THE UNIVERSITY OF ADELAIDE
FACULTY OF THE PROFESSIONS
SCHOOL OF ECONOMICS

ESSAYS ON THE TWIN DEVELOPMENT CRISES OF PUBLIC DEBT AND CLIMATE DISTRESS: EVIDENCE FROM DEVELOPING ECONOMIES

a thesis

by

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submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

October 2020

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Abstract

Transitioning to financially stable and environmentally sustainable economic growth is a major development challenge for developing economies awash in unsustainable public debt. Tackling the twin development crises, public debt and climate distress, would help developing countries move towards a sustainable development trajectory. As developing economies struggle to contain an increasing debt, measures to confront debt crises may collide with climate protection efforts.

To this end, this thesis aims to provide a framework that will guide the policy makers pursuit a rational and sustainable economic development. The thesis comprises of three main chapters. The first chapter investigates the public debt–growth nexus, while the second and third chapters evaluate the success of existing climate change policies in developing economies.

The first chapter explores the public debt–growth nexus to examine the existence of debt thresholds in developing economies. Soaring debt can dampen financial stability, thus maintaining sustainable debt thresholds could foster economic growth. Empirical studies have focused mainly on developed countries and implicitly include strong homogeneity assumptions. This chapter fills this gap by focusing on developing countries and on various heterogeneities across geographic location, income, and governance quality. Using a dynamic panel threshold regression technique on 111 developing economies over the period 1993–2017, the chapter finds debt threshold effects are not common across developing countries. In addition, heterogeneous debt threshold effects are observed across income and governance quality. Beyond the debt threshold, high debt does not impede growth for developing economies, however, the accumulation of larger debt stocks is dis-

couraged as a sensible policy measure for sustainable debt management.

The second chapter investigates the effectiveness of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (REDD) in conserving tropical forests for emissions reduction. Studies on REDD policy show limited use of quantitative methods and good quality forest cover data. This chapter fills this gap by employing a novel econometric methodology, a staggered difference–in–differences approach, on Earth observation satellite data on forest cover. The results indicate that REDD is successful in curbing tropical deforestation and emissions. It takes time for the policy effect to be materialised: smaller policy effects are observed in the first few years, while much larger policy effects are seen as time progresses. Heterogeneous effects are also observed across regions and income levels. In particular, strong policy effect is seen only in the region of Latin America and the Caribbean while upper–middle income and high income countries also benefit from the policy compared to low income countries. Incorporating such heterogeneous effects in the policy–making decisions could amplify the global efforts in protecting tropical forests.

The third chapter examines the effectiveness of Kyoto's Clean Development Mechanism (CDM) on emissions reduction in developing countries. Impact assessment studies on the CDM have typically used mean–type regression estimations and been limited to aggregate effects. This chapter fills this gap by using a conditional quantile difference–in–differences strategy to understand the policy effects along the emissions distribution and across various heterogeneities. The chapter finds that the CDM is effective in reducing emissions at the lower quantiles while it has not been so effective in high–emitting developing countries. Decomposition by emission type and sectors indicates that CDM has the expected positive impact only on fluorinated gases and agriculture and industrial sectors at the upper tail. Geographic location– and income–based heterogeneities suggest policy impact is stronger in the Latin America and the Caribbean region and the low income economies only. Overall, the CDM has not been a very successful climate policy for developing countries. As such, it is important to adapt the design and implementation changes that are required to deliver better outcomes in future.

Acknowledgement

I am grateful to my principal supervisor, Associate Professor Firmin Doko Tchatoka whose guidance, support and encouragement has been invaluable throughout this period. I am thankful for the thoughtful comments and recommendations received on my research and for all the life lessons shared.

I would like to express my sincere gratitude to my co-supervisor, Dr Stephanie McWhinnie for her enthusiastic assistance which was always beyond expectation.

I am thankful to Prof. Gareth Myles, Head of School Economics and all the Academic Staff for their inspiration in many ways. My sincere gratitude to the University of Adelaide, Australia for the opportunity provided to carry out this doctoral program.

I appreciate the friendship of all my fellow colleagues in the PhD lab and thankful to all the staff for keeping a better study environment. A sincere appreciation to Ms. Miranda Roccisano for her assistance in editing this thesis.

I wish to extend my heartfelt gratitude to Mr. Anuradha Kumarasiri, Director General of the Department of National Planning, Ministry of Finance and the Government of Sri Lanka for permitting me to pursue an overseas doctorate. A word of appreciation to the most wonderful people I have met throughout this journey: Prof. Mohammad Alauddin, Prof. Lalithasiri Gunaruwan, Mrs. Malanie Gamage, Mrs. Chandanie Wijayawardhana, Mr. Sanjaya Mudalige, Mrs. Malarmathy Gangatharan, Mrs. Shiranthi Rathnayake, Mrs. Christine Perera, Ms. Sumana Yapa and Mrs. Noor Rizna Annes. I am forever grateful to Mr. S. A. Karunarathna and Mr. O.K. Nayanananda for the inspiration and humbleness in sharing their knowledge. I am truly blessed to have mentors like you in my life.

My sincere appreciation to my dear friends, Saranga, Dhananjaya, Geethanjali, Chaminda ayya, Madhuka and Ratnavali for being considerate whenever I want you all the most. I am eternally thankful to the pillars of this success, my parents, my dear sister, *Udeni* and *Roshan ayya* for always believing in me and encouraging me to follow my dreams. Finally, I am forever grateful to *Sheril*, for always been there by my side.

A very special thanks to my dear daughter, Dineli, the joy of my life, for never ever failing me in her love and understanding.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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WARNAKULASOORIYA LAKMINI PRIYANTHI FERNANDO

SIGNATURE.. DATE. 14.05.2021 ....

Dedication

To my dearest daughter,

Dineli Fernando

Chapter 1
Introduction

Transitioning to financially stable and environmentally sustainable economic growth is a major development challenge for developing economies awash in unsustainable public debt. The International Monetary Fund (IMF) and the World Bank estimate about 50% of the world's poorest countries are at high risk of debt distress, while an annual investment of USD 2.4 trillion is required to halt global warming. As developing economies struggle to contain an increasing debt which is accumulated at a faster rate than ever, along with seeing their economies contracting further through the COVID-19 pandemic era, measures to confront debt crises may collide with climate protection efforts. Conversely, environmental challenges are often compounded by high indebtedness, creating a vicious economic cycle that constrains the capacity of developing countries to effectively address their vulnerabilities. Monitoring sustainable debt along with international cooperation to mitigate climate change would help developing countries move towards a sustainable development trajectory. This thesis aims to provide a framework that will guide policy makers pursuit a rational and sustainable economic development. To achieve this goal, the thesis covers two important topics widely recognised as some of the most difficult challenges facing the world – public debt–economic growth nexus and climate change.

Empirical studies on the public debt–growth nexus have focused mainly on developed countries (Baum et al., 2013, Checherita-Westphal and Rother, 2012, Reinhart and Rogoff, 2010) and assumed strong homogeneity across countries.

Impact assessments on international climate policies, on the other hand, have mostly followed qualitative evaluation approaches (Agung et al., 2014, Bayrak and Marafa, 2016, Minang et al., 2014, Pistorius, 2012) and lacked availability of good quality forestry data (Köthke et al., 2013, Rudel et al., 2000). The findings of most of these studies are limited to the average aggregate effects, thus ignoring heterogeneities across geographical location, levels of economic development and quality of governance.

To this end, the first chapter of this thesis investigates the public debt–growth nexus, while the second and third chapters evaluate the success of existing climate change policies in developing economies. Public debt in the developing world has surged by 28% over the period 2008–2017. These large debt stocks are often escalated by climate risks (Feyen et al., 2020). Further, Dell et al. (2012) suggest that temperature shocks have substantial negative impacts on poor countries, for instance, a 1^0C increase in temperature reduces economic growth by 1.3%. In addition, higher temperatures have negative impact not only on national production, agricultural and industrial outputs, but also on political stability (Burke and Leigh, 2010). Climate change imposes significant economic and social costs and has the potential to reverse the development gains made in developing economies. Empirical evidence, however, suggests that investments in climate adaptation enhance economic well being (Dell et al., 2008, Stern, 2008, Tol, 2009). As resource–constrained economies often require external financial assistance to overcome their development challenges, the thesis examines the effectiveness of these two mechanisms.

To be specific, the thesis contains three main chapters, each employing a recent econometric methodology that accounts for heterogeneity analyses across countries, with cross–country data collected from various sources. The number of countries and time period studied in each chapter vary due to data availability. As mentioned above, the first chapter examines the relationship between public debt and economic growth in developing economies by investigating the existence of debt threshold effects in these economies. Identifying the debt thresholds is important as the existence of such threshold implies that countries can monitor their debt to avoid the levels of their debt that will negatively impact on economic growth. It is widely argued in the literature that a soaring debt can dampen financial stability, thus maintaining sustainable debt thresholds could foster economic growth in developing economies. Empirical studies have focused mainly on developed countries and implicitly include strong homogeneity assumptions. This chapter fills this gap by focusing on developing countries and on various heterogeneities across geographic location, income, and governance quality. Public debt data are extracted from the IMF's global debt database, which includes total gross debt of 190 countries worldwide (Mbaye et al., 2018). The other variables are obtained from the World Bank's World Development Indicators (WDI, 2019). In particular, the study uses data on 111 developing economies over the period 1993–2017. The chapter employs the dynamic panel threshold regression technique which advances the static panel threshold estimation model of (Hansen, 1999) and the dynamic cross–sectional threshold model of (Caner and Hansen, 2004). Kremer et al. (2013) have used a similar approach in studying the inflation thresholds in the inflation–growth nexus. The dynamic panel threshold regression technique is a novel approach used in estimating threshold effects. It estimates threshold effects and the marginal impact of debt at low– and high–debt levels simultaneously. The findings provide strong evidence for the presence of a debt threshold only in Latin America and the Caribbean region at 25% of debt–to–GDP. Amongst developing countries, therefore, the debt threshold effect is uncommon. Heterogeneous debt threshold effects are however, observed across income and governance quality. In particular, debt thresholds are seen for the lowest income countries at 37% of debt–to–GDP and the lowest governance quality at 38% of debt–to–GDP. Counter to conventional concerns, the marginal impact of debt in the high–debt regime seems growth–enhancing. That is, beyond the debt–threshold, increase in economic growth for low–income and lowest governance quality countries is 0.01%. These findings suggest high–debt does not necessarily impede the economic development process, however, the accumulation of larger debt stocks is discouraged as a sensible policy measure for sustainable debt management in developing countries.

The second chapter investigates the impact of global environmental policies on conservation of tropical forests and climate change mitigation. In particular, the chapter evaluates the effectiveness of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (REDD) – the world's largest payment for ecosystem service – in forested developing countries. Most of the early studies on REDD policy suffer from the limited use of quantitative methods (Agung et al., 2014, Bayrak and Marafa, 2016, Minang et al., 2014, Pistorius, 2012) and low accuracy and comparability of forest cover data (Köthke et al., 2013, Zabala, 2018). This chapter fills this gap by investigating whether the changed forest governance that is triggered by the adoption of the REDD policy has been able to reduce deforestation and emissions in developing countries. The chapter contributes to the literature by: (1) employing a novel econometric technique – a staggered difference–in–differences approach recently developed by Athey and Imbens (2018) – to evaluate the success of the REDD policy at the national level; (2) using Earth observation satellite data on forest cover that are spatially more accurate and derived through internally consistent approach in the analyses; and (3) examining the heterogeneous impact of the policy effect across regions and income. Specifically, this chapter uses country–level data from 102 developing countries in a balanced panel setting over the period 2001–2018. Deforestation and emissions data were obtained from the Global Forest Watch web platform (GFW, 2019) and all the other explanatory variables are from the World Bank's World Development Indicators (WDI, 2019). The results indicate that REDD is successful in curbing deforestation and emissions in developing countries. Although the monetary incentives received from REDD have led developing countries towards positive forest cover changes, it takes time for the policy effect to be materialised. As such, smaller policy effects on deforestation and emissions are observed in the first few years, while much larger policy effects are seen as time progresses. Heterogeneous effects are also observed across regions and income levels. In particular, strong policy effect is seen only in the region of Latin America and the Caribbean while upper–middle income and high income countries also benefit from the policy compared to low income countries. Incorporating such heterogeneous effects in the policy–making decisions could amplify the global efforts in protecting tropical forests.

The third chapter examines the effect of international climate policies on the climate change abatement in developing countries. In particular, this chapter investigates the impact of the Clean Development Mechanism (CDM), pledged under the Kyoto protocol of the United Nations Framework Convention on Climate Change, on emissions reduction in developing countries. Impact assessment studies on the CDM have typically used mean–type regression estimations and been limited to aggregate effects, thus ignoring the effects at disaggregated levels and other heterogeneities. The chapter evaluates whether the CDM has been an effective global policy in reducing emissions. The data used is a balanced panel of 104 developing countries over the period 1996–2016. The emissions data were obtained from the Climate Analysis Indicators Tool developed by the World Resource Institute (WRI, 2017). Carbon intensity data were obtained from the Our World in Data web platform (OWD, 2020). The other variables are extracted mainly from the World Development Indicators of the World Bank (WDI, 2019) and financial openness is from Chinn and Ito (2006). Using a conditional quantile difference–in–differences strategy developed by Powell (2016), the study finds notable heterogeneity across the emissions distribution. A similar approach of Ampofo and Doko Tchatoka (2019) on the the effectiveness of wage policies in Ghana has been closely followed in this chapter. Reductions in emissions from the CDM are only seen in countries at the lower quantiles of emissions. Thus, the CDM has not been so effective in reducing emissions in high–emitting developing countries. Decomposition by emission type and sectors indicates that CDM has the expected positive impact only on fluorinated gases and agriculture and industrial sectors at the upper tail. Geographic location– and income–based heterogeneities suggest policy impact is stronger in the Latin America and the Caribbean region and the low–income economies only. Overall, the CDM has not been a very successful climate policy for developing countries. As such, it is important to adapt the design and implementation changes to deliver better outcomes in future.

The rest of the thesis is structured as follows. Chapter 2 investigates the link between public debt and economic growth to examine the existence of debt thresholds in developing economies. Chapter 3 examines the effectiveness of the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation on conserving tropical forests and emissions reduction. Chapter 4 explores the effectiveness of Kyoto's Clean Development Mechanism on emissions reduction in developing countries. Chapters 2, 3 and 4 are presented as independent papers with separate references and appendices and are followed by concluding remarks in Chapter 5.

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Chapter 2
Public Debt–Growth Nexus: Evidence from Developing Economies

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Statement of Authorship

Title of Paper	Public Debt-Growth Nexus: Evidence from Developing Economies
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
Publication Details	

Principal Author

Name of Principal Author (Candidate)	Warnakulasooriya Lakmini Priyanthi Fernando		
Contribution to the Paper	I have partly contributed in literature review, data collection, estimation, interpretation of results and writing the manuscript.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Abstract

This chapter explores the link between public debt and economic growth to examine the existence of debt thresholds in developing economies. Using a dynamic panel threshold regression technique on a balanced panel of 111 developing economies over the period 1993–2017, we find evidence for a debt threshold effect only in Latin America and the Caribbean region. As such, the existence of a public debt threshold effect cannot be generalised to developing economies worldwide. In addition, heterogeneous debt threshold effects are observed across income and governance quality. In particular, debt thresholds are found at 37% and 38% of debt–to–GDP for countries with the lowest income and lowest quality of governance, respectively. We also find that high debt is growth–enhancing for these two country groups. Beyond the debt threshold, more debt has increased growth by 0.01% for both low income economies and the economies with lowest governance quality. This indicates high debt does not necessarily impede the economic development process in developing economies.

