014; Selseng et al., 2022). Therefore, this study includes the DEMOC variable as the next step in the regression model to examine if the estimations and interpretations change. Lastly, all data were gathered from the mentioned data sources in April-May 2022.

4.2 Data Handling

Dataset taken from UNEP CCC (2022) contains 12524 CDM projects in various sectors with different status stages (e.g. validation, registered, withdrawal, etc.). As a first step for cleaning the CDM projects dataset, we selected projects with the statuses validation, de-registered, registered, registration request and request review. Other statuses are connected to unsuccessful project implementation and withdrawals from the projects, which are irrelevant to our study. Subsequently, since our emissions are taken from the energy sector, we went through the projects and eliminated those unrelated to the energy sector (e.g. methane reduction, agriculture, transport, deforestation), resulting in 6184 CDM projects.

Accordingly, we created a list of countries and eliminated those with less than 17 observations in any variable included in the regression model. After that, we created the country list with the number of CDM projects calculated cumulatively for each country in respective years. Finally, to create the number of CDM projects per capita, we divided the number of projects by the population and multiplied it by one million (e.g. the number of projects = population /1000000). By doing so, we believe that per capita reflects a better perspective for this analysis. The list of countries we have left after various applications to the CDM data set is the main scope of this analysis – i.e. 69 developing countries. A detailed list of the countries, their first registered CDM project year, and the number of projects are provided in Appendix 2 (see Table A2).

Furthermore, the dataset related to the emissions contained information about over 100 countries for the time period of 1850-2021. We eliminated years and countries that are out of interest. Carbon dioxide emissions per capita represent oil, gas and fuel usage for energy production, including cement production. As a next step, we extracted the emissions from cement production so that we only get emissions produced for energy purposes. In this dataset, land-use change is excluded. Lastly, for the datasets related to GDP, DEMOC and POP variables, we only selected the countries and time periods related to our study. Most data cleaning processes were done in Excel, while the statistical computations were carried out in Stata and EViews.

4.3 Descriptive Statistics

Table 2 represents the descriptive statistics of the variables included in the analysis. There are 1,380 observations, except for the variables GDP and GDP^2. Since there are missing values for the GDP and GDP^2 variables, we have unbalanced panel data.[8] All variables except DEMOC, CDM and POP are in log form. As expected, the variable representing population (i.e. POP) has the highest values for each category. Similar values for mean and median emphasize that there are not many outliers in each dataset. It is observed that only the POP variable has a significant difference between the mean and median, implying that the population of 69 selected countries differs substantially from each other.

Furthermore, among the other variables than population, GDP^2 has the highest average of 58.85 with a standard deviation of 19.14, while CO_2 has the lowest average of 0.23 with a standard deviation of 1.39. A higher standard deviation represents a spread out from the mean, so GDP^2 has the biggest spread compared to other variables. Regarding the shape of the data and skewness, CO_2, GDP, GDP^2, and DEMOC are fairly/relatively symmetrical. However, CDM and Population are right-skewed since their skewness values are greater than one.

Table 2. Descriptive statistics of the variables.

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max	Skewness
CO_2	1,380	.2299895	.3418145	1.385827	-3.35240	3.552945	-.300254
CDM	1,380	.236098	0	.6416184	0	6.214902	4.37607
GDP	1,376	7.572877	7.545501	1.227363	4.84383	10.92498	.309110
GDP^2	1,376	58.85379	56.93459	19.14108	23.4627	119.3551	.658699
DEMOC	1,380	2.644928	5	6.436842	-10	10	-.587587
POP*	1,380	63.89635	12.47253	200.434	.53190	1354.19	5.29954

*Note: Population is represented in millions.

[8] Unbalanced panel datasets refer to datasets with missing values for some observations for some of the groups. In the case of a balanced panel dataset, all groups have the same number of observations.

4.4 Data Limitations

As different procedures are applied, we face some limitations within the scope of this analysis. The paper focuses on 69 developing countries, and the list of countries is shaped mainly according to the CDM projects done in the energy sector. Considering the multiple implications of cleaning the CDM dataset in the previous section, many projects from other sectors and some developing countries from the list were eliminated. In that sense, the number of countries in our analysis is restricted, so drawing general conclusions about other countries might not entirely reflect reality. Besides, each country has different emission development paths. The magnitude of the CDM's impact on emissions might also be determined by country-specific characteristics, which are not included in the scope of this analysis.

5. Methodology

A panel data analysis is employed in this paper to examine the impact of CDM projects on carbon dioxide emissions per capita since it brings various advantages over a time-series analysis. Panel data, also known as longitudinal data, includes observations over time on a number of cross-sectional units such as individuals, firms or countries. Such data is used to examine the variability across time and variables. As provided under Section 4.3 Descriptive Statistics, for each variable, the number of observations is changing; therefore, we have unbalanced panel data in this analysis.

Panel data is advantageous when the main aim is to observe a group rather than an individual (i.e. a country). In that sense, the analysis does not lose much information, and with the panel data structure, the noise created in individual time series is eliminated. It can be used when dynamic changes occur because of repeated cross-sectional observations. Besides, the panel data structure includes cross-sections and time-series, represented by N and T. Here, N refers to a number of groups (e.g. countries), and T refers to the number of years. In this analysis, we have N=69 and T=20.

Moreover, selecting an appropriate model for panel data analysis is essential since wrong model specifications might lead to biased estimates with unreliable results. Since we are handling a dynamic process, capturing all these features with a unique method is crucial. In the following subsections, we introduce the generic form of the Auto-regressive Distributed Lag (ARDL) model used in dynamic processes, subsequently requiring steps to justify the model selection. After that, a model specification for this research is provided.

5.1 Auto-regressive Distributed Lag (ARDL) Model

Auto-regressive Distributed Lag (ARDL) model has gained significant attention over the last decades, and it is seen as a valuable method to investigate the short-run and long-run relationships for economic time-series. The model was introduced by Pesaran & Shin (1999) and a few years later extended by Pesaran et al. (2001). The model can be used when there are variables either I(0), I(1), stationary or non-stationary, respectively, or a mixture of both.[9] A time series is stationary if its value turns to its long-run average value and its characteristics are not affected by changes over time, with a constant mean, variance and covariance. On the other hand, a time series is non-stationary if it does not turn to its long-run average value where its mean, variance and covariance change over time. In the case of non-stationary series, we cannot apply the Ordinary Least Square (OLS) or Vector Autoregressive (VAR) model for the required estimation. Such an application would lead to spurious regressions[10] and cause misinterpretations.

It is possible to take a difference of the non-stationary variable to make it stationary; in other words, transforming I(1) to I(0). Nevertheless, this implication causes to lose the information related to the long-run relationship. Thus, differencing the time series is not an option when the focus is observing both short-run and long-run relationships. Pesaran et al. (2001) introduced the auto-regressive distributed lag (ARDL) model for such purpose, where the model has numerous advantages when there are variables with I(0), I(1) or partially cointegrated. The model's outcome provides short-run and long-run relationships simultaneously, and it is also suitable for use when there is a small sample size (Pesaran et al., 2001). When ARDL is employed, residual correlations are not an issue; therefore, endogeneity is not a problem within this model (Pesaran & Shin, 1999).

One concern within the ARDL model is deciding on the optimal lags. Including the unnecessary lagged version of dependent and independent variables might cause multicollinearity. So, it is essential to decide on optimal lags for the required analysis. In addition to that, when handling time-series or panel data, it is vital to understand the characteristics of the variables included in the study and their integrations and interactions over a time period (Shrestha & Bhatta, 2018). Thus, before using the ARDL model, we need to be sure that our variables are fulfilling the requirements of the model (i.e. variables are solely I(0), solely I(1) or partially cointegrated). The following sub-section provides a background for this purpose.

5.1.1 Unit Root Test

Most macroeconomic variables show non-stationary characteristics, making it essential to examine the integration order of the considered variables. As mentioned in section 5.1, to satisfy the ARDL model requirements, we need to ensure that included variables should be I(0), I(1) or mutually cointegrated. In the case of I(2) and higher integration orders, we cannot use the ARDL model. In the case of I (1), it is possible to acquire a long-run relationship between the variables.

[9] Here, I(0) and I(1) show the order of integration of zero and one. The order of integration represents the minimum number of differences demanded to acquire a covariance-stationary series. For instance, for I(1), we can take the difference of the variable once, then make it I(0) – i.e. stationary.
[10] Spurious regressions occur when ordinary least square or similar methods are applied to time series with non-stationary. This regression shows a significant relationship between variables, which in fact they do not have any correlation. Therefore, the interpretation of such relationships would be misleading.

There are multiple ways of checking whether the time series is stationary or non-stationary. The first way is to create graphs of the variables to observe how they change over time. The stationary variables follow a trend which is constant over time, whereas non-stationary variables follow an increasing or decreasing path over time. Although creating graphs can give an intuition, it is required to do a statistical computation for making a final decision.