Keywords: Public debt; Economic growth; Threshold effects; Dynamic panel threshold analysis

JEL classification: H63, O40, E62, C20

2.1 Introduction

Sustainable debt management is a major policy concern as mounting public debt can stymie the economic growth of nations. Since the Great Financial Crisis, public debt has surged in many countries and is expected to increase further, given the current policies in those countries. The belief that reducing debt to a safe threshold can foster economic growth and help achieve development targets has gained increasing consensus. This debt threshold, if it exists, is publicised as the level above which the marginal impact of debt turns negative (Reinhart and Rogoff, 2010), and it appears to vary across countries (Baum et al., 2013, Checherita-Westphal and Rother, 2012, Kumar and Woo, 2010). Maintaining debt at a common threshold across countries, therefore, is not a viable economic strategy. Given the high cost involved in sustaining debt, only robust evidence will persuade policy makers to set thresholds for public debt. Despite the considerable increase in public debt in developing economies, recent literature on the public debt–growth nexus focuses mainly on developed economies, with inconclusive results. Furthermore, most of these studies build on the assumption that nations are homogeneous, which is often not supported by actual data. Most recent literature is skewed toward external borrowing. However, there is a clear trend that developing countries are moving away from external borrowing and instead move towards domestic borrowing as the former involves high risks and definite debt repayment commitments. Further, public debt is the total debt portfolio of a country and contains both foreign currency denominated debt and local currency denominated debt. Hence, the analysis on how pubic debt affect economic growth over time is important.

This chapter aims to fill this gap and take a new look at the empirical relationship between debt and growth in developing countries, by providing an holistic analytical view and by allowing for heterogeneities across different regions, income, and quality of governance. In particular, our study investigates the existence of debt thresholds in 111 developing countries, using the dynamic panel threshold regression framework to identify the existence of threshold effect. We find strong evidence for the debt threshold effect only in Latin America and the Caribbean. As such, the existence of a public debt threshold effect cannot be generalised to developing nations worldwide. In addition, heterogeneous debt threshold effects on economic growth are observed across income and governance quality levels. In particular, higher public debt often results in higher growth for low income countries and for countries with the lowest quality of governance. A number of robustness exercises are performed, but do not significantly affect our findings.

Our findings are similar to those of Herndon et al. (2014), who find no evidence for the existence of a public debt threshold in advanced economies. Further, they reveal increased economic growth with public debt loads greater than 90% of GDP. Minea and Parent (2012) claim that decline in growth is not static and is limited to between 90% and 115% of GDP, beyond which growth increases. Future growth prospects depend not only on the level of debt but on the debt trajectory (Pescatori et al., 2014). High debt and low debt countries attain faster growth, given their debts are on a downward trajectory and are supported by credible fiscal policy. According to Kourtellos et al. (2013), the public debt threshold effects are determined by the degree of institutional quality: at lower levels of institutional quality, high debt reduces growth while higher institutional quality seems to be growth neutral.

Our results do not follow the debt overhang hypothesis in general, which postulates that fiscal deterioration caused by high-debt can lead to poor real economic conditions. In empirical studies focused on advanced economies, Reinhart et al. (2012) and other experts Baum et al. (2013), Checherita-Westphal and Rother (2012) debate the relationship between fiscal position and growth, confirming that high levels of debt cause low growth. Studies based on both advanced and emerging economies also claim that debt overhang exists, but at different degrees for different country groupings (Caner et al., 2010, Kumar and Woo, 2010). The reasons for such growth deterioration are, firstly, that a high level of debt places upward pressure on the interest rates; and secondly, that inefficient government expenditure widens the fiscal deficit, distorting private sector decision making on investments. Eventually, the crowding out of investment results in stagnant economies.

By empirically investigating the existence of public debt threshold in developing economies, our study contributes, firstly, to the existing literature on the public debt overhang hypothesis, and also sheds a new light on the disparity between developed and developing countries on this topic. To the best of our knowledge, this is the first comprehensive study to empirically examine the debt threshold effect in developing countries using the novel dynamic panel threshold regression techniques as proposed by Hansen (1999), Caner and Hansen (2004) and Kremer et al. (2013). Secondly, most studies on the debt–growth nexus have been limited to a selected smaller number of developing countries. By contrast, our analysis of the debt threshold uses a larger data set of developing countries, which includes countries in Africa, Asia, and Latin America and the Caribbean. Thirdly, by allowing for heterogeneities in income and governance quality, we show that the debt threshold effect is not uniform across these characteristics.

The remainder of the chapter is structured as follows. Section 2.2 introduces the data, then provides a brief description on public debt trends and a descriptive analysis of data. Section 2.3 details our empirical strategy. Section 2.4 discusses the research findings and in Section 2.5 we provide some robustness checks. Section 2.6 concludes the chapter by highlighting the policy implications.

2.2 Public debt data, trends and threshold effects

As described above, this chapter complements existing studies of debt thresholds in developed countries. Like those papers, we frame our analysis of economic growth as a straightforward Solow specification augmented with public debt. To motivate our analysis we provide details of data in our sample in subsection 2.2.1, public debt trends in 2.2.2 and existence of debt thresholds employing simple descriptive analysis in 2.2.3.

2.2.1 Data

In this study, we use a balanced panel of 111 developing countries in Africa (47), Asia (38), and Latin America and the Caribbean (26) covering the period 1993–2017. The selection of a larger sample of countries is a significant improvement to the existing literature on the debt–growth nexus in developing countries (see e.g. Caner et al. (2010), who use 74 countries)[1].

We employ a Solow–growth specification augmented with public debt to estimate the threshold effects in developing economies. Our analysis therefore contains a set of standard Solow growth determinants: trade openness, public investment, population growth and secondary school enrolment (Panizza and Presbitero, 2013, Presbitero, 2012). The dependent variable is the real GDP growth rate and it is measured as the log difference in the real GDP (constant 2000 US$). The treatment variable is public debt, which is used as the single regime–dependent variable and also the threshold variable in the threshold analysis. For the majority of countries, public debt is reported as the central government debt, measured as a share of GDP[2]. A set of control variables is used as the other explanatory variables: trade openness (defined as exports plus imports as a share of GDP), public investment (defined as the gross fixed capital formation as a share of GDP), population growth (measured as the annual population growth rate) and secondary school enrolment (given as duration in years).

The majority of the countries in our sample are primary commodity exporters and are vulnerable to external shocks. Following the literature, we include the trade openness variable to control the degree of openness to external trade. The more the countries are open the higher is their long–term growth rate of real income (Sachs et al., 1995). Public investment and population growth are the two proxy variables used to represent two factor inputs of the production process,

[1]The list of developing countries in our sample is in the Table A.1 in the Appendix. Selection of the sample of developing countries is based on the United Nations report on world economic situation prospects 2019 (UN, 2019). We exclude 15 developing countries owing to poor data availability.

[2]For a few countries the general government debt is used.

namely, capital and labour. Secondary school enrolment is used as the proxy for the quality of human capital (Barro and Lee, 2013). We use another 13 variables for the robustness tests based on the theoretical and empirical growth literature. They are foreign direct investment, inflation, unemployment rate, labour force, labour force participation ratio, age dependency ratio, life expectancy at birth, fertility rate, population, urban population, land area, human development index and primary education. A description of all the variables is provided in Table A.4 in the Appendix. Public debt data were obtained from the Global Debt Database and the Historical Debt Database published by the International Monetary Fund (IMF) (IMF, 2019). All the other variables are from the World Bank's World Development Indicators (WDI, 2019).

In this study, gross government debt is used as the indicator for public debt. The IMF's Global Debt Database defines debt as the gross outstanding stock of all liabilities that are debt instruments, in line with the System of National Accounts 2008 (Mbaye et al., 2018); however, net debt is the more appropriate measure for indebtedness (Panizza and Presbitero, 2013). Net government debt is calculated by subtracting gross debt from the assets held by the government. Measuring financial assets and liabilities held by a country is a cumbersome process; consequently the data on net debt are generally scarce and incomplete. Therefore, following the existing literature, gross government debt is used as the indicator for public debt.

The gross government debt is reported as either central government debt or general government debt, which includes the debt issued by both the central government and the regional authorities. Our main indicator choice for public debt is central government debt. However, due to reporting issues we use general government debt in nine cases (Cambodia, China, Democratic Republic of the Congo, Ethiopia, Mauritius, Panama, Philippines, Tanzania and the United Arab Emirates). Considering all these limitations and the unavailability of a homogeneously defined debt variable, the two selected indicators are treated as comparable indicators for public debt. However, this assumption leads to another concern, that the relationship between debt and growth may be affected by the composition of public debt.

To assess whether the debt–growth relationship is influenced by the quality of governance, we use country ratings and statuses published by the annual Freedom in the World Survey which was first compiled in the year 1972 (Freedom House, 2018). The two indicators used in the survey are the political rights (PR) and civil liberties (CL). The indicators are measured on a scale from 1 to 7, with 1 representing the highest degree of freedom and 7 the lowest. The countries are then categorised into three statuses based on combined average ratings for PR and CL. Those that fell between 1.0 and 3.0 were designated as 'free'; between 3.0 and 5.5 'partly free'; and between 5.5 and 7.0 'not free'. We also use the 'scores' of the Freedom of the Press data published by the same institution as a robustness check for the governance quality. The countries with scores between 0 and 30 are designated as free; between 31 and 60 as partly free and between 61 and 100 as not free.

2.2.2 Public debt trends

Debt in developed countries is responsible for most of the global debt. The average debt–to–GDP level in developed countries is much higher than that of the developing countries and the economies in transition (Figure 2.1). Nevertheless, the debt increase in developed and developing countries over the period 2008–2017 is 34% and 28% respectively. This means that over the past decade, developing countries have contributed to global debt as much as the developed countries.

The historical debt data show that public debt in developing countries has decreased sharply for many reasons, including the debt write–off offered by the IMF. However, 2009 is a remarkable year, after which the declining trend in debt is reversed and continues to increase. Moreover, the countries in Africa show debt levels that are higher than the developing country debt average (Figure 2.1). Barbados, Lebanon and Eritrea are the top three most indebted countries, with debt–to–GDP ratios of 159, 147 and 131 respectively in 2017[3]. The average debt–

[3]In 2017, the top ten most indebted developing countries in terms of public debt–to–GDP ratios were Barbados (159%), Lebanon (147%), Eritrea (131%), Republic of Congo (130%), Cabo Verde (126%), Sudan (122%), Singapore (112%), Bhutan (106%), Egypt (104%) and Jamaica (103%). Most indebted countries in the world are

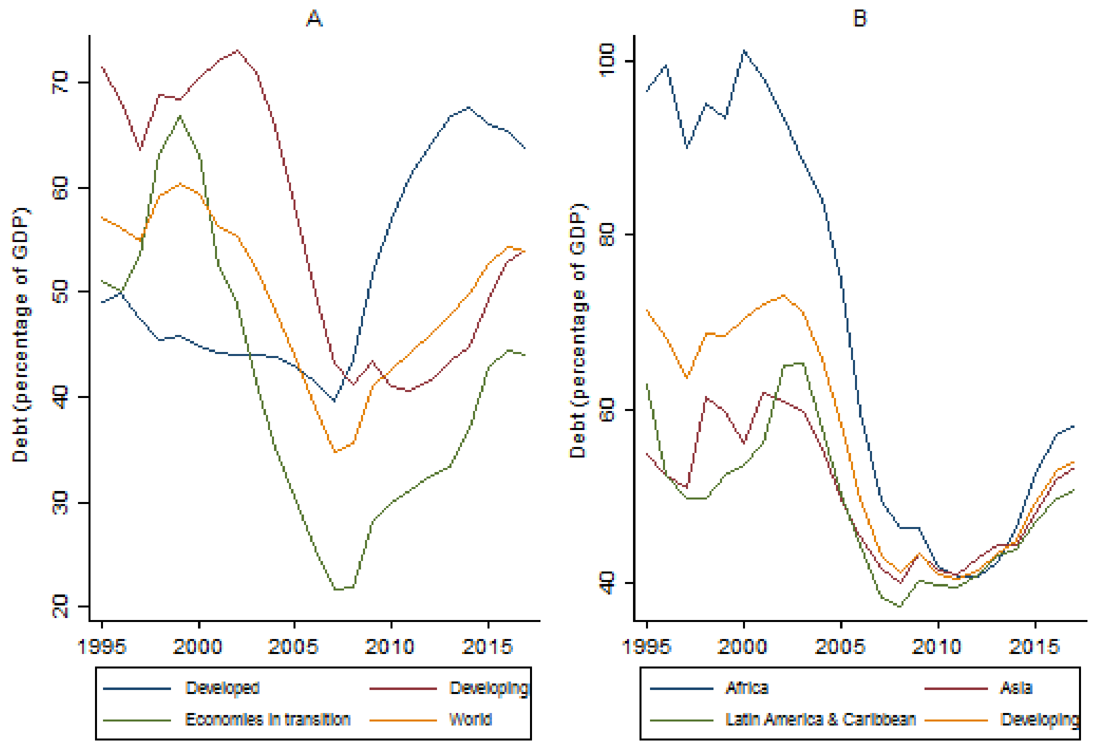

Figure 2.1: Public debt trends, 1995–2017

to–GDP ratio is 60% for the entire sample (Africa: 71.2%, Asia: 51.1% and Latin America and the Caribbean: 51.4%). (Descriptive statistics of all the variables are given in Table A.5 in the Appendix). The average debt of 44 countries (i.e. 40% of the countries in the sample) is higher than the developing country average debt of 60%. As such, the debt levels in the majority of the developing countries are still at a low–to–moderate level. However, given the increasing trend in debt accumulation, it is safer to take precautionary measures beforehand.

The distribution of average public debt and average real GDP growth rates over the period 1993–2017 indicates periods of high public debt have been followed by lower average growth rates and vice versa (Panel A of Figure A.2 in the Appendix). Median growth also shows a similar pattern of change. Therefore, we can assume a negative correlation between growth and public debt. Growth slowed down sharply in 2009, when public debt approximates 44% of debt–to–GDP. High

shown in Figure A.1 in the Appendix

growth accompanies subsequent debt decrease in early 2000 and lower growth is preceded by high debt accumulation, where the direction of causality is difficult to disentangle. Panel B of Figure A.2 in the Appendix shows country distribution for which the public debt–to–GDP ratios are within the four debt regimes as explained by Reinhart and Rogoff (2010). The average debt levels of the majority of the developing countries lie in the debt regime of 30–60% of debt–to–GDP. There are very few countries (less than 10) recording debt levels higher than 90% for any given time period after 2005. This indicates that public debt levels are still at a low to moderate level for the majority of the countries in our sample.

A simple correlation analysis indicates a negative and significant relationship between public debt and economic growth (see Table A.6 in the Appendix). However, negative correlation does not necessarily mean that high debt causes low growth. All the other main control variables seems to foster economic growth. Next, the relationship between public debt and economic growth is examined using a series of scatter plots. We aggregate the data into one big cross-section covering the period 1993–2017 to show the correlation of real GDP growth against the ratio of public debt–to–GDP. It suggests that in developing countries debt and growth are negatively associated with economic growth, although not strongly (see Figure A.3 in the Appendix). This is even true for the other regions, except the Asian region (see Figure A.4 in the Appendix).

2.2.3 Debt threshold effects

Reinhart and Rogoff (2010) discuss the presence of a debt threshold at 90% of the debt–to–GDP ratio, after which economic growth dramatically declines in advanced economies. Similarly, we analyse our data set to understand the existence of any such debt threshold for the developing countries. We plot the average and median growth variations under two different debt regime specifications using simple descriptive statistics. Firstly, following Reinhart and Rogoff (2010) we set four debt regimes at much wider debt intervals of (1) $< 30\%$ of GDP, (2) $30 - 60\%$ of GDP, (3) $60 - 90\%$ of GDP and (4) $> 90\%$ of GDP. Secondly, we set ten debt regimes, each at a 10% interval. The use of a large number of debt regimes at shorter intervals minimises aggregation bias, which may result from using wider intervals, as done by Reinhart and Rogoff (2010).

Table 2.1 shows the growth variation in the aforementioned debt regime specifications. According to the first specification, for the pooled sample of developing countries and for the two sub samples that represent Africa and Asia, a debt threshold exists at 90% of debt–to–GDP, whereas it is at 60% of debt–to–GDP for Latin America and the Caribbean (Panel A of Table 2.1 and Figure 2.2). However, in the second specification with ten debt regimes, we did not observe such systematic variation in growth over increasing debt levels for any of the samples (Panel B of Table 2.1 and Figure 2.3). This indicates that under the first specification we may have observed debt thresholds caused by an aggregation effect. When the narrower debt regimes are used in the second specification, debt thresholds are no longer visible, as the use of shorter debt intervals minimises the aggregation bias.