This paper employs two unit root tests that can be used with heterogeneous panels for testing stationarity: Im, Pesaran and Smith (IPS) unit root test proposed by Im et al. (2003) and Cross-sectional Augmented Dickey-Fuller (CADF) unit root test proposed by Pesaran (2003). Both tests have a null hypothesis as the series has a unit root (i.e. the series is non-stationary). The reason behind using two unit root test is that the IPS test assumes cross-section units are cross-sectional independent; in contrast, the CADF test includes cross-sectional dependency in testing.[11] Considered countries in our analysis might be politically, economically or culturally related to each other, meaning that there might be a presence of cross-sectional dependence. If so, the IPS test results will not provide correct interpretations. Thus, comparing two test results will provide insight into cross dependence and if the interpretations of test results change significantly.

5.2 Cointegration Test and the Error Correction Model

In the case of non-stationary variables with I(1), there might be a case where linear combinations of those variables are stationary, i.e. I(0). Granger (1981) introduced the concept of cointegration, and Engle & Granger (1987) extended this context by providing a method of testing cointegration. However, one drawback of this method is that in the case of multiple variables included in the analysis, it might show more than two cointegrating relationships. Unlike Engle & Granger (1987), Johansen (1988) also provided a test for cointegration where it allows for more than one cointegration relationship. However, this method can only be used when all the variables included in the regression are in the same integration order, i.e. I(1). In our case, having variables with I(0) and I(1), we assess the F-bounds test provided by Pesaran et al. (2001).

F-bounds test is based on standard F- and t-statistics, which are used for testing the significance of lagged levels of the variables in a univariate equilibrium correction mechanism. With the F-bounds test, one can check possible cointegration, hence, understand if there is a long-run relationship between the variables. The test provides two asymptotic critical values: one if all variables are solely I(1) and the other if all variables are solely I(0). Such two critical values provide a span for including all possible categorizations of the regressors that are purely I(0), purely

[11] Cross-sectional dependence refers to a situation where units in the cross-section are correlated due to common shocks and unobserved components.

I(1) or a mutually cointegrated (Pesaran et al., 2001). The null and the alternative hypothesis of F-bounds defined as follows:

H_o: no cointegration
H_a: cointegration

If the estimated test statistics is greater than the upper critical value (i.e. critical value for I(1)), the null hypothesis is rejected. However, if the estimated test statistics are smaller than the lower bound (i.e. critical value for I(0)), we fail to reject the null hypothesis of no cointegration; hence a long-run relationship does not exist. If the estimated F-statistics lies between the two critical values (i.e. I(0) and I(1)), then the test is inconclusive. When the null hypothesis of no cointegration is rejected, we can examine both short-run and long-run relationships between the variables. According to Engle and Granger (1987), in the presence of cointegration and variables with I(1), it is possible to acquire the long-run relationship by deriving the Error Correction Model (ECM). This derivation is provided in the following section.

5.3 Model Specification

This study assumes that synergies between CDM projects and CO_2 are represented by the unrestricted ARDL(p,q,q,q) model, as follows:

$$\begin{aligned} CO_{2it} = \sum_{j=1}^{p} \alpha_{ij} CO_{2i,t-j} & \\ & + \sum_{j=0}^{q} \beta_{ij} CDM_{i,t-j} \\ & + \sum_{j=0}^{q} \gamma_{ij} GDP_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} GDP_{i,t-j}^{2} + \theta_i t + \mu_i + v_{it} \qquad (\mathbf{1}) \end{aligned}$$

where
$i = 1,2, \dots ,69 \ and \ t = 1, \dots ,20$

In equation **(1)**, the dependent variable is CO_{2it}, while CDM_{it}, GDP_{it} and GDP^2_{it} represent the explanatory variables. θ_i represents time trend, μ_i shows unobservable country-specific effects, and v_{it} represents assumed well-behaved errors; in other words, v_{it} is serially uncorrelated and independently distributed across countries. This paper employs the ARDL(1,1,1,1) model due to Pesaran et al. (1999). With the inclusion of the GDP and GDP^2 variables, this study allows the possibility of the presence of the Environmental Kuznets Curve (EKC).[12] So, the coefficient signs of these two variables will provide insight into whether the EKC can be validated.