Table 2.1: Economic growth variation in different debt regimes

Debt Regimes	GDP growth rate (percentage)							
	Developing		Africa		Asia		Latin America & the Caribbean	
	Average	Median	Average	Median	Average	Median	Average	Median
A: Four debt regimes (Reinhart and Rogoff, 2010)								
(1) < 30	3.7	3.8	3.9	4.1	4.2	4.2	2.8	3.3
(2) $30 - 60$	3.8	4.1	4.0	4.3	4.3	4.5	3.1	3.5
(3) $60 - 90$	5.5	4.5	4.2	4.7	5.5	5.8	2.5	2.5
(4) > 90	3.4	4.0	3.3	4.5	3.9	4.0	2.8	2.9
B: Ten debt regimes								
(1) $10 - 20$	3.5	4.3	3.7	3.8	3.2	3.5	3.8	4.5
(2) $20 - 30$	3.8	3.7	4.1	4.5	5.0	4.4	2.5	2.8
(3) $30 - 40$	3.6	4.1	-	-	4.6	4.2	3.1	3.8
(4) $40 - 50$	3.7	4.1	4.0	4.3	4.0	5.0	2.1	2.3
(5) $50 - 60$	4.1	4.2	4.1	4.2	4.3	4.9	4.0	4.1
(6) $60 - 70$	4.1	4.5	4.0	4.5	4.7	5.3	2.6	3.0
(7) $70 - 80$	5.0	5.4	4.3	3.6	6.1	6.9	3.5	3.3
(8) $80 - 90$	4.6	4.5	4.6	4.7	6.3	6.1	1.5	1.2
(9) $90 - 100$	3.4	4.1	2.7	4.0	3.8	4.1	-	-
(10) > 100	3.3	3.7	3.5	4.1	4.3	3.2	2.8	3.5

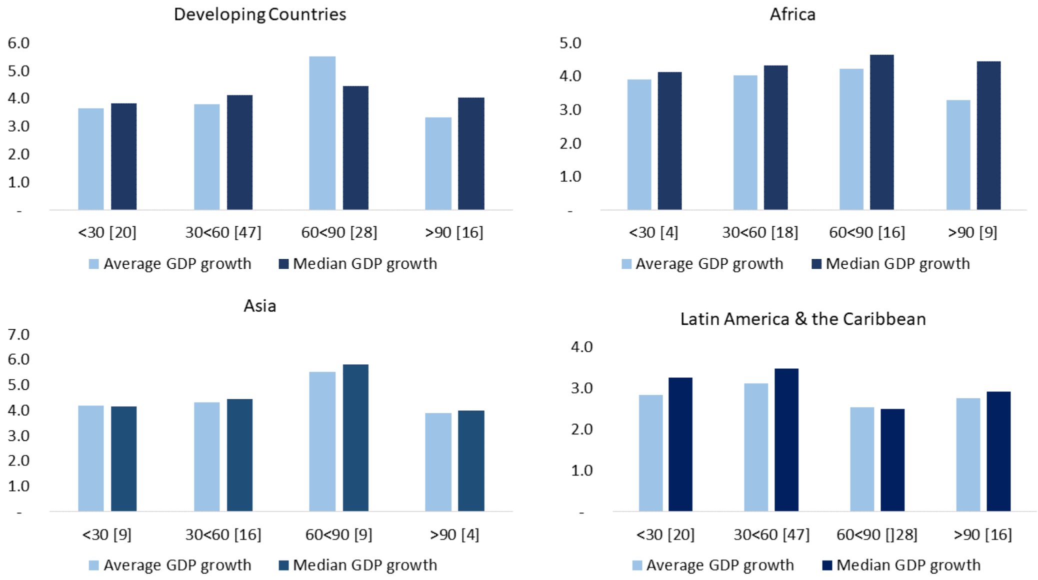

Figure 2.2: Growth variation in four (wide) debt regimes

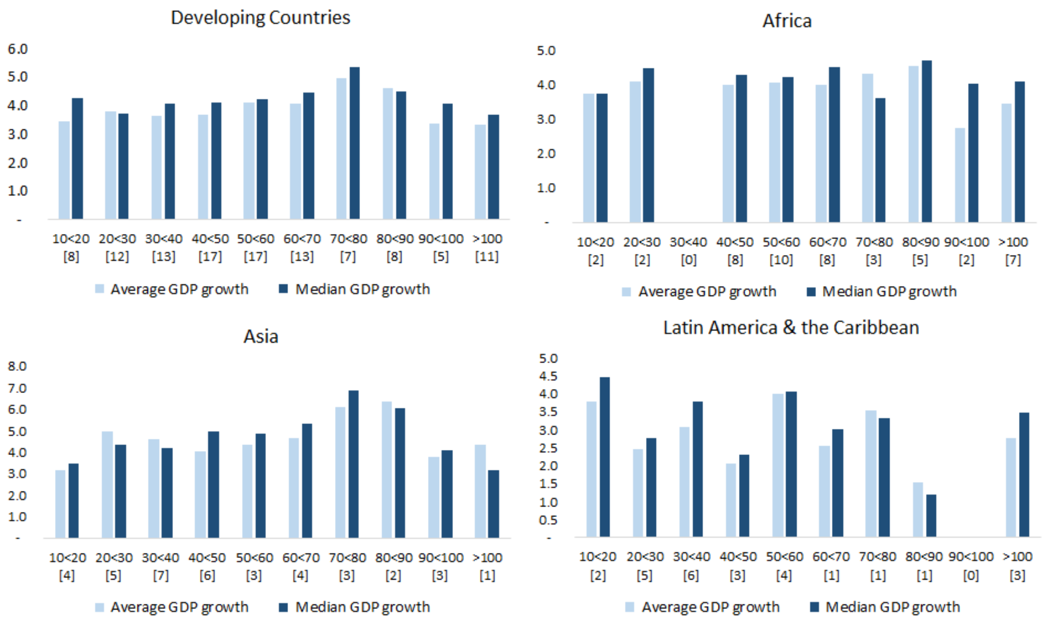

Figure 2.3: Growth variation in ten (narrow) debt regimes

Note: The number of countries in each debt regime is given in square brackets.

2.3 Empirical strategy

2.3.1 Model specification

We explore the public debt–growth nexus to examine the presence of debt thresholds in developing countries. Using the dynamic panel threshold model, that advances the static panel threshold estimation model of Hansen (1999) and the dynamic cross–sectional threshold model of Caner and Hansen (2004), we investigate the presence of debt threshold effects. A similar setting was used by Kremer et al. (2013) to analyse inflation thresholds in the inflation–growth nexus. In our analysis, we adopt a Solow–growth specification augmented with public debt to estimate the following specification:

$$\Delta gdp_{it} = \chi \Delta gdp_{i,t-1} + \beta_1 d_{it} I(d_{it} \leq \gamma) + \beta_2 d_{it} I(d_{it} > \gamma) + \alpha' X_{it} + \eta_t + \mu_i + e_{it} \tag{2.3.1}$$

where the subscript $i = 1, ..., N$ indexes the country and the subscript $t = 1, ..., T$ indexes the time. The outcome variable is real GDP growth rate of country i at time t, Δgdp_{it}, measured by the log difference in real GDP. The lagged dependent variable is $\Delta gdp_{i,t-1}$. Our variable of interest is d_{it}, the public debt of country i at time t with two coefficients of interest: β_1 and β_2. It is considered as both the threshold variable and the regime–dependent regressor. $I(.)$ is the indicator function specifying the regime by the threshold variable, d_{it}, and the threshold level, γ. The threshold variable (d_{it}) splits the sample into two 'regimes' based on whether the threshold variable is lower or higher than the threshold level (γ). Therefore, the indicator function takes the value 0 if $d_{it} \leq \gamma$ (Regime 1) and the value 1 if $d_{it} > \gamma$ (Regime 2). Here, we do not know which observation belongs to which regime (i.e. we do not know the threshold value, γ), but we can observe the threshold variable, d_{it}. The parameters of interest are β_1 and β_2, which are the two regime regression slopes. β_1 is the marginal impact of the threshold variable when the threshold variable is less than or equal to the threshold value, and β_2 is the marginal impact of threshold variable when the threshold variable is greater than the threshold value. X_{it} is a vector of control variables considered to be regime independent. It contains a set of standard Solow growth determinants (trade openness, public investment, population growth and secondary school enrolment) and its coefficient vector α estimates the effect of a change in each of these variables on real GDP growth rate. The unobserved heterogeneity is controlled using year– and country–specific fixed effects, η_t and μ_i, respectively. The year fixed effects account for various economic and political changes that evolve over time (e.g. global business cycle changes). The country–specific fixed effects capture the effect on economic growth of time–invariant traits such as culture, population preferences and history and are the same in both regimes (Hansen, 1999). Omission of these unobservable characteristics might affect the identification of debt thresholds.

The general specification in equation 2.3.1 allows us to study only two debt regimes (one threshold parameter). However, the model can be studied with more than two regimes and the estimation procedure of Hansen (1999) facilitates a specification with k regimes. A threshold model with three regimes (two threshold parameters) takes the following form:

$$\begin{aligned}\Delta gdp_{it} = \chi \Delta gdp_{i,t-1} + \alpha' X_{it} + \beta_1 d_{it} I(d_{it} \leq \gamma_1) + \beta_2 d_{it} I(\gamma_1 < d_{it} \leq \gamma_2) + \\ \beta_3 d_{it} I(d_{it} > \gamma_2) + \eta_t + \mu_i + e_{it}\end{aligned} \tag{2.3.2}$$

where we assume that the threshold parameters γ_j satisfy $\gamma_1 < \gamma_2$.

2.3.2 Estimation

The dynamic panel threshold regression (DPTR) model has been used extensively in studying the debt–growth nexus but has remained scarce in similar literature focusing on developing countries. It is considered a superior technique in estimating nonlinear functions as it allows simultaneous estimation of the threshold level, its significance, the coefficients of the different regimes and their significance. In this section we describe how we employ the DPTR model in our analysis. In particular, we allow for a dynamic panel framework that allows for endogeneity in a way that estimates both the threshold and the coefficients either side of the threshold.

Converting to dynamic panel framework by eliminating fixed effects

Caner and Hansen (2004) develop their model to endogenous variables and an exogenous threshold variable under a cross–sectional approach. To apply this framework to deal with country–specific fixed effects, we first need to eliminate the fixed effects via a fixed effects transformation without violating the distributional assumptions in Hansen (1999) and Caner and Hansen (2004). The standard within–group transformation does not eliminate dynamic panel bias and leads to inconsistent estimates, as the transformed lagged dependent variable negatively correlates with the transformed error term (Nickell, 1981). Therefore, to eliminate the individual fixed effects we use forward orthogonal transformation, as suggested by Arellano and Bover (1995). This ensures the uncorrelatedness of the error terms and allows the use of static model of Hansen (1999) and cross sectional model of Caner and Hansen (2004) into a dynamic panel threshold setting.

Dealing with endogeneity

Structural equation (2.3.1) requires a set of suitable instruments to solve the problem of endogeneity. As there is no clear guideline on identification restrictions, we use T-1 moment conditions (i.e. use all available lags of the dependent variable) as instruments. Then, following Caner and Hansen (2004), we estimate the reduced form regression by ordinary least squares for the endogenous variable using all available lags of the dependent variable as instruments. Next, we replace the original values of the dependent variable, $gdp_{i,t-1}$, in equation (2.3.1) with its predicted values, $g\hat{d}p_{i,t-1}$, and estimate the threshold point using least squares.

Estimating the threshold value

The specific threshold value is determined following the strategy proposed by Hansen (1999), which involves the following three main steps.

1. We conduct a series of least squares minimisations. That is, we estimate equation (2.3.1) with two–stage least squares for each value of the thresh-

old series. The corresponding estimates of the parameters and the sum of squared residuals are kept.

2. We select the threshold value of d_{it} as the value that best minimises the sum of square residuals ($S(\gamma)$), $\hat{\gamma} = argmin\ S(\gamma)$. Then, the confidence interval for the threshold variable, d_{it} can be constructed as $\Gamma = \gamma : LR(\gamma) \leq C(\alpha)$ where Γ is an asymptotic confidence region for γ; $C(\alpha)$ is the percentile asymptotic confidence interval for threshold values of the asymptotic likelihood ratio statistics, $LR(\gamma)$.

3. We test for the significance of the chosen threshold value. The threshold parameter is not identified under the null hypothesis of a linear model i.e. no threshold effect ($H_0 : \beta_1 = \beta_2$), therefore classical tests have non-standard distributions (known as the 'Davies' Problem'). Hence, we use a bootstrap method to simulate the asymptotic distribution of the likelihood ratio test.

Estimating the slope coefficients

Finally, with the selected threshold value, $\hat{\gamma}$, which splits the sample into low debt and high debt regimes, the slope coefficients of both regimes are estimated using generalised methods of moments (GMM). The GMM estimators are easily seen to be efficient estimators of β_1 and β_2. We can allow for the possibility of more than one threshold, which gives rise to more than two debt regimes in the estimation procedure. However, since, the first threshold is not significant in the majority of the specifications, we ignore the possibility of the existence of multiple thresholds in our data.

The DPTR chooses the estimate that minimises the residual sum of squares as the debt threshold (Hansen, 1999). The statistical significance of the threshold estimates is examined using LR statistic, measured as the difference between the residual sum of squares of the model for a generic value of the threshold and the corresponding estimated threshold (scaled by the variance of the sample residuals). Testing for the threshold is similar to testing for whether or not the coefficients are the same in each regime. We use bootstrap on the critical values of the F-statistic to test the significance of the threshold effect. At the threshold, $LR = 0$. The coverage rate of the threshold estimator gets wider as n or T increases (Wang, 2015).

2.3.3 Threats to identifying a significant debt–growth nexus

Higher public debt acts as a drag on economic growth. However, causality may run in the other direction, where slow growth reduces the tax revenue and increases the need for more public expenditure, widening the fiscal deficit. The causality can be assessed based on different timings of the change in growth and public debt ratio: contemporaneous growth (indicates causality is ambiguous); five–year forward (leading) average growth (indicates causality running from debt to growth); and five–year past (lagging) average growth (indicates reverse causality from growth to debt).

Autocorrelation in the error term for growth means negative shocks to growth are persistent and the shock is passed to the debt process, increasing the level of debt in the long run. Therefore, in a contemporaneous regression, autocorrelation in the growth equation will erroneously lead to the conclusion that public debt is bad for growth. Averaging growth in to the future over several years reduces this bias. Therefore, we focus mainly on the forward five–year average growth in our analysis so as to mitigate bias in the estimates.

The endogeneity bias of the lagged dependent variable makes the estimates inconsistent. This issue is addressed by using lags of the dependent variable ($\Delta gdp_{i,t-1}$, ..., $\Delta gdp_{i,t-p}$) as instruments (Arellano and Bover, 1995). The choice of number of instruments (p) creates bias/efficiency trade–off in finite samples (Roodman, 2009); hence, we consider two regressions: First, with all available lags of the dependent variable ($p = t$) to increase efficiency; and second, with one lag ($p = 1$) only, to avoid overfit of instrument variables. The results indicate there is no significant difference between the choice of instruments.

The DPTR considers two sets of variables: exogenous (or pre–determined) and endogenous. The model addresses only the endogeneity bias of the lagged dependent variable as discussed above and ignores the simultaneity bias of the other remaining variables, (e.g. the exogeneity assumption of the threshold variable). This is dealt with by using their first lags in the estimation as it is difficult to find external instruments that are uncorrelated with the regressors and error term.

The estimation procedures can be affected by the presence of cross–sectionally correlated errors (Pesaran, 2006). One caveat is the unavailability of a method to control for cross–section dependence in the DPTR, which may serve as scope for future research.

2.4 Results

This section provides the DPTR estimates on public debt–growth nexus. Section 2.4.1 presents the estimates on the presence of debt thresholds. Then, the heterogeneous debt threshold effects across income and governance quality are shown in sections 2.4.2 and 2.4.3, respectively.

2.4.1 Presence of debt thresholds

Table 2.2 shows the DPTR estimates on the relationship between public debt and growth in developing countries based on the baseline specification in equation (2.3.1). The estimates in Panel A of Table 2.2 with no individual controls provide evidence for a debt threshold effect of 26% of debt–to–GDP only for Latin America and the Caribbean. Including controls for trade openness, public investment, population growth and secondary school enrolment, reduces this debt threshold to 25% of debt–to–GDP (Panel B of Table 2.2 and Figure 2.4).

The change in the size of the debt threshold shows the importance of inclusion of control variables in the estimation. We observe threshold effects only for Latin America and the Caribbean, as such, the existence of a public debt threshold effect

Table 2.2: DPTR estimates of debt on forward growth

	Developing	Africa	Asia	Latin America & the Caribbean
A-Forward growth excluding controls				
Threshold estimates $\hat{\gamma}$	76.099	75.730	26.461	25.750
95% confidence interval	[73.06 76.64]	[72.87 75.94]	[26.05 26.66]	[25.03 26.15]
Threshold effect test: p-value	0.451	0.495	0.297	0.062
Threshold effect	No	No	No	Yes
Impact of debt on growth				
$\hat{\beta}_1$	0.021***	0.027***	0.090***	-0.060***
	(0.003)	(0.005)	(0.018)	(0.012)
$\hat{\beta}_2$	0.011***	0.013***	0.025***	0.001
	(0.001)	(0.002)	(0.004)	(0.002)
Regime independent controls	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	111/2,331	47/987	38/798	26/546
B-Forward growth including controls				
Threshold estimates $\hat{\gamma}$	37.549	31.690	39.552	25.160
95% confidence interval	[37.07 37.70]	[30.82 31.95]	[36.09 39.56]	[24.75 25.19]
Threshold effect test: p-value	0.157	0.331	0.675	0.010
Threshold effect	No	No	No	Yes
Impact of debt on growth				
$\hat{\beta}_1$	-0.007	-0.021**	0.002	-0.050***
	(0.005)	(0.010)	(0.008)	(0.010)
$\hat{\beta}_2$	0.010***	0.011***	0.021***	0.001
	(0.001)	(0.002)	(0.004)	(0.002)
Regime independent controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	111/2,331	47/987	38/798	26/546

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses. ***, **, and * indicate significant p values at 1%, 5% and 10% level, respectively.

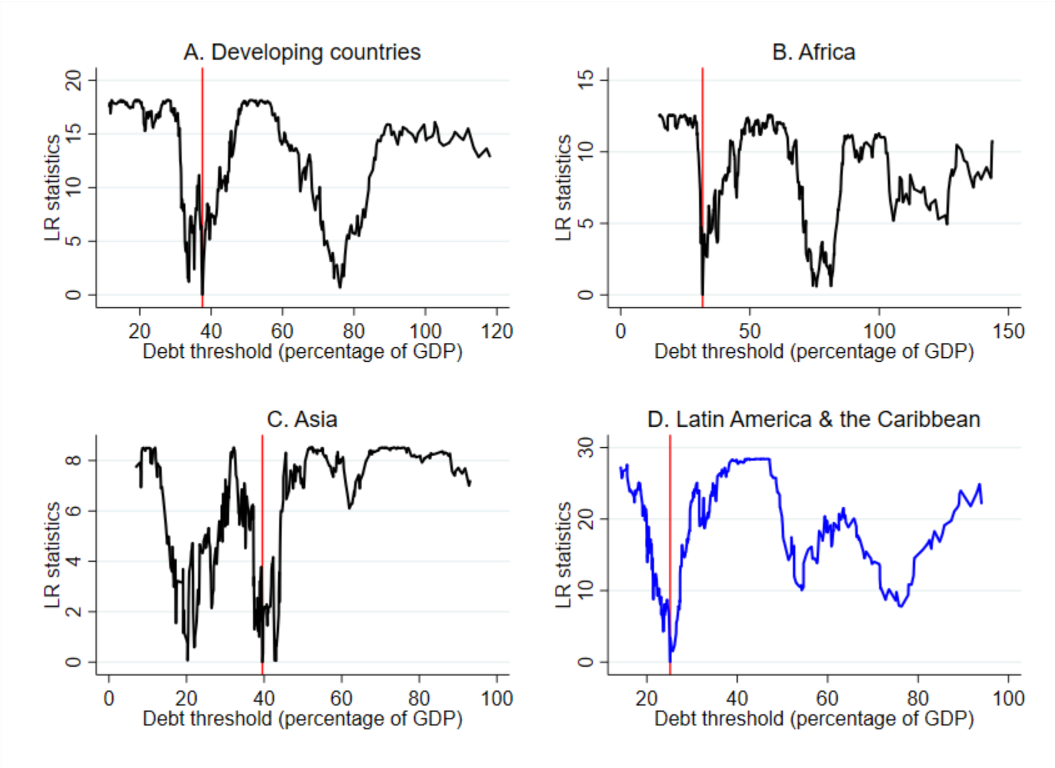

Figure 2.4: Public debt thresholds

Note: The figure illustrates the public debt thresholds in developing economies. A threshold effect of 25% debt–to–GDP is significant only in Latin America and the Caribbean region.

cannot be generalised to developing economies worldwide.

The regime–dependent coefficient at high debt regime is positive for Latin America and the Caribbean (Panel B of Table 2.2). This indicates although the debt approaches high levels (or beyond the threshold level of 25% of debt–to–GDP), it does not impede economic growth. Therefore, we can conclude that irrespective of accumulating high debt stocks, public debt is growth–enhancing for Latin America and the Caribbean region.

Our analysis is based on the forward overlapping five–year average growth as this indicates causality running from debt to growth and aids in mitigating the bias in the estimates. As a robustness exercise, we estimate the equation (2.3.1) on non–overlapping forward five–year growth averages (1993–1997, 1998–2002, 2003–2007, 2008–2012, 2013–2017) (Table A.7 in the Appendix). This reduces the number of data points in our sample to five ($t = 5$). The results are quite similar to overlapping five–year growth averages, with strong evidence for the existence of debt thresholds only for the Latin America and the Caribbean region. We then re–estimate the equation (2.3.1) on contemporaneous growth. However, the results show no evidence for the presence of threshold effects for developing economies or for any of the regional sub–groups. (Table A.8 in the Appendix). The rest of our study therefore, focuses mainly on the forward overlapping five–year averages of growth and public debt as it indicates that causality may run from public debt to growth. It may assist in disentangling the relationship between debt and growth effectively.

2.4.2 Heterogeneity across income

Table 2.3 shows the income–based heterogeneity analysis on the existence of threshold effects in developing countries. The list of developing countries by level of income is given in Table A.2 in the Appendix. The debt threshold effect is seen only amongst low income countries at 37% of debt–to–GDP (Panel B of Table 2.3). The marginal impact of debt in the high debt regime for the low income countries is significant and positive. This indicates that as the public debt level exceeds the threshold value of 37% debt–to–GDP, a 100% increase in public debt leads to a 1% increase in economic growth for the low income countries.

Figure A.5 in the Appendix visually presents the debt threshold effects in the developing economies for the income based four sub–groups. The debt threshold effect visible in the lower income category is no longer observed with increasing income. Approximately 85% of the countries in the low income group comprises of countries in Africa[4]. As the production structures significantly vary across the level of development paradigm, the presence of debt thresholds may have impacted by the existing structural differences.

Low income economies have accumulated substantially larger debt stocks in

[4]Low income country group comprises of countries in the regions of Africa (23), Asia (3) and Latin America and the Caribbean (1).

Table 2.3: DPTR estimates of debt on growth, by income

	Low Income	Lower–Middle Income	Upper–Middle Income	High Income
A-Forward growth excluding controls				
Threshold estimates $\hat{\gamma}$	37.367	64.674	69.855	19.384
95% confidence interval	[36.87 37.67]	[54.33 65.17]	[67.49 70.24]	[19.17 19.58]
Threshold effect test: p-value	0.294	0.809	0.041	0.993
Threshold effect	No	No	Yes	No
Impact of debt on growth				
$\hat{\beta}_1$	-0.061***	0.023***	0.027***	0.061*
	(0.017)	(0.005)	(0.006)	(0.032)
$\hat{\beta}_2$	0.003	0.011***	0.003	0.013*
	(0.004)	(0.002)	(0.003)	(0.007)
Regime independent controls	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	27/567	38/798	30/630	16/336
B-Forward growth including controls				
Threshold estimates $\hat{\gamma}$	37.367	64.674	72.863	60.895
95% confidence interval	[37.09 37.66]	[59.30 65.17]	[69.96 73.77]	[54.21 60.98]
Threshold effect test: p-value	0.019	0.760	0.081	0.348
Threshold effect	Yes	No	No	No
Impact of debt on growth				
$\hat{\beta}_1$	-0.050***	0.021***	0.020***	0.049***
	(0.013)	(0.004)	(0.005)	(0.010)
$\hat{\beta}_2$	0.010***	0.011***	0.003	0.026***
	(0.004)	(0.001)	(0.003)	(0.006)
Regime independent controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	27/567	38/798	30/630	16/336

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses. ***, **, and * indicate significant p values at 1%, 5% and 10% level, respectively.

recent years. The increase in median public debt is as high as 20% of GDP since 2013 which is comprised mainly of non–concessional and privately sourced debts (Essl et al., 2019). Therefore, interest payments are absorbing an increasing proportion of government revenues. The majority of low income countries are susceptible to weakening in trade or global financial conditions given high levels of external debt, lack of fiscal space, low foreign currency reserves, and undiversified exports. As such, proactive efforts in identifying and reducing debt–related vulnerabilities is a top priority for developing economies. In this context, the governments should be encouraged to mobilize domestic resources, improve debt transparency, and strengthen debt management practices. Furthermore, it is advisable to complement these by focusing on ways to strengthen fiscal frameworks, improve the efficiency of public expenditures and public investment management, and develop domestic financial systems.

2.4.3 Heterogeneity across governance quality

Table 2.4 shows the DPTR estimates across the quality of governance. The list of developing countries by level of governance quality is given in Table A.3 in the Appendix. When we allow the debt–growth relationship to vary according to governance quality, we find that governance quality indeed matters. In particular, we observe the presence of debt thresholds only in the countries with the lowest governance quality ('not free'). The public debt threshold for the country group 'not free' is at 38% of debt–to–GDP. Beyond this debt threshold, a 100% increase in debt leads to 1% increase in growth. As in the previous case, high debt is not growth–reducing for countries with the poorest quality of governance. If the debt ratio is above the threshold value, the marginal impact of debt on growth is positive. This indicates that once a debt threshold is surpassed, public debt for developing countries with poor governance quality is growth–enhancing.

The effect of public debt on growth depends not only on the level of indebtedness but also on other country characteristics, such as institutional quality, and governance quality (Kourtellos et al., 2013). If the debt–growth relationship depends on characteristics other than indebtedness, separate DPTR regressions based on three geographical regions: Africa, Asia and Latin America and the Caribbean would not be meaningful here, as they would split the sample along the same dimensions as before. Therefore, we estimate the equation (2.3.1) on sub–samples based on the level of governance quality, i.e. according to the com-

Table 2.4: DPTR estimates of debt on growth, by governance quality

	Free	Partly Free	Not Free
A-Forward growth excluding controls			
Threshold estimates $\hat{\gamma}$	77.054	105.986	49.996
95% confidence interval	[75.20 77.73]	[104.09 106.65]	[49.73 50.71]
Threshold effect test: p-value	0.138	0.318	0.139
Threshold effect	No	No	No
Impact of debt on growth			
$\hat{\beta}_1$	0.038***	0.011***	-0.045***
	(0.005)	(0.003)	(0.013)
$\hat{\beta}_2$	0.016***	0.001	0.012***
	(0.002)	(0.002)	(0.004)
Regime independent controls	No	No	No
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Countries/Observations	29/609	57/1,197	25/525
B-Forward growth including controls			
Threshold estimates $\hat{\gamma}$	77.019	71.543	37.533
95% confidence interval	[74.53 77.05]	[69.39 71.62]	[37.26 37.74]
Threshold effect test: p-value	0.101	0.119	0.012
Threshold effect	No	No	Yes
Impact of debt on growth			
$\hat{\beta}_1$	0.034***	0.019***	-0.060***
	(0.004)	(0.003)	(0.013)
$\hat{\beta}_2$	0.017***	0.009***	0.010***
	(0.002)	(0.002)	(0.003)
Regime independent controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Countries/Observations	29/609	57/1,197	25/525

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses. ***, **, and * indicate significant p values at 1%, 5% and 10% level, respectively.

bined average ratings for political rights and civil liberties, as reported in the annual Freedom in the World Survey (Freedom House, 2018).

Finally, we can conclude that the findings emphasise the role individual factors play in determining the debt–growth relationship when the estimation is controlled using an indicator for the quality of governance. We find governance quality better explains the non–linearity between public debt and economic growth, suggesting the existence of debt thresholds for developing economies.

Despite the importance of governance quality in determining the nature of the debt–growth relationship, poor governance quality has not been identified a reason for reduced growth in developing countries. This may partly explain why very high levels of debt may not matter for economic growth in developing countries. Our findings are similar to those of Cordella et al. (2010), who found that very high debt levels have not hampered the economic growth in heavily indebted poor countries. Further, they confirmed that net transfers and investment do not depend on the stock of debt. We therefore conclude that, in developing economies, debt reduction would be growth–enhancing irrespective of the level of governance quality. However, this does not necessarily encourage the accumulation of high debt or prevalence of poor governance quality as opposed to low debt and good governance quality. Moreover, there can be other channels through which public debt affects growth, an important area for future research. Overall in our analysis, we find that high debt has not reduced economic growth in developing countries. The negative effects of public debt are not yet that drastic, possibly because debt levels may not be as high in developing countries as in the case of developed countries.

2.5 Robustness checks

We conduct a number of robustness tests to ensure that our results are robust throughout a range of specifications. These include estimation with additional variables; analysis with heterogeneity along each of the cross–sectional and time dimensions; and estimation with alternative measures for governance quality. For the majority of these tests the results are supportive of our primary analysis.

The DPTR estimation for public debt and forward five–year average growth rate is carried out including an additional thirteen explanatory variables selected based on the available theoretical and empirical growth literature. These are foreign direct investment, inflation, unemployment rate, labour force, labour force participation ratio, age dependency ratio, life expectancy at birth, fertility rate, population, urban population, land, human development index and primary education. All variables are used as one–period lagged variables to avoid further endogeneity in the model. The results are robust over all these regressors for the full sample of developing countries and the three sub–samples representing Africa, Asia, and Latin America and the Caribbean.

Given the importance of including both low– and high debt countries in the analysis, restricting the sample is problematic for the objective of our study. Yet, as an econometric robustness check, we eliminate countries one at a time from the sample, starting with the debt outliers: ten countries with the highest and the lowest, average and median debt. We find the estimation results are robust across all these specifications. We also conduct robustness checks with restricted samples along time dimensions: for five–year periods; and for the periods before and after the financial crisis. The debt threshold values deviate slightly before and after the financial crisis, yet the significance and the direction of results are robust for the high debt regime.

To check the robustness of the existence of a debt threshold in countries with the worst governance quality, we run the DPTR estimation using other indicators for governance quality: freedom of press and individual variables on civil liberty and property rights. Results obtained using 'freedom of press' as an indicator are more statistically significant, and the pattern that emerges survives for the high debt regime in all the specifications.

To examine the sensitivity of the type of public debt (whether it is the general government debt which we used as the main indicator for public debt or the central government debt) on our results, we re-estimate (2.3.1) by excluding the nine countries that measure public debt as general government debt. Except for a slight change in estimate magnitudes, there is no substantial difference in the level of statistical significance compared to our baseline results. This indicates that the use of general government debt has no substantial qualitative impact on our findings.