5.3.1 Transforming Specified Model to Error Correction Model

Previous studies showed that CO_{2it}, GDP_{it} and GDP^2_{it} are cointegrated (e.g. Müller-Fürstenberger & Wagner, 2007; Perman & Stern, 2003). We test this issue under Section 6 to compare our results with the existing literature. According to Engle and Granger (1987), if there is cointegration Error Correction Model should be derived, which considers the co-movements of the variables over time. By using equation **(1)**, we can redefine our model specification in terms of the Error Correction Model as follows:

$$\Delta CO_{2it} = \alpha'_{i1}\left(CO_{2i,t-1} + \frac{\mu'_i}{\propto'_{i1}} + \frac{\beta'_{i1}}{\propto'_{i1}} CDM_{it} + \frac{\gamma'_{i1}}{\propto'_{i1}} GDP_{it} + \frac{\delta'_{i1}}{\propto'_{i1}} GDP^2_{it}\right) - \beta_{i1}\Delta CDM_{\mathrm{i,t-1}} - \gamma_{i1}\,\Delta \mathrm{GDP}_{\mathrm{i,t-1}} - \delta_{i1}\Delta\,\mathrm{GDP}^2_{\mathrm{i,t-1}} + \theta_{it} + v_{it} \qquad (\mathbf{2})$$

$$\mathrm{i} = 1,2,\dots,69 \text{ and } \mathrm{t} = 1,\dots,20$$

where

$$\propto'_{i1} = -(1-\alpha_{i1})$$
$$\mu'_i = \mu_i$$
$$\beta'_{i1} = \beta_{i0} + \beta_{i1}$$
$$\gamma'_{i1} = \gamma_{i0} + \gamma_{i1}$$
$$\delta'_{i1} = \delta_{i0} + \delta_{i1}$$

Here, $\propto'_{i1}$ represent the coefficient for the speed of adjustment, while $\frac{\beta'_{i1}}{\propto'_{i1}}$, $\frac{\gamma'_{i1}}{\propto'_{i1}}$ and $\frac{\delta'_{i1}}{\propto'_{i1}}$ represent the long-run coefficients for CDM_{it}, GDP_{it} and GDP_{it}^2, respectively. Short-run coefficients of CDM_{it}, GDP_{it} and GDP_{it}^2 are represented by β_{i1}, γ_{i1} and δ_{i1}, respectively.

[12] According to Kuznets (1955), industrializing nations first experience an increase and then a decrease in income equality. A similar approach is also applied to the environmental context (Environmental Kuznets Curve, EKC), where an inverted U-shape represents the relationship between pollution and growth. Thus, industrializing nations first experience an increase in pollution with increasing growth, but then a decline of such pollution as growth continues to increase.

5.3.2 Pooled Mean Group (PMG) Estimator

The Pooled Mean Group (PMG) estimator was introduced by Pesaran et al. (1999) to overcome back draws with the mean group and traditional pooled estimators (fixed and random effects). The Mean Group (MG) estimator creates consistent estimates of the average parameters (Pesaran & Smith, 1995); however, it cannot detect that particular parameters can be the same across groups. Fixed and random effects are also counted as extremes since they allow the intercepts to vary across groups; meanwhile, all other coefficients and error variances are constrained to be the same. PMG was introduced as an intermediate estimator and includes both pooling and averaging. It allows the intercepts, error variances and the short-run coefficients to vary across groups while it constrains the long-run coefficients to be the same.

There are some assumptions made for the PMG estimator: (i) error terms are uncorrelated, (ii) there exists a long-run relationship between the dependent and the explanatory variables, (iii) long-run coefficients are homogeneous across groups. The last assumption regarding the long-run homogeneity across groups is represented mathematically from the Equation $(\mathbf{2})$ as follows:

$$
\begin{aligned}
\propto'_{i1} &= -(1-\alpha_{i1}) \\
\mu'_{i} &= \mu_{i} \\
\beta'_{i1} &= \beta_{i0} + \beta_{i1} \\
\gamma'_{i1} &= \gamma_{i0} + \gamma_{i1} \\
\delta'_{i1} &= \delta_{i0} + \delta_{i1}
\end{aligned}
$$

Additionally, Pesaran et al. (1999) state that when T is large (as in our case), the PMG estimator is robust to outliers and the lag selection for the ARDL model. Therefore, this paper employs the ARDL (1,1,1,1) model to investigate the long-term relationship between the CDM projects and emissions.

6. Results

This section provides the empirical results of the theories discussed in the previous section. First, we test the integration order of the variables with two different unit root tests, followed by a cointegration test to examine a possible long-run relationship. Afterwards, long-run and short-run relationships are estimated with the PMG estimator.

6.1 Unit Root Test for Stationarity

IPS and CADF unit root tests are adopted to investigate the order of integration of the variables, and tests are computed at a level and first difference to observe if non-stationary variables become stationary after differencing once. The null hypothesis for both tests is that the series has a unit root (i.e. the series is non-stationary). To satisfy the requirement of the ARDL model, there should not be any variable with I(2) or a higher order of integration.

Table 3 summarizes the test statistics and their corresponding p-values in parenthesis. The decision column summarizes the order of integration for each variable for the respective tests, and statistical significances are considered at the 5% level and marked with an asterisk. Considering the IPS test results, it is observed that CO_2, CDM, GDP and GDP^2 became stationary after first differencing, implying that they have I(1). At the same time, the DEMOC variable is already stationary at the level, so differencing does not change the order of integration. On the contrary, the CADF test shows that CO_2, GDP, and DEMOC variables became stationary after the first difference, indicating they have I(1). Additionally, CADF test results yield that CDM and GDP^2 variables are already stationary at level; therefore, differencing does not change the order of integration in this case as well.

As mentioned in Section 5.1.1, with cross-sectional dependency, the IPS test might yield that variables are non-stationary, in fact they are stationary. Therefore, the difference between these two tests might occur due to cross-sectional dependency. Nevertheless, the most important thing is that none of the variables has I(2) or a higher order of integration; hence, the ARDL model can be used safely.

Table 3. Results of the unit root tests.
Source: Author's calculation on EViews and Stata.

	IPS test			CADF test		
Variables	Level	First difference	**Decision**	Level	First difference	**Decision**
CO_2	4.00688 (1.000)	-7.10737* (0.0000)	**I(1)**	-1.608 (1.000)	-2.686* (0.000)	**I(1)**
CDM	17.6926 (1.000)	-2.97057* (0.0015)	**I(1)**	-1.944* (0.041)	-2.806* (0.000)	**I(0)**
GDP	3.07541 (0.9989)	-8.19394* (0.0000)	**I(1)**	-1.466 (0.071)	-7.461* (0.000)	**I(1)**
GDP^2	4.04079 (1.0000)	-8.19384* (0.0000)	**I(1)**	-3.389* (0.000)	-7.461* (0.000)	**I(0)**
DEMOC	-8.7000* (0.000)	-9.23799* (0.0000)	**I(0)**	-1.380 (1.000)	-2.073* (0.003)	**I(1)**

Note: P-values are provided in parenthesis. Intercept and trend are included while tests are carried out. For Im, Pesaran and Smith (IPS) unit root test, probabilities are computed assuming asymptotic normality. Statistical significancy is shown with * at the 5% level.

6.2 F-bounds Test for Cointegration

The F-bounds test is used in this section to examine if the variables included in the regression models are cointegrated. Table 4 summarizes the test results. The first estimated model shows that CDM, GDP and GDP^2 are taken as explanatory variables. In addition to the explanatory variables in the first model, the second model also includes the DEMOC variable. In both models, it is observed that F statistics (8.800 and 7.200) are over the I(1) bound at 10%, 5% and 1% levels. This outcome implies that the null hypothesis of no cointegration is rejected since both F-statistics are over the I(1) bounds at every significance level; hence, there is cointegration between the dependent and independent variables.

Table 4. F-bounds test results for cointegration.
Source: Author's calculation on Stata.

Estimated model	F-statistic	10% critical value		5% critical value		1% critical value	
		I(0)	I(1)	I(0)	(I)	I(0)	I(1)
CO_2 ~ CDM, GDP,GDP^2	**8.800**	3.470	4.450	4.010	5.070	5.170	6.360
CO_2 ~ CDM, GDP, GDP^2, DEMOC	**7.200**	3.030	4.060	3.470	4.570	4.400	5.720

6.3 Pooled Mean Group (PMG) Estimator for Short-run and Long-run Relationships

The previous section proved that variables included in the analysis are cointegrated, so the long-run relationship between them can be acquired. Table 5 represents the estimation of the ARDL(1,1,1,1) model with the PMG estimator by providing short- and long-run coefficients, where we focused on the impact of CDM projects on carbon dioxide emissions per capita for 69 countries from 1993 to 2012. The dependent variable is CO_2, while the independent variables are CDM, GDP and GDP^2. The PMG estimator allows the short-run adjustments to vary between countries while the long-run coefficients are the same (i.e. homogenous). The results also provide a speed of adjustment, representing the pace of the model returning to its long-run equilibrium after any structural changes, which usually takes a value between 0 and -1.