2.6 Policy implications and concluding remarks

The idea that debt reduction may induce economic growth and help achieve the development targets of the developing countries is gaining increasing consensus. In this chapter, we examine the relationship between public debt and economic growth and the existence of debt thresholds in developing countries by considering heterogeneities across regions, income and quality of governance.

Although research on the debt–growth nexus has been revamped since the financial crisis, it has focused mainly on developed countries, despite the increasing debts in developing countries. The main objective of our study is to carry out a comprehensive debt analysis to better understand the relationship between public debt–growth nexus and the presence of debt thresholds in developing economies. Using a larger annual data set of 111 developing countries over the period 1993–2017, we employ the DPTR model to estimate debt thresholds. Our study provides the first evidence of applying this econometric technique to a large number of developing countries covering the three regions of Africa, Asia, and Latin America and the Caribbean. The study has an extant value as developing countries show increased preference for domestic borrowing, due to lower costs and fewer risks, compared to the external borrowing.

Employing the DPTR, we show that there is no evidence for debt thresholds for the developing countries except for the Latin America and the Caribbean region, where the debt turning point lies at around 25% of debt–to–GDP. Our results are similar to Chudik et al. (2017), Pescatori et al. (2014) and Bentour (2021) who find no evidence of a threshold effect. Pescatori et al. (2014) found the debt trajectory is important in understanding future growth prospects, as countries with high but declining debt appear to grow equally as fast as countries with low debt. We observe a similar pattern as high debt has not reduced the growth of developing economies. Further, estimating region–specific or country–specific debt thresholds might be useful rather than estimating common debt thresholds for all the developing countries. Further, contemporary literature suggests that threshold analysis is extremely sensitive to the econometric technique, sample selection and the time period. Therefore, the results need to be interpreted with caution.

The public debt–growth nexus may depend not only on the level of indebtedness but also on other country characteristics (Kourtellos et al., 2013). As regional country categories based on geographical location do not provide meaningful analytical groups when investigating the impact of other country characteristics (income and governance quality) on the public debt–growth nexus, we differentiate countries firstly into four sub–groups according to their income (low income, lower–middle income, upper–middle income and high income) and secondly into three sub–groups based on level of governance quality (free, partly free and not free). This classification of countries drives different results for the value of the debt threshold, yet high public debt is growth–enhancing in all these specifications. We find strong evidence for debt threshold effects based on income and governance quality, which indicates that marginal impact of debt on growth starts to differentiate at a debt threshold of 37% debt–to–GDP for countries in the low income group and at 38% debt–to–GDP for countries with poorer governance quality. It is worth noting that the majority of countries in these two groups represent the African region.

Our finding that beyond the debt threshold, high debt is not growth–reducing, does not necessarily encourage debt accumulations or dismisses the need to improve the quality of governance in developing countries. Moreover, the absence of significance at the marginally high levels of debt does not imply that the absence of average debt reduction may have no impact on growth. Although small reductions in debt shows no impact, large reductions might still significantly improve the growth performance. Thus, further analysis considering the heterogeneities across sub–regions and single country studies may also beneficial in deriving sensible policies to ensure sustainable debt management in developing economies.

Appendix A

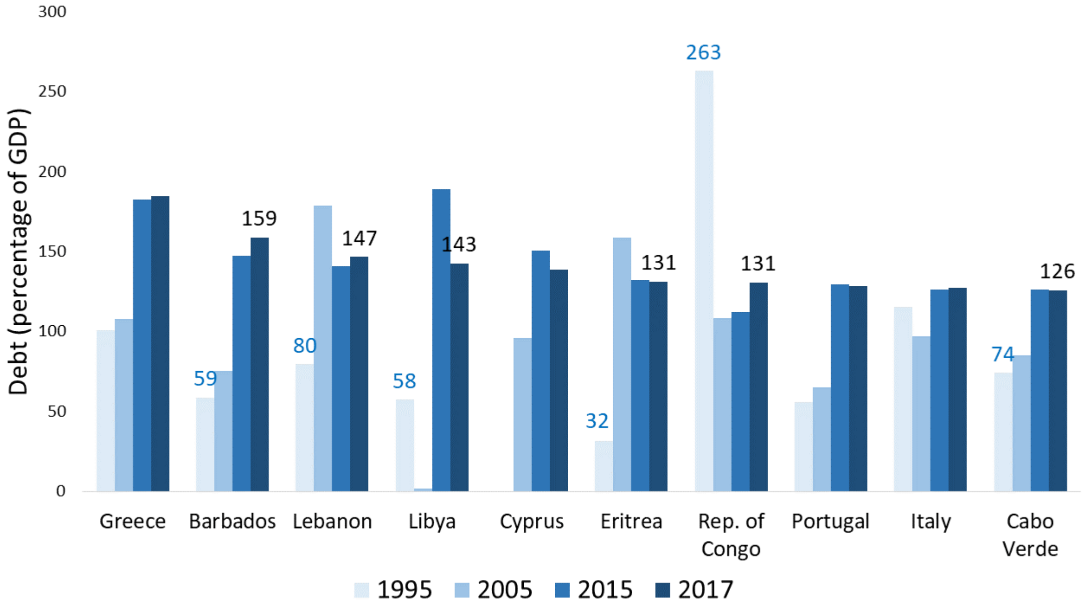

Figure A.1: Most indebted countries in the world - 2017

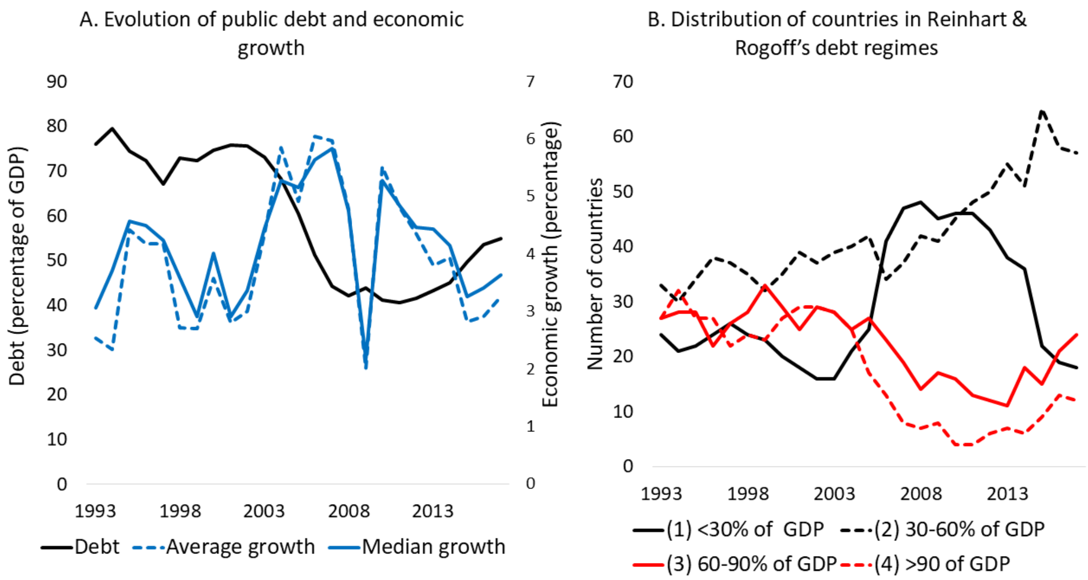

Figure A.2: Public debt trends in developing countries

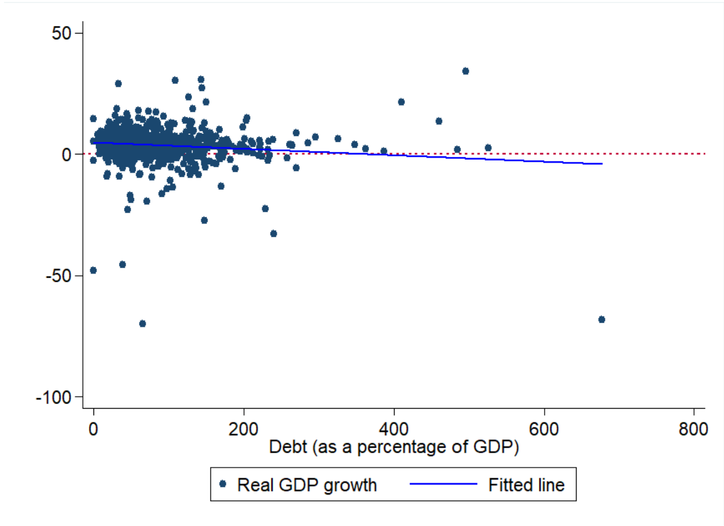

Figure A.3: Public debt and real GDP growth: pooled developing countries

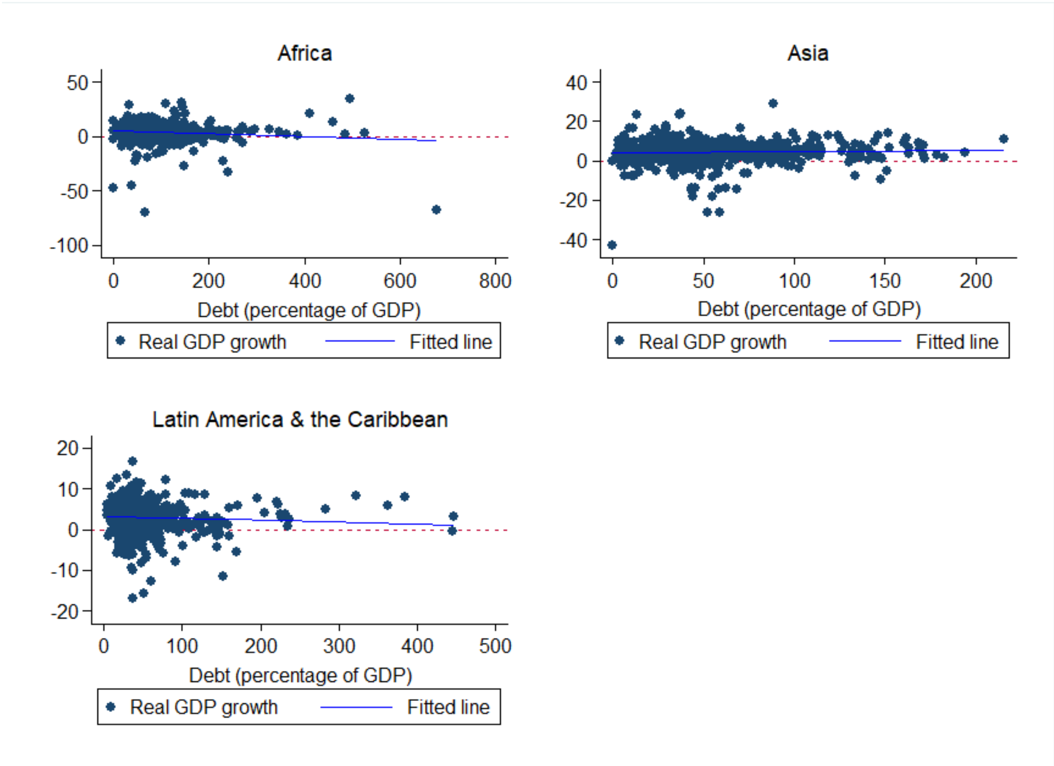

Figure A.4: Public debt and real GDP growth: regional differences

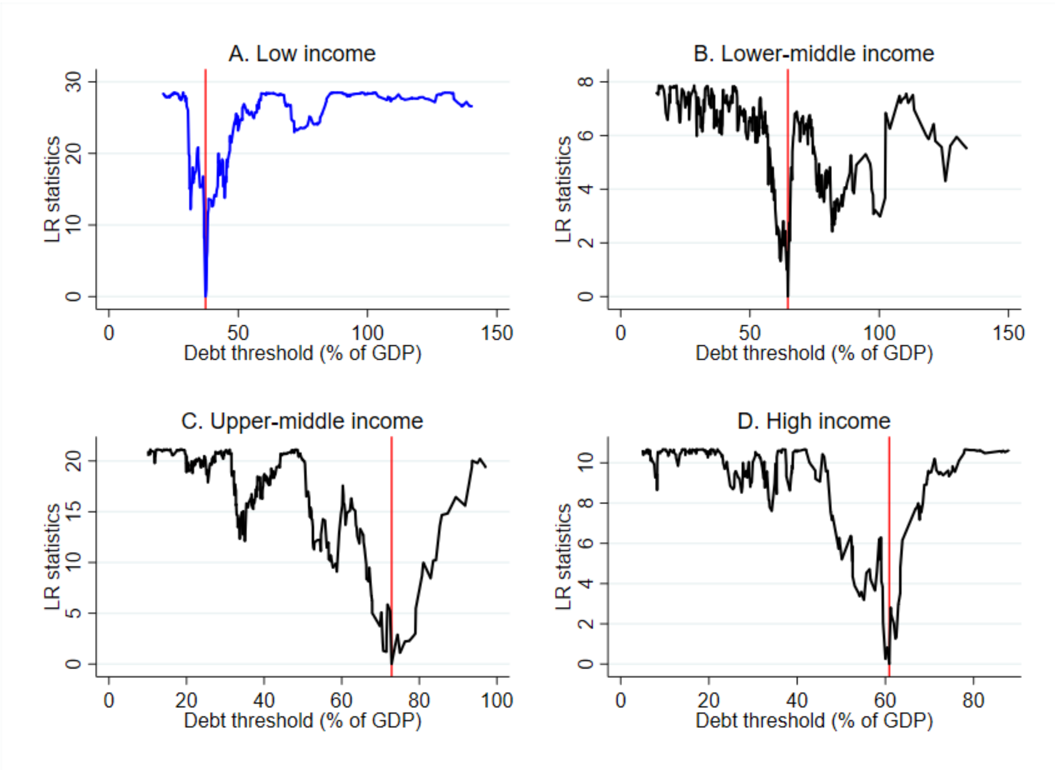

Figure A.5: Public debt thresholds, income heterogeneity

Note: The figure illustrates the presence of a significant public debt threshold (red) of 37% debt–to–GDP for the low income countries.

Table A.1: List of developing countries

Africa		Asia		Latin America and the Caribbean
North Africa	*Southern Africa*	*East Asia*	*Western Asia*	*Caribbean*
Algeria	Angola	Cambodia	Bahrain	Bahamas
Egypt	Botswana	China	Israel	Barbados
Mauritania	Eswatini	Fiji	Jordan	Belize
Morocco	Lesotho	Indonesia	Kuwait	Guyana
Sudan	Malawi	Kiribati	Lebanon	Jamaica
Tunisia	Mauritius	Laos	Oman	Suriname
	Namibia	Malaysia	Qatar	Trinidad & Tobago
Central Africa	South Africa	Mongolia	Saudi Arabia	
Cameroon	Zambia	Myanmar	Syria	*Mexico & Central America*
Central African Rep.	Zimbabwe	PNG	Turkey	Costa Rica
Chad		Philippines	UAE	Dominican Rep.
Congo	*West Africa*	Rep. of Korea	Yemen	El Salvador
Gabon	Benin	Samoa		Guatemala
Sao Tome & Principe	Burkina Faso	Singapore		Haiti
	Cabo Verde	Solomon Islands		Honduras
East Africa	Cote d'Ivoire	Thailand		Mexico
Burundi	Gambia	Vanuatu		Nicaragua
Comoros	Ghana	Vietnam		Panama
Congo, Dem.Rep.	Guinea			
Djibouti	Guinea-Bissau	*South Asia*		*South America*
Eritrea	Mali	Bangladesh		Argentina
Ethiopia	Niger	Bhutan		Bolivia
Kenya	Nigeria	India		Brazil
Madagascar	Senegal	Iran		Chile
Rwanda	Sierra Leone	Maldives		Colombia
Uganda	Togo	Nepal		Ecuador
Tanzania		Pakistan		Paraguay
		Sri Lanka		Peru
				Uruguay
				Venezuela

Note: The United Nations World Economic Situation Prospects 2019 Report classifies countries into three groups: developed economies, economies in transition and developing economies. There are 126 developing countries: 53 in Africa, 46 in Asia and 27 in Latin America and the Caribbean region. We exclude 15 countries from the sample due to unavailability of reliable debt data.