The results in Table 5 indicate that the coefficient for the speed of adjustment is significant, and when there is any structural break or change, the model moves from a short-run state to a long-run equilibrium at a rate of 0.491. This outcome can also be interpreted as approximately 49% of disequilibrium is corrected within one year (since our data is taken annually). Regarding the long-run coefficients, all variables are significant. The positive coefficient sign of the CDM variable means that an increase in the number of CDM projects per capita would lead to increased emissions, which contradicts the CDM's emission reduction objective. Moreover, the results indicate that GDP and GDP^2 are positively and negatively related to CO_2. This outcome implies that an increase in GDP would increase CO_2; however, after a certain point, it would decrease CO_2, which validates the Environmental Kuznets Curve (EKC). Considering the short-run outcomes, none of the variables is significant. However, in the short run, the negative coefficient sign of the CDM variable implies that with the implementation of CDM projects, emissions will be reduced.

Table 5. PMG estimator for the long-run and short-run relationships.
Source: Author's calculation on Stata.

Dependent variable: CO_{2it}	
Speed of adjustment	-0.491**
	(-2.98)
Long-run coefficients	
CDM_{it}	0.0370*
	(2.00)
GDP_{it}	0.901***
	(6.83)
GDP_{it}^2	-0.0507***
	(-6.03)

Short-run coefficients	
$\Delta CDM_{i, t-1}$	-0.893
	(-1.71)
$\Delta GDP_{i, t-1}$	1.874
	(0.79)
$\Delta GDP^2_{i,t-1}$	-0.0931
	(-0.68)
Trend	0.00921
	(1.30)
Constant	-20.37
	(-1.36)
Observations	1307
Number of countries	69

Note: PMG estimator is used for estimating ARDL (1,1,1,1) model, including a time trend. T-statistics are provided in parentheses.
Significance levels:
*** $p < 0.001$;
** $p < 0.01$;
* $p < 0.05$.

Next, we include the DEMOC variable in the regression model to test if the interpretations would change. The results of this estimation are summarized in Table 6. Compared to the previous results, the coefficient of the speed of adjustment decreased slightly and became insignificant. In the long-run, all variables are still significant, and the absolute value of the coefficients has increased slightly. The coefficient sign of the CDM variable is still positive, referring that emissions are increased with the implementation of CDM projects. Similarly, coefficient signs of the GDP and GDP^2 are still in line with the previous estimation, validating the EKC.

Moreover, it is also observed that the DEMOC variable has a significant and positive effect on emissions, meaning that a higher democracy level (or better governance and higher institutional quality) leads to higher emissions. Previous studies focused on the synergies between democracy and economic growth found a significant and positive relationship (e.g. Acemoglu et al., 2019; Persson & Tabellini, 2009). Our results confirmed the positive relationship between GDP and CO_2; therefore, a higher democracy level triggers higher economic growth, stimulating higher emissions.

Nevertheless, our results regarding the positive relationship between democracy level and emissions contradict some studies which highlight a negative relationship between democracy level and environmental commitment (e.g. Neumayer, 2002; Chou et al., 2019). Such differences might stem from different variables used as proxies to measure democracy level.

Table 6. PMG estimator for the long-run and short-run relationships, including the DEMOC variable. Source: Author's calculation on Stata.

Dependent variable: CO_{2it}	
Speed of adjustment	-0.341
	(-1.46)
Long-run coefficients	
CDM_{it}	0.0600**
	(2.88)
GDP_{it}	1.369***
	(7.28)
GDP_{it}^2	-0.0870***
	(-6.96)
DEMOC	0.0384***
	(7.94)
Short-run coefficients	
$\Delta CDM_{i,t-1}$	-0.605
	(-1.23)
$\Delta GDP_{i,t-1}$	2.851
	(1.19)
$\Delta GDP^2_{i,t-1}$	-0.163
	(-1.18)
$\Delta DEMOC_{i,t-1}$	-0.00399
	(-0.67)
Trend	0.00458
	(0.61)
Constant	-11.26
	(-0.69)
Observations	1307
Number of countries	69

Note: PMG estimator is used for estimating ARDL (1,1,1,1) model, including a time trend. T-statistics are provided in parentheses.
Significance levels:
*** $p < 0.001$;
** $p < 0.01$;
* $p < 0.05$.

To sum, by allowing heterogeneity across 69 developing countries, this paper provides a significant and positive relationship between CDM projects and carbon dioxide emissions per capita, implying that with the implementation of CDM projects, emissions increased over 1993-2012. Our results validate the Environmental Kuznets Curve (EKC), and findings related to a positive relationship between CDM-CO_2 and GDP-CO_2 reflect previous studies (e.g. Schneider, 2007;

Rosendahl & Strand, 2009; Schneider et al., 2010; Osadume & University, 2021; Sharma, 2011).