Table A.2: List of developing countries, by income

Low Income	Lower-Middle Income	Upper-Middle Income	High Income
Benin	Angola	Algeria	Argentina
Burkina Faso	Bangladesh	Belize	Bahamas
Burundi	Bhutan	Botswana	Bahrain
Central African Republic	Bolivia	Brazil	Barbados
Chad	Cabo Verde	China	Chile
Comoros	Cambodia	Colombia	Israel
Congo, Dem. Rep.	Cameroon	Costa Rica	Korea, Rep.
Eritrea	Congo, Rep.	Dominican Republic	Kuwait
Ethiopia	Cote d'Ivoire	Ecuador	Oman
Gambia	Djibouti	Fiji	Panama
Guinea	Egypt	Gabon	Qatar
Guinea-Bissau	El Salvador	Guatemala	Saudi Arabia
Haiti	Eswatini	Guyana	Singapore
Madagascar	Ghana	Iran	Trinidad and Tobago
Malawi	Honduras	Jamaica	UAE
Mali	India	Jordan	Uruguay
Nepal	Indonesia	Lebanon	
Niger	Kenya	Malaysia	
Rwanda	Kiribati	Maldives	
Senegal	Lao PDR	Mauritius	
Sierra Leone	Lesotho	Mexico	
Syria	Mauritania	Namibia	
Tanzania	Mongolia	Paraguay	
Togo	Morocco	Peru	
Uganda	Myanmar	Samoa	
Yemen	Nicaragua	South Africa	
Zambia	Nigeria	Suriname	
Zimbabwe	Pakistan	Thailand	
	Philippines	Turkey	
	PNG	Venezuela	
	Sao Tome and Principe		
	Solomon Islands		
	Sri Lanka		
	Sudan		
	Tunisia		
	Vanuatu		
	Vietnam		

Table A.3: List of developing countries, by governance quality

Free	Partly Free		Not Free
Argentina	Bangladesh	Malaysia	Algeria
Bahamas	Bhutan	Maldives	Angola
Barbados	Bolivia	Mali	Bahrain
Belize	Burkina Faso	Mauritania	Burundi
Benin	Central African Republic	Mexico	Cambodia
Botswana	Colombia	Morocco	Cameroon
Brazil	Comoros	Nepal	Chad
Cabo Verde	Congo, Dem. Rep.	Nicaragua	China
Chile	Cote d'Ivoire	Niger	Congo, Rep.
Costa Rica	Djibouti	Nigeria	Egypt
Dominican Republic	Ecuador	Pakistan	Eritrea
El Salvador	Ethiopia	PNG	Eswatini
Ghana	Fiji	Paraguay	Iran
Guyana	Gabon	Peru	Lao PDR
Israel	Gambia	Philippines	Myanmar
Jamaica	Guatemala	Senegal	Oman
Kiribati	Guinea	Sierra Leone	Qatar
Korea, Rep.	Guinea-Bissau	Singapore	Rwanda
Mauritius	Haiti	Solomon Islands	Saudi Arabia
Mongolia	Honduras	Sri Lanka	Sudan
Namibia	India	Tanzania	Syria
Panama	Indonesia	Thailand	UAE
Samoa	Jordan	Togo	Vietnam
Sao Tome and Principe	Kenya	Tunisia	Yemen
South Africa	Kuwait	Turkey	Zimbabwe
Suriname	Lebanon	Uganda	
Trinidad and Tobago	Lesotho	Venezuela	
Uruguay	Madagascar	Zambia	
Vanuatu	Malawi		

Table A.4: Basic information of the variables

Variable	Description	Source
Outcome variable		
Δgdp	Real GDP growth rate (%)	WB
Threshold variable		
d	Public debt–to–GDP ratio (as a % of GDP)	IMF
Explanatory variables: main analysis		
$open$	Exports and imports of goods and services (as a % of GDP)	WB
i	Gross fixed capital formation (as a % of GDP)	WB
$gpop$	Population growth (annual, %)	WB
edu	Secondary education, duration (years)	WB
pr	Political rights, degree of freedom, (Scale 1-7; 1=highest; 7=lowest)	Freedom House
cl	Civil liberties, degree of freedom, (Scale 1-7; 1=highest; 7=lowest)	Freedom House
Explanatory variables: robustness checks		
fdi	Foreign direct investment, net inflows (as a % of GDP)	WB
inf	Inflation, GDP deflator (annual %)	WB
$unemp$	Unemployment rate, total (% of total labor force)	WB
lf	Labour force, total (people ages 15 and older who supply labor)	WB
$lfpr$	Labour force participation rate, total (% of total population ages 15+) (modeled International Labour Organization estimate)	WB
dr	Age dependency ratio (% of working-age population)	WB
$life$	Life expectancy at birth, total (years)	WB
$ferti$	Fertility rate, total (births per woman)	WB
pop	Population, total	WB
$upop$	Urban population (% of total population)	WB
$land$	Land area (Sq.km)	WB
hdi	Human development index	WB
$pedu$	Primary education, duration (years)	WB
$press$	Freedom of press, degree of freedom, (Scale 0-30; 0=highest; 30=lowest)	Freedom House

Note: IMF = Global debt database published by the International Monetary Fund; WB = World Development Indicators published by the World Bank.

Table A.5: Descriptive statistics, annual data

Variables	Obs.	Mean	Median	Std. dev.	Min	Max
Developing countries						
Real GDP growth rate	2,775	3.91	4.17	5.17	-69.81	34.20
Debt to GDP ratio	2,775	59.67	47.91	50.37	0.00	677.18
Trade openness	2,775	77.72	71.23	43.68	12.07	402.25
Public investment	2,775	22.56	20.78	9.88	1.60	80.25
Population growth	2,775	2.06	1.94	1.36	-6.18	16.33
Secondary school enrolment	2,775	6.16	6.00	0.78	4.00	8.00
Africa						
Real GDP growth rate	1,175	3.95	4.20	6.10	-69.81	34.20
Debt to GDP ratio	1,175	71.24	56.68	59.45	0.00	677.18
Trade openness	1,175	67.69	56.68	31.29	12.07	160.98
Public investment	1,175	22.19	20.32	10.82	1.60	74.36
Population growth	1,175	2.39	2.57	0.92	-6.19	7.91
Secondary school enrolment	1,175	6.27	6.00	0.74	4.00	8.00
Asia						
Real GDP growth rate	950	4.53	4.86	4.79	-42.78	29.26
Debt to GDP ratio	950	51.06	43.93	33.83	0.00	216.04
Trade openness	950	91.76	83.55	55.66	16.01	402.25
Public investment	950	23.89	22.42	9.84	4.65	64.34
Population growth	950	2.14	1.77	1.89	-3.11	16.33
Secondary school enrolment	950	6.30	6.00	0.82	4.00	8.00
Latin America and the Caribbean						
Real GDP growth rate	650	2.94	3.31	3.52	-17.00	16.79
Debt to GDP ratio	650	51.35	37.36	48.60	4.09	446.57
Trade openness	650	75.32	72.29	31.76	12.53	181.64
Public investment	650	21.30	19.77	7.68	6.66	80.25
Population growth	650	1.34	1.35	0.68	-0.35	3.84
Secondary school enrolment	650	5.74	6.00	0.64	4.00	7.00

Table A.6: Correlation matrix

	Δgdp	Δgdp_{t-1}	d	$open$	i	$gpop$	edu
Δgdp	1.0000						
Δgdp_{t-1}	0.2252*	1.0000					
d	-0.0781*	-0.1049*	1.0000				
$open$	0.0552*	0.0634*	-0.0403*	1.0000			
i	0.1361*	0.1478*	-0.0772*	0.2200*	1.0000		
$gpop$	0.1465*	0.1436*	0.0129	0.0380*	-0.0029	1.0000	
edu	0.0007	0.0017	-0.0452*	-0.2025*	-0.0180	0.0873*	1.0000

Note: *Denotes statistical significance at 10% level.

Table A.7: DPTR estimates of debt on forward growth, non-overlapping

	Developing	Africa	Asia	Latin America and the Caribbean
Threshold estimates $\hat{\gamma}$	63.808	38.363	44.336	22.013
95% confidence interval	[61.54 63.82]	[31.45 38.88]	[44.32 44.96]	[21.55 22.26]
Threshold effect test: P-value	0.147	0.370	0.554	0.019
Threshold effect	No	No	No	Yes
Impact of debt				
$\hat{\beta}_1$	0.036***	-0.013	-0.015	-0.132***
	(0.009)	(0.021)	(0.025)	(0.035)
$\hat{\beta}_2$	0.017***	0.016***	0.010	-0.008
	(0.004)	(0.005)	(0.011)	(0.006)
Regime independent controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	111/555	47/235	38/190	26/130

Note: The estimates are of the baseline specification including the controls. Bootstrapped standard errors with 1000 replications are shown in parentheses. ***, **, and * indicate significant p values at 1%, 5% and 10% level, respectively.

Table A.8: DPTR estimates of debt on contemporaneous growth

	Developing	Africa	Asia	Latin America & the Caribbean
Threshold estimates $\hat{\gamma}$	48.589	48.901	32.452	20.031
95% confidence interval	[46.63 48.86]	[48.74 48.98]	[32.39 32.48]	[20.03 20.04]
Threshold effect test: P-value	0.172	0.435	0.452	0.938
Threshold effect	No	No	No	No
Impact of debt				
$\hat{\beta}_1$	0.034***	0.046***	0.077***	0.041
	(0.009)	(0.015)	(0.022)	(0.028)
$\hat{\beta}_2$	0.012***	0.013***	0.028***	0.003
	(0.003)	(0.004)	(0.008)	(0.004)
Regime independent controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Countries/Observations	111/2,775	47/1,175	38/950	26/650

Note: The estimates are of the baseline specification including the controls. Bootstrapped standard errors with 1000 replications are shown in parentheses. ***, **, and * indicate significant p values at 1%, 5% and 10% level, respectively.

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Chapter 3
The Effectiveness of the UN-REDD Programme as a Guardian of Tropical Forests in Developing Countries

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Statement of Authorship

Title of Paper	The Effectiveness of the REDD Programme as a Guardian of Tropical Forests
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☑ Unpublished and Unsubmitted work written in manuscript style
Publication Details	

Principal Author

Name of Principal Author (Candidate)	Warnakulasooriya Lakmini Priyanthi Fernando		
Contribution to the Paper	I have partly contributed in literature review, data collection, estimation, interpretation of results and writing the manuscript.		
Overall percentage (%)	60%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	07.10.2020

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i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Abstract

This paper examines the effectiveness of the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) in Developing Countries. We employ a novel staggered difference-in-differences approach recently proposed by Athey and Imbens (2018) to analyse deforestation and carbon dioxide emissions data from 2001 to 2018. We show that on average adoption of UN-REDD reduces deforestation and associated emissions, but that these effects take 9-10 years to be seen. In addition, heterogeneous programme effects are observed across geographical regions and economic development levels. Latin America and the Caribbean countries have a strong reduction in both deforestation and associated emissions, while countries in Africa and Asia-Pacific have no deforestation reductions and slightly increased emissions. Across income levels, only upper-middle income countries have lower deforestation and associated emissions while emissions rose in low income countries.

Keywords: UN-REDD; Deforestation; Emissions; Staggered difference–in–differences, Heterogeneous programme effects.

JEL classification: O13, O19, Q23, Q50, C54.

3.1 Introduction

The role of tropical forests in combating climate change and preserving biological diversity has made the conservation of forests a major policy challenge for developing countries (Amelung, 1993, Dawson et al., 2018, Skutsch and Turnhout, 2020). Historically, national policies have not been enough to curtail deforestation and success in combating climate change requires coupling them with international agreements. The United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (henceforth, UN-REDD programme) is recognized as the first global joint initiative on tackling climate change. UN-REDD works with developing partner countries to implement REDD+ activities that provides incentives for protecting the environment by valuing carbon stored in forests.

Existing studies on the impact evaluation of the UN-REDD programme have employed qualitative approaches or limited quantitative policy evaluation techniques (Agung et al., 2014, Bayrak and Marafa, 2016, Minang et al., 2014, Pistorius, 2012). We evaluate the UN-REDD programme impact by employing a novel econometric technique; the staggered difference–in–differences (henceforth, staggered DID), to identify whether changes to forest governance triggered by REDD+ activities have reduced deforestation and associated emissions in developing countries. The staggered DID approach has several advantages. First, it allows to quantify the impact of the UN-REDD programme over time, which is not possible in the standard DID setting. Second, it enables to identify the causal effects of the UN-REDD programme even in the presence of confounding factors that may have also contributed to changes in deforestation and emissions during the sample period. Third, it is well known that in the assessment of environmental policies, the accuracy and comparability of spatial data on deforestation is paramount (see e.g. Zabala, 2018), as new information is often revealed by the choice of good data (Köthke et al., 2013, Rudel et al., 2000). However, the lack of good quality data is widely acknowledged in the forest literature and previous studies often use questionable spatial data on forests from the Food and Agriculture Organization (FAO) which are collected across countries following different methodologies (Hansen and DeFries, 2004, Hansen et al., 2013). Furthermore, Hansen et al. (2013) find that the UN-REDD programme outcomes depend on the institutional investment and scientific capacity to utilise global observation records. By contrast, our analysis of the UN-REDD policy employs satellite data which are spatially more accurate and derived through an internally consistent approach. Unequivocally, using these satellite contributes to improve existing knowledge of global forest changes. Unequivocally, use of satellite data contributes to the improvements in existing knowledge of global forest changes.

By emphasising on identifying the causal effect of the UN-REDD programme over time, our study contributes to the existing literature on global environmental policies, and also sheds new light on the disparities across developing countries related to this topic. To the best of our knowledge, this is the first cross-country study that investigates the effect of a global environmental policy in developing countries by employing recent programme evaluation econometric techniques.

Results show that overall the UN-REDD programme has reduced both deforestation and emissions in developing countries over time. While smaller impacts on deforestation and emissions are observed in the first few years of the programme adoption, much larger effects are evidenced over longer periods. This time varying nature of the UN-REDD programme impact can only be evidenced in our staggered DID framework. Furthermore, heterogeneous programme effects are also observed across regions and economic development levels. In particular, the UN-REDD programme has been relatively successful in Latin America and the Caribbean region compared to Africa and Asia-Pacific. Similarly, among the developing world, upper-middle and high income countries are better off compared to lower-middle and low income countries. By distinguishing these heterogeneous groups, our results show clearly that the effects of the UN-REDD programme is not uniform across geographical locations and levels of economic development.

The success of the UN-REDD programme has been at the core of numerous debates among economists and scientists recently. Although the impact assessments on payments for environmental services (PES) schemes in Brazil (Simonet et al., 2019) and Uganda (Jayachandran et al., 2017) provide strong evidence in support of the UN-REDD programme success, Bluffstone et al. (2013) argue that insecure and poorly defined community forest tenure in developing countries makes it difficult to envision it as a successful forest-climate policy. The UN-REDD program, they argue, could become another contingency-based aid like structural adjustment programme rather than a cost-effective carbon sequestration mechanism. A critical evaluation of the UN-REDD programme by Pistorius (2012) reveals that its effectiveness and integrity is at stake, despite increased country participation. Clearly, the complexities in forest governance and the absence of clear implementation and funding modalities for the UN-REDD programme impede its achievement of the intended goals. Despite the growing number of countries adopting the programme, the ambiguity of its performance could jeopardise its fate as an effective global environmental policy (Reinecke et al., 2014). However, our results indicate that the longer a country is exposed to the UN-REDD programme, the stronger the programme effect is. This finding supports the belief that as time evolves, the UN-REDD programme incentives override its transaction costs to deliver a positive policy effect (Libecap, 2014). Such transaction costs include negotiation, monitoring (verification) and enforcement costs between forest users, governments, and donors (Corbera, 2012). Understanding and minimising these transaction costs in the UN-REDD programme implementation process is critical for its success, as existing institutional structures of developing countries often impede on the performance of PES schemes; see, e.g., Alston and Andersson (2011). Our results on regional differences are also in line with the literature on PES assessments on deforestation, which demonstrates the existence of substantial regional variations in deforestation (Jayachandran et al., 2017, Libecap, 2014, Robalino and Pfaff, 2013, Scullion et al., 2011). Contextual factors and policy design are vital in determining PES outcomes (Börner et al., 2017). Low levels of pre–programme compliance, low opportunity cost of participation and well–established property rights are some of the contextual factors that ensure PES success. Scullion et al. (2011) suggest the inclusion of risk-integrated payments, robust monitoring and enforcement programmes ensures environmental policies effectiveness. However, PES schemes are different from traditional policy instruments that are abide by legal regulations, sanction mechanisms or taxes (Börner et al., 2017). As such, a careful design of the UN-REDD programme is crucial to deliver the expected outcomes effectively. Our finding on the heterogeneous programme effects across economic development levels aligns with the literature on growth impacts on income inequality and environmental degradation (Ota, 2017). Indeed, low income economies often have competing needs over conservation and economic/social welfare. Economic growth impacts on environment degradation are generally larger for countries with lower income. Environmental policies are almost non-existent in many low income countries, and some developing nations in their quest to economic prosperity through increased income often triggers the introduction of environmental regulations at varying degrees. This may explain why deforestation and emissions have reduced in UN-REDD programme adopting upper-middle and high income countries but have increased in UN-REDD programme adopting lower-middle and low income countries.