7. Discussion

The previous section provided empirical results that CDM projects did not contribute to emission reductions in developing countries over 1993-2012. The main reason for observing an emission increase with the implementation of CDM projects might be how the projects are assessed concerning additionality and how the estimated emission reductions are issued. CDM is considered an offsetting mechanism since reductions made in developing countries are used to offset emissions made in developed countries (Paulsson, 2009). In that sense, assessments related to additionality and produced CERs should be done carefully and reflect reality. As long as non-additional projects are operated within the CDM and CERs do not reflect the actual emission reductions, it is likely to observe increased emissions with the implementation of CDM projects.

According to Carbon Market Watch (2018), most of the emission credits (CERs) issued under CDM would likely happen anyway. Even on some occasions, the mechanism encouraged companies to intensify their emissions to generate more emission credits for their destruction. This issue is commonly discussed and highlighted in previous studies, which explains why we observe a positive impact of CDM projects on emissions. For instance, project designers might manipulate the baselines by claiming higher baseline emission rates to show that their project leads to higher emission reductions. Such a situation would likely produce higher CERs, making the project attractive for investors and providing a higher investment flow for host countries. However, if more CERs are produced than emissions are reduced, CDM will increase total emissions.

Another factor why CDM projects' implementation led to emission increases can be explained due to asymmetric information. For projects to be implemented, the project's cost should be in a range where there is an adequately high cost for the project not to be implemented without CDM but sufficiently low to make the project feasible under CDM. However, the regulators cannot assess how high the cost might be in real life (Rosendahl & Strand, 2009); thus, the actors cannot simply evaluate optimal benefits due to diverse needs, interests and information gaps (Wang, 2010). Moreover, such asymmetric information could also affect the assessments regarding additionality, which might trigger ineffective projects to be implemented within the mechanism.

Additionally, the methodology called barrier analysis[13] (i.e. a most commonly used method assessing the additionality of CDM projects) cannot distinguish between additional and non-additional projects (Schneider, 2007). Unfortunately, the implication process of the barrier analysis is vastly subjective and ambiguous; therefore, it is hard to validate the process in an objective and transparent way. Moreover, CDM projects can be perceived as foreign direct investments (FDI) since projects provide investment flows to host countries. Previous studies describe FDI as a trigger for economic growth and found a significant and positive relationship between FDI and GDP (e.g. Ghatak and Halicioglu, 2007; Neuhaus, 2006). As shown in the previous section, our results also proved a significant and positive relationship between GDP and CO_2, implying that FDI would have an indirect and positive impact on emissions.

These mentioned problems might likely prevent CDM from delivering its emission reduction purpose. Therefore, increased transparency, improved methodologies and better governance regarding the additionality assessments should be ensured to overcome such issues. In addition, increased partnerships between countries to learn more about their sectors can also eliminate or reduce asymmetric information. Nevertheless, results among previous studies change significantly depending on which methodology, period and region are selected. This study included a range of countries from different continents with different sizes in terms of population, economic growth and democracy. Thus, including other relevant variables or more countries on the list might affect the results substantially.

Lastly, it is also noteworthy to mention that this paper employs a PMG estimator with an ARDL model to examine the long-run and short-run relationships between the CDM projects and emission development. However, one back draw with the PMG estimator is that if the time period is short (e.g. less than ten years), it cannot provide efficient estimates, which is a limitation within the model. Therefore, one can consider employing other estimators or models when the focus is studying short time periods.

[13] The barrier analysis must show that obstacles would prevent the proposed project from being implemented if the project activity were not registered as a CDM activity.

8. Conclusion

As the first global mechanism where developed and developing countries are provided with a channel to cooperate for climate change mitigation, CDM has received many criticisms. Although the mechanism has created a global market for greenhouse gas emissions, it failed to deliver its emission reduction purpose. However, the experiences from CDM and understanding of how to improve the mechanism play an essential role in shaping future work related to global climate change mitigation.