Indeed, low income economies often have competing needs over conservation and economic/social welfare. Growth impact on environment degradation is generally larger for countries with lower income. As environmental policies are almost non-existent in most low income countries, increasing income triggers the introduction of environmental regulations at varying degrees. This could explain why we observe a positive policy effect for high income economies.

The remainder of the study is organised as follows. Section 3.2 introduces the UN-REDD programme background. Section 3.3 details our empirical strategy, and Section 3.4 describes the data and the variables. Section 3.5 contains the results, while some robustness checks are reported in Section 3.6. Finally, Section 3.7 concludes.

3.2 Programme background

According to the Intergovernmental Panel on Climate Change, greenhouse gas emissions have increased to unprecedented levels in the past few decades (IPCC, 2016). Anthropogenic greenhouse gas emissions are the leading cause of the earth's rapidly changing climate, while the burning of fossil fuels is the primary source of human-induced emissions. A second major source is deforestation – logging, clear-cutting, fires and other forms of forest deforestation – contributing to 20% of global emissions. Tropical deforestation and forest degradation alone accounts for 11% of these emissions, which is a larger contribution than the entire global transport sector. Forests are the most cost-effective and immediate solution to climate change. Reducing emissions from tropical forests will substantially avert the disastrous climate change. In 2018, global forest cover fell below 4 billion hectares, emitting 8 gigatonnes of carbon dioxide to the atmosphere (see Table 3.1). Between 2001 and 2018, the rate of deforestation in developing countries ranked highest, at 10.7 million hectares per annum – twice as large as developed countries – and total forest cover decreased by 3.5% to 2,120 million hectares. Although the highest annual rate of deforestation occurs in the Asia-Pacific (0.6%) the area of tropical forests cleared in Latin America and the Caribbean, 5.1 million hectares, is almost as large as the forest area cleared in Africa and the Asia-Pacific put together.[5]

Launched in 2008, the UN-REDD programme is the first global joint UN initiative on climate change and deploys the support of three agencies: the Food and Agriculture Organization of the United Nations (FAO), the United Nations Development Programme (UNDP) and the United Nations Environment Programme (UNEP). The overall development goal of the programme is to enhance carbon stocks in tropical forests while contributing to national sustainable development. Specifically, the UN-REDD programme aims to provide national deforestation reference levels, develop monitoring systems and promote the adoption of national

[5] Figure B.1 in the Appendix shows the global and regional deforestation trends between 2001 and 2018.

Table 3.1: Deforestation and emissions trends, 2001-2018

Region	Forest cover (million ha)		CO_2 emissions (gigatonnes)		Annual deforestation (2001-2018)	
	2001	2018	2001	2018	(million ha)	%
World (150)	**4,034.6**	**3,973.3**	**3.7**	**8.2**	**19.7**	**0.5**
Developed countries (36)	983.6	992.4	1.0	1.5	5.7	0.6
Economies in transition (12)	852.3	859.1	0.3	1.1	3.3	0.4
Developing countries (102)	2,198.7	2,121.8	2.5	5.6	10.7	0.5
Africa (46)	659.0	607.0	0.5	1.7	2.3	0.4
Asia–Pacific (34)	565.4	590.4	0.7	1.7	3.4	0.6
Latin Am. & Caribbean (22)	974.4	924.4	1.3	2.3	5.1	0.5

Source: Global Forest Watch (GFW, 2019)

Note: In the region column, the numbers in parenthesis indicate the number of countries that have adopted the policy.

strategies to facilitate the implementation of the programme (Davis et al., 2009). In addition, it drives the establishment of good governance, which is a prerequisite for the sustainable use of forest resources. This includes clarity on tenure of forest lands, enforcement of forest laws and empowerment of forest-dependent communities to participate in forest management. Participating countries receive results-based payments complemented by technical assistance, capacity building, and policy advice for their efforts in implementing REDD+. From 2009-2018, 62 developing countries adopted this policy. Among them, more than 30 countries have advanced their national REDD+ strategies or action plans, 40 countries were supported in developing national forest monitoring systems, and 15 countries developed country-based approaches to meet the social and environmental safeguards requirements of the United Nations Framework Convention on Climate Change (UNFCCC); see UNREDD (2008).

In our sample, deforestation increases from an annual average tree cover loss of 71,000 hectares in 2001 to 127,000 hectares in 2018, as shown in Figure 3.1. During that time, countries have substantially adopted the UN-REDD policy. The black dotted line in the figure shows the rise in countries adopting the policy since 2009. The prevalence of deforestation observed in the blue graph suggests the adoption of the UN-REDD programme may not have been persistent enough to curb deforestation. A similar pattern in terms of change in annual average emissions is displayed in Figure B.2 in the Appendix. Between 2001-2018, emissions have more than doubled, from 24 megatonnes to 56 megatonnes.

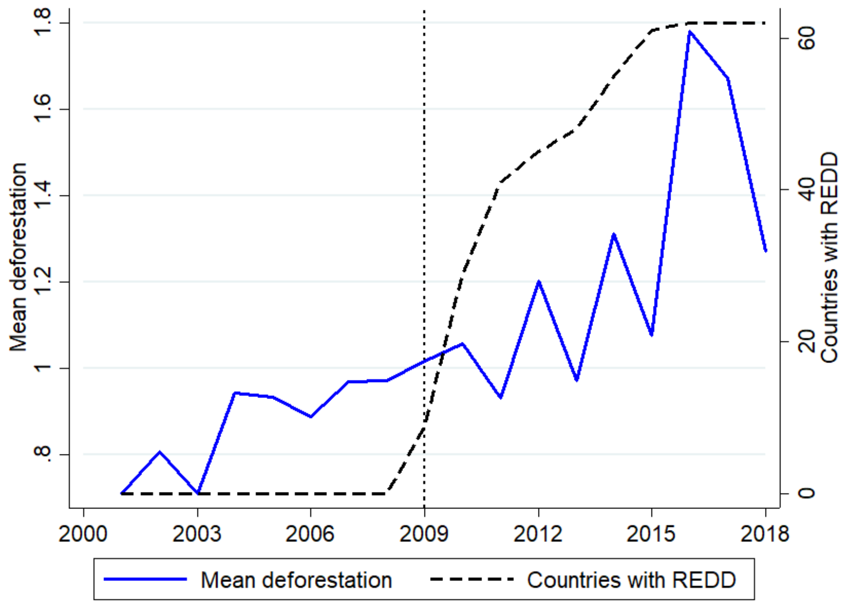

Figure 3.1: Tropical deforestation trends in UN-REDD policy adoption

Note: Average deforestation is shown against the number of developing countries that have adopted the UN-REDD policy between 2009-2018. Average deforestation is expressed in hundred thousand hectares of tree cover loss.

The unsustainable exploitation of natural resources is inevitable in the context of using ecosystem services for human well being. The introduction of payment schemes for ecosystem services curbs the loss of tropical forests (Pistorius, 2012) and success at the local and national level encourages the up–scaling of these ecosystem payment schemes to the international level. The UN-REDD programme, negotiated under the UNFCCC, is such an international financial mechanism. The mandate of this convention frames the loss of forests as a climate mitigation issue. Thus, the implementation of an international compensation mechanism for developing countries that succeed in reducing their forest sector emissions slows down climate change. Despite the belief that the UN-REDD programme is a promising option for addressing the depletion of forests, the modalities for participation and compensation payments remain unclear. The programme goes beyond a simple compensation mechanism and entails technical and political complexities with the main concerns over the establishment of developing countries' emission targets and accounting responsibilities. Consequently, the opportunity for the UN-REDD programme to become the future climate agreement under the convention is at stake. As such, the positive incentives of the programme will encourage voluntary participation only if they do not impair countries' own development ability.

3.3 Empirical econometric strategy

To identify the impact of the UN-REDD programme on the climate variables, we employ a staggered difference-in-differences (DID) approach. This method was proposed recently by Athey and Imbens (2018) and, in contrast to the standard DID estimation, it accounts for the variation in timing of a policy (or programme) adoption. We first detail the empirical specification in Section 3.3.1, and then discuss the threats to identifying the programme impact in Section 3.3.2.

3.3.1 Model specification

We consider the staggered DID setting under the potential outcome framework for causal inference (see Athey and Imbens, 2018). The population of interest consists of N countries (units). Each of these N countries is characterized by a set of potential outcomes in T periods for $T+1$ treatment levels, $Y_{it}(a)$, $i \in \{1, \dots, N\}$ indexes the countries, $t \in \mathbb{T} = \{1, \dots, T\}$ indexes the time period, and the argument of the potential outcome function $Y_{it}(\cdot)$, $a \in \mathbb{A} = \mathbb{T} \cup \{\infty\} = \{1, \dots, T, \infty\}$ indexes the discrete treatment, the date that the binary policy (here the UN-REDD programme) was first adopted by country. Countries can adopt the policy at any period $t = 1, \dots, T$ or not adopt the policy at all during the entire period

T, in which case the adoption date is set at ∞. Once the country adopts the programme, it remains exposed to the treatment for all periods afterwards. Consequently, the date of policy adoption varies across countries.[6] This contrasts to most of the DID literature where the binary indicator whether a unit is exposed to the treatment in the current period indexes the potential outcomes. We observe for each country in the sample the adoption date $A_i \in \mathbb{A}$ and the sequence of T realized outcomes, $Y_{it} \equiv Y_{it}(A_i)$, for a given time period $t \in \mathbb{T}$ and a given country $i \in \{1, \ldots, N\}$. We assume that countries are not affected by the treatments (adoption dates) of other countries, the potential outcomes are deterministic, and the adoption dates and realized outcomes are stochastic. As such, the distributions of estimators depend on adoption date distribution, number of countries and number of time periods. This distribution is referred to as a randomisation or design-based distribution.

Our goal is to measure the causal impact of the UN-REDD programme on two outcome variables, so hereafter, Y_{it} refers to either deforestation and emissions. For this purpose, we focus on the parametric setting in which the potential outcome satisfies (similar to Wolfers, 2006):

$$Y_{it} = (REDD_i \times POST_{it})'\beta + X'_{it}\gamma + \sum_i \mu_i + \sum_t \eta_t + \sum_i Country_i \times Time_t + \varepsilon_{it} \tag{3.3.1}$$

where the outcome Y_{it} refers to either deforestation and emissions of country i at time t, $REDD_i$ is country i binary treatment and $POST_{it}$ its post treatment adoption date dummy, X_{it} is a vector of covariates (real GDP growth, population growth, trade openness, agricultural exports, share of rural population, employment in agriculture, share of agricultural land and share of arable land), μ_i and η_t are country and year fixed effects respectively, the second last summation term in (3.3.1) represents country-specific linear trends that control for any potential

[6] This design is a special case of the standard DID approach, which usually estimates the treatment effect by comparing the pre- and post-treatment differences in the outcome of a treatment and a control group, where the control group remains untreated at any time period (i.e., both pre- and post- policy periods), whereas the treatment group is untreated before the policy but receives treatment after the policy implementation.

endogeneity in the policy variable of interest, $REDD_i \times POST_{it}$. In (3.3.1), ε_{it} are idiosyncratic errors, β is the coefficient of interest and it capturing the effect of the UN-REDD programme adoption on deforestation or emissions, γ is the coefficient vector on covariates and it measures the effect of a change in these covariates on the outcome variables (deforestation or emissions).

With panel data, the role of cross-country heterogeneity in deforestation can be explored in more detail, without having to be specific about the sources of heterogeneity. Country fixed effects, μ_i, control for unobserved influences on deforestation that vary across countries, so that the effect of the UN-REDD programme is identified from its variation within a country over time. Clearly, the presence of μ_i in (3.3.1) is important to capture country-level unobserved factors that explain deforestation, such as culture and geography. This mainly motivates our focusing on cross-country setting which enables us to control for μ_i (we assembled a panel of country-level deforestation data over 18 year, where the data record virtually all deforestation in developing countries). Using longitudinal data also allows the inclusion of time fixed effects η_t, which control for evolving unobserved national attributes that affect the likelihood of deforestation and emissions. This includes common shocks, such as government policy amendments.

Despite the presence of μ_i and η_t in (3.3.1), the factors that influence deforestation may vary within a country over time, thus confounding the estimates of the country effects. That will also bias the estimate of the treatment parameter of interest β if the time-varying factors are correlated with the policy adoption across countries, or if such factors do not change uniformly at the national level and are picked up by the year fixed effects. Specification (3.3.1) allows for controlling such changing influences within a country over time by including a time trend, $Country \times Time$, which captures linear trends in country-level characteristics that influence deforestation and emissions, with the slopes of the trends allowed to vary across countries.

Let $\bar{Y}_t(a)$ denote the population average of the potential outcome in period t for adoption date a, i.e.

$$\bar{Y}_t(a) \equiv \frac{1}{N}\sum_{i=1}^{N} Y_{it}(a). \tag{3.3.2}$$

Also, let $\tau_{t,aa'}$ be the average causal effect of adoption date $a^{'}$ relative to a, on the outcome in period t, i.e.

$$\tau_{t,aa'} \equiv \bar{Y}_t(a^{'}) - \bar{Y}_t(a) = \frac{1}{N}\sum_{i=1}^{N}\Big[Y_{it}(a^{'}) - Y_{it}(a)\Big]. \tag{3.3.3}$$

Then, the average causal effect of switching the entire population (countries) from never adopting the UN-REDD policy ($a = \infty$) to adopting it in the first period ($a = 1$) is given by

$$\tau_{t,\infty 1} = \frac{1}{N}\sum_{i=1}^{N}\Big[Y_{it}(1) - Y_{it}(\infty)\Big]. \tag{3.3.4}$$

$\tau_{t,\infty 1}$ is a useful benchmark measure compared to $\tau_{t,aa'}$ in (3.3.3). Indeed, for any country i and any time period t, the comparison $Y_{it}(1)-Y_{it}(\infty)$ is between potential outcomes for adoption prior to or at time t (adoption date $a = 1$) and potential outcomes for adoption later than t (never adopting $a = \infty$). In contrast, any other average effect $\tau_{t,aa'}$ will for some t involve comparing potential outcomes neither of which corresponds to having adopted the treatment yet, or comparing potential outcomes both of which correspond to having adopted the treatment already. As such, $\tau_{t,\infty 1}$ reflects more on the effect of having adopted the policy than any other $\tau_{t,aa'}$. In an ideal situation where countries enter the UN-REDD programme randomly, $\tau_{t,\infty 1}$ (or similarly $\tau_{t,aa'}$) estimate both the average treatment effect (or average causal effect of adoption date a' relative to a) and the average treatment effect for the treated (countries that have adopted the programme). However, one might expect that the average treatment effect for countries who choose to participate in the programme is somewhat larger than the average treatment effect for all countries together (including those who did not adopt the programme). Put it differently, on might expect that the decision to participate is partly determined by the gains from the programme. In this case, alternative ways are needed to estimate the treatment parameters. A suitable framework to do this is to consider a parametric specification setting as in (3.3.1). Under mild assumptions on the model variables and parameters (Athey and Imbens, 2018, see e.g.), the least squares estimator of β in (3.3.1) consistently estimate the true programme effect.