In order to examine the empirical link between CDM projects and carbon dioxide emissions per capita, this study employs dynamic heterogeneous panel data for 69 eligible host countries from 1993 to 2012. The study mainly focuses on Pooled Mean Group (PMG) estimator that allows short-run coefficients to alter between groups but restricts long-run coefficients to be the same across groups. The results indicate a significant and positive relationship between CDM projects and emissions in the long run, implying that with the implementation of CDM projects, it is anticipated that emissions would also increase. This outcome aligns with most of the literature investigating the additionality of CDM projects, i.e. whether the developing countries experience emission reductions without implementing such projects. Our results also validate the Environmental Kuznets Curve (EKC). In order to improve the mechanism and achieve emission reductions, how the methodologies are defined and carried out, subsequently, how this process is followed up should be improved. Indeed, increased transparency and enhanced evaluation regarding the additionality of CDM projects also play an essential role.

Nonetheless, it is vital to keep in mind that this study considers only the first commitment period of the Kyoto Protocol (i.e. 2008-2012), which was the very beginning of this mechanism in practice. Experiences and learnings from the first commitment period have also shaped the overall work of the second commitment period. Therefore, by limiting the scope of the study to the first commitment period, we might not capture the full effect of the CDM on emission development in developing countries. As a future research idea, one can consider extending the time period (e.g. 1993-2020) to get a better interpretation. Certainly, a more extended period can provide a better policy framework for countries. One can also consider redefining the CDM variable (such as volume of CDM credits - CERs) and include other relevant variables into the estimations (e.g. trade) to observe if the interpretations of the results change.

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Appendix 1

Table A1. Correlation matrix.
Source: Author's calculation on Stata.

	CO_2	CDM	GDP	GDP^2	DEMOC	POP
CO_2	1.0000					
CDM	0.1524	1.0000				
GDP	0.7892	0.3367	1.0000			
GDP^2	0.7770	0.3417	0.9955	1.0000		
DEMOC	0.0414	0.2049	0.1465	0.1289	1.0000	
POP	0.0528	0.0193	-0.1022	-0.1051	-0.0628	1.000

Appendix 2

Table A2. List of countries, first registration year and the number of CDM projects. Source: UNEP Copenhagen Climate Centre CDM/JI Analysis and Database (2022)

Country code	**Country name**	**1st CDM project year**	**Total CDM projects over 2008-2012**
ALB	Albania	2008	3
ARG	Argentina	2004	48
ARM	Armenia	2005	6
AZE	Azerbaijan	2011	2
BGD	Bangladesh	2006	3
BTN	Bhutan	2005	1
BOL	Bolivia	2002	4
BRA	Brazil	2003	286
KHM	Cambodia	2008	6
CMR	Cameroon	2011	2
CHL	Chile	2004	95
CHN	China	2004	3757
COL	Colombia	2005	64
CRI	Costa Rica	2004	16
CIV	Côte d'Ivoire	2008	4
CUB	Cuba	2006	1
CYP	Cyprus	2006	6
DOM	Dominican Republic	2006	14
ECU	Ecuador	2004	24
EGY	Egypt	2006	13
SLV	El Salvador	2005	4
FJI	Fiji	2005	1
GEO	Georgia	2008	4
GTM	Guatemala	2003	13
GUY	Guyana	2006	1
HND	Honduras	2004	27
IND	India	2004	1424
IDN	Indonesia	2005	61
IRN	Iran	2010	14
ISR	Israel	2006	15
JAM	Jamaica	2005	2
JOR	Jordan	2007	2
KEN	Kenya	2006	14
LAO	Laos	2006	4

LBY	Libya	2011	2
MDG	Madagascar	2008	3
MYS	Malaysia	2005	51
MLI	Mali	2007	1
MUS	Mauritius	2010	1
MEX	Mexico	2004	53
MDA	Moldova	2005	5
MNG	Mongolia	2006	4
MAR	Morocco	2004	12
NPL	Nepal	2010	2
NIC	Nicaragua	2005	7
NGA	Nigeria	2008	4
MKD	North Macedonia	2008	6
PAK	Pakistan	2006	31
PAN	Panama	2005	17
PNG	Papua New Guinea	2006	1
PER	Peru	2005	52
PHL	Philippines	2005	23
RWA	Rwanda	2009	1
SAU	Saudi Arabia	2012	1
SEN	Senegal	2008	3
SGP	Singapore	2008	2
ZAF	South Africa	2004	46
KOR	South Korea	2005	70
LKA	Sri Lanka	2005	12
SYR	Syria	2009	2
TZA	Tanzania	2011	1
THA	Thailand	2005	59
TUN	Tunisia	2010	2
UGA	Uganda	2005	5
ARE	United Arab Emirates	2008	11
URY	Uruguay	2005	21
UZB	Uzbekistan	2010	7
VNM	Vietnam	2005	216
ZMB	Zambia	2008	1

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