3.3.2 Threats to identification

To avoid making erroneous inferences, it is necessary to better understand the sources of a policy change. A change in deforestation and emissions could be the result of a series of factors, not necessarily policy change. Another important factor to consider is the control group (non-adopter of the UN-REDD programme) with which the treated group is being compared. Being part of the control group is assumed to be an equally viable option for countries that adopted the UN-REDD programme. Countries in the control group could be better explained as 'untreated' countries because, while they obviously act as controls, treated countries do, too.

The success of evaluating the UN-REDD programme using staggered DID estimation depends on whether the policy can be framed as an experimental design: policy adoption needs to be independent and time-varying random events and should not have spillover effects on non-adopting countries. In the ideal situation, the parametric specification (3.3.1) yields an unbiased estimate of the average treatment effect, β. However, the setting of the UN-REDD programme deviates from this baseline assumption, as the programme adoption cannot be viewed as an independent event, an important caveat in this study. The UN-REDD implements in five-year strategic frameworks. At both the UN and country delivery, policy management in the 2016-2020 UN-REDD programme strategic framework has improved over that in the 2011-2015 framework. Preparation of the 2016-2020 strategic framework was visibly underway, so countries may have responded pre-emptively, possibly by changing their deforestation propensities before signing onto the programme or vice versa. Additionally, the assistance received might have spillover effects– improvements to monitoring, reporting and verification (MRV) systems– in adopting countries. The staggered DID may not be able to capture these effects, thereby potentially underestimating the total contribution of policy change to deforestation and emissions.

In our analysis, we assume that the policy change has two virtues. Firstly, the policy change is discrete. Secondly, policy adoption by a country is an idiosyncratic function of deforestation propensities. Disposition of policy reforms and the timing of a change to forest governance is likely to be, in part, unanticipated. Hence, even partly unanticipated policy changes may generate discontinuous impacts on deforestation. The experimental design in our study identifies the extent of these discontinuous impacts even though such limitations coexist.

3.4 Data and preliminary analysis

We use data covering the period 2001-2018 from over 102 developing countries: 46 countries from Africa, 34 from Asia-Pacific and 22 from Latin America and the Caribbean. These countries provide a comparable set of environmental and economic conditions across the geographical regions. Since the launch of the UN-REDD programme in 2008, 65 developing countries have adopted the programme but 3 among them do not available data (i.e., Jamaica, Samoa, and South Sudan). This leaves us with 62 developing countries (treated group) in our sample that adopted the programme from 2009-2018.

Table B.4 in the appendix contains all countries in our sample divided into control and treated groups in each region (Africa, Asia-Pacific, Latin America and the Caribbean), whereas the treated countries by programme adoption year are shown in Table B.2. Non-adopting countries are categorised in the control group because there is a possibility for these countries to adopt the programme in the future. For non-adopters, the monetary incentives is a clear-cut to participating in the UN-REDD programme or not. From that perspective, we are interested in the existence of factors that could result in changes in deforestation and emissions in favour of both the treatment and control. In our staggered DID setting, all treated countries except the early adopters are categorised as controls, and then treated as time involves; see Section 3.3 for further details.

Data on the outcome variables (deforestation and emissions) were obtained from the Global Forest Watch web platform (GFW, 2019). This data set includes tree cover, tree cover loss, CO_2 emissions and biomass loss at the country-level and at first and second sub-national levels. Our analyses use country-level data. The tree cover data were produced by the Global Land Analysis and Discovery (GLAD) laboratory from the University of Maryland in partnership with Google (GLAD, 2019). Above-ground biomass loss estimates are based on the collocation of above-ground live woody biomass density values for the year 2000 from Baccini et al. (2012) and annual tree cover loss data from Hansen et al. (2013). The carbon dioxide emissions data quantify the amount of CO_2 emissions to the atmosphere based on above-ground biomass loss. All values are presented at different percentage canopy cover levels (≥10%, 15%, 20%, 25%, 30%, 50% and 75%). We use a ≥30% canopy cover threshold following the Global Forest Watch website. Here, "tree cover" includes all vegetation over five meters in height and may take the form of natural forests or plantations across a range of canopy densities. Deforestation is defined as the hundred thousand hectares of tree cover loss - removal or mortality of tree cover - at the national level by 30% canopy cover. Emissions are measured per gigatonnes of carbon dioxide release to the atmosphere as a result of above-ground biomass loss, at the national level by 30% canopy cover.

Accuracy in quantifying the global forest cover change is vital in forest ecosystem studies. Spatially and temporally detailed information on global-scale forest change does not exist and previous efforts have been either sample-based or employed coarse spatial resolution data (Hansen and DeFries, 2004, Hansen et al., 2013, 2010). Using the Earth observation satellite data of Hansen et al. (2013), our study improves on existing knowledge of global forest cover changes. These data are spatially explicit, quantify gross forest loss and gain, and provide annual loss information, and are derived through an internally consistent approach. In contrast, the widely used forestry data of the FAO suffer from several limitations, thus making comparability an issue: the FAO quantifies deforestation according to land use instead of land cover; forest area changes are reported only at net values, although forest definitions have changed over time. The use of this new data set offers a unique level of precision on forest losses and is therefore, a significant contribution of our study to the literature.

Data on covariates were extracted from the World Development Indicators of the World Bank (WDI, 2019). A detailed description of these covariates is given in Table B.5 in the Appendix. In our empirical analysis, we use aggregated data at the national level. Our choice of covariates follows the Environment Kuznets Curve (EKC) literature on direct and underlying causes of deforestation (Barbier and Burgess, 2001, Barbier et al., 2010, 1991, Bhattarai and Hammig, 2001, Foster and Rosenzweig, 2003, Leblois et al., 2017). Economic development, agricultural activity and population pressure are thus considered important drivers of deforestation at the national level. A simple correlation analysis show that except for arable land and agricultural exports, all covariates show positive and significant relationship to deforestation (Table B.7) and emissions (Table B.8). The positive relationship of arable land and negative relationship of agricultural exports to deforestation and emissions are both insignificant. All covariates show low correlation to both outcome variables.

To account for the effect of economic development (at least in quantitative point of view), we use real GDP growth rate, as it is acknowledged that economic growth is a possible way to slow down deforestation (Foster and Rosenzweig, 2003). Slowing down deforestation through economic growth can change the path of forest transition. The pressure towards deforestation comes from the wider economy and the level of economic development, not just the forestry sector. Therefore, as an economy develops, the influences change. In the context of developing countries, deforestation occurs due to increased demand resulting from economic growth. The expansion of income leads to high demand for forestland conversion to generate agricultural and forestry products. Beyond a certain higher income level, economic growth can reduce the pressure on forests by improving off-farm employment opportunities. Countries with high incomes may demand that forests be protected rather than depleted.

Considering the role of population pressure on the tropical deforestation process, we use two variables, population growth and rural population, in our analysis. Through this approach, we highlight the impact of population structure, whether it is the rural population or the overall population that matters in deforestation. It is hypothesised that an increase in both these variables leads to an increase in deforestation in tropical forests. Population growth leads to migration to the forests by peasants seeking land to clear for subsistence farming. Population growth also increases the collection of fuel wood, which removes nutrients from forests. If nutrient loss is sufficiently intense, the result is slowed regeneration and degradation of forest cover. Positive population growth is associated with deforestation but the effect is not immediate (Deacon, 1994).

Empirical evidence at both the national level (Leblois et al., 2017) and the subnational level (Faria and Almeida, 2016) shows that openness to trade increases deforestation. We use the sum of import and export values as a percentage of total GDP to indicate trade openness in the analysis. Trade-led deforestation includes export-oriented agricultural production, commercial agriculture and industrial plantations leading to mass destruction of forested areas in the tropics.

Economic liberalisation may increase global demand and the prices for agricultural exports, accelerating the rate of deforestation (Barbier, 2004). We use agricultural raw materials exports as a percentage of merchandise exports to control for the contribution of agricultural exports to deforestation. Employment in agriculture as a percentage of total employment is used to control for the effect of agriculture sector employment on deforestation. Agricultural expansion is a primary cause of forest conversion; thus, we use agricultural land as a percentage of land area to test the role of cultivated land in deforestation. Arable land as a percentage of total land area is used to control for the impact of surface area on deforestation.

Summary statistics for both the pre-UN-REDD programme period (2001-2008) and the adoption period (2018) are provided in Table B.6 in the Appendix B. During the programme adoption period, deforestation and emissions are on average higher, probably because of the mixing of treatment and control groups. However, the preliminary analysis in Table B.9 of the Appendix comparing the treatment group to the control group suggests that the UN-REDD programme may have been successful in reducing deforestation and emissions.

Figure 3.2 shows the plots of average deforestation and average emissions accounting for differences in the timing of treatment, where 2009 is the first year of adoption. In each subfigure, the solid blue graph indicates the treated group whereas the dash dark graph represents the control group. The average deforestation and emissions were higher in the treated group during the pre-programme period, signaling the importance of controlling for pre-existing differences between countries through the inclusion of country specific effects. These differences in outcome variables (deforestation and emissions) between treated and control countries provides a coarse comparison of the relative pre-existing trends. It shows a clear rising trend in deforestation and emissions in treated countries relative to control countries prior to the programme first adoption year (2009). As such, controlling for these trends is paramount to consistently identifying the true programme impact on deforestation and emissions. As more and more countries enter the programme after 2009, average deforestation and emissions in the treated group decrease sharply to level the control group average outcome at the end of the period. While both outcome variables (deforestation and emissions) are different, the graphical representations in Figure 3.2 narrates the same story, thus reinforcing the perception that the UN-REDD programme may have been successful towards achieving its goal. Section 3.5 our main results.

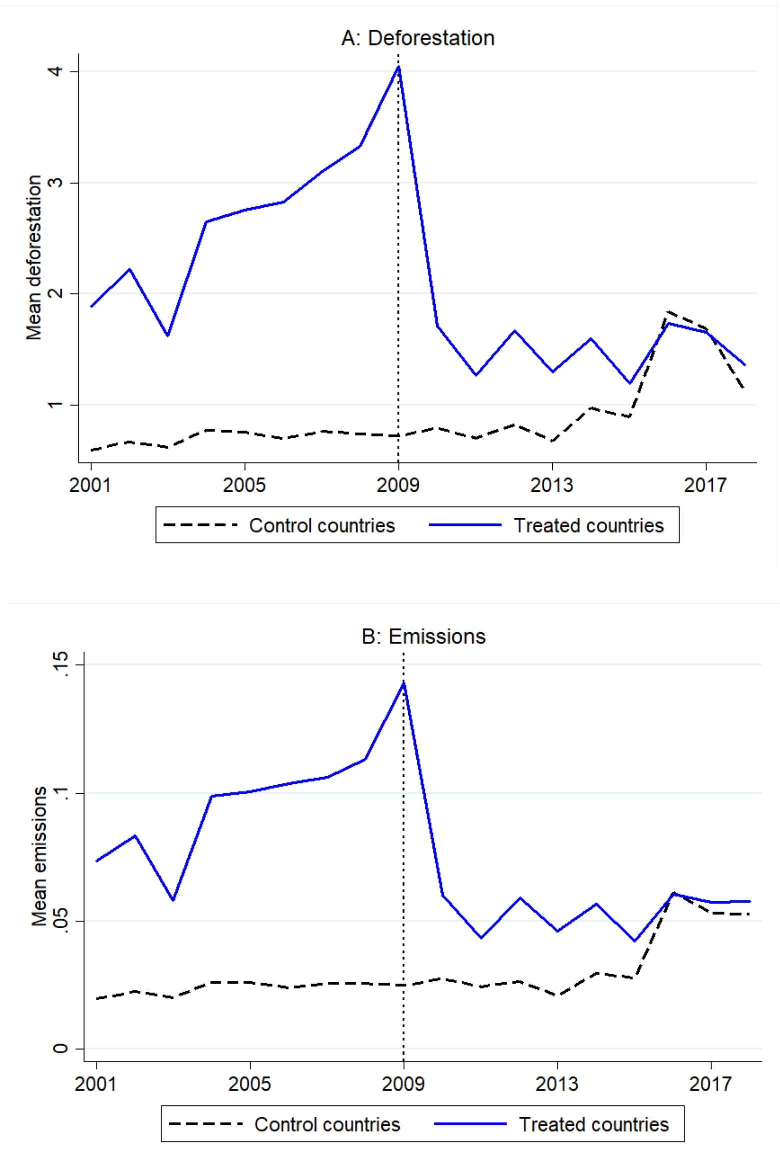

Figure 3.2: Deforestation and Emissions– control group versus treated group

Note: From 2009 (first adoption year) onward, countries that were in the control group switched to treatment the year following their adoption year. The graphs in Figure 3.2 accounts for this redistribution between treated and control groups over time. In 2018, the control group consists of non-adopter only.

3.5 Main results

We first analyse the UN-REDD programme impact with the pooled sample of the 102 countries in Section 3.5.1. We then emphasize on the programme heterogenous effects across geographical location (Section 3.5.2) and income (Section 3.5.3).

3.5.1 Policy effect over time

Table 3.2 presents the estimates of the UN-REDD programme impact on deforestation and emissions over time. As is usually the case in staggered DID analysis, the impact of the programme is evaluated by year intervals to accommodate all adoption years within the entire period 2001-2018. Particularly in our case, five dummies are created and interacted with the treatment variable: one dummy for the first 2 years, one for each of years 3-4, 5-6, 7-8 and 9-10. This contrasts to the standard DID estimation that usually includes a single dummy for adoption year. In the table, we only report the estimated programme effect to shorten the presentation, i.e., the impact of covariates and fixed effects are left out for briefly. In the table, **Panel A** contains the results with no observable covariate included in the regressions, whereas **Panel B** shows the results where observed covariates are controlled for. For each outcome variable (deforestation or emissions) and each panel, column (1) differs from column (2) through the inclusion of country-specific linear trend in the latter.

Looking first at the estimated programme effects in **Panel A** and **Panel B**, we see that they substantially differ in both the sign and the magnitude, indicating the exclusion of covariates is important. Therefore, we shall focus mainly on the results of **Panel B** in the remaining of this section. Now, regarding the programme estimated effects in **Panel B**, in the specification of both deforestation and emissions, the sign of the estimates is positive in columns (1) whereas it is negative in columns (2). Aside the fact some of the estimates are not statistically significant due probably to a lack of precision (high standard error estimates), these results clearly highlight the importance of controlling for country-specific linear trends, as failing to do so yield positive estimates wrongly suggesting that the programme may not have been successful in curbing deforestation and emissions. The plots of the estimated programme effects over time in Figure 3.3 illustrates clearly the role country-specific linear trends play in the identification of the UN-REDD programme true impact. In this figure, the DID estimates in both the deforestation and emissions specifications, with or without country-specific linear trends, are plotted over time. More specifically, in each subfigure, the blue curve with dot-markers shows the estimated programme impact over time with country-specific linear trends controlled for (Table 3.2-**Panel B**-(2)) whereas the dark curve with triangle-markers represents the policy estimates over time without country-specific linear trends controlled for (Table 3.2-**Panel B**-(1)). In both deforestation and emissions models, there is a sharp rise over time in the programme estimated impact when country-specific linear trends are not controlled for (dark curves with triangle-markers), while there is a deep decrease in the negative territory once country-specific linear trends are controlled for (blue curves with dot-markers). This shows clearly that failing to control for country-specific linear trends identify the wrong programme impact. Thus, a suitable model must control for country-specific linear trends, as in Table 3.2-**Panel B**-(2). The remaining of our analysis focus on these suitable specifications.

Table 3.2: Estimates of policy effects over time

	Deforestation		Emissions	
Panel A: With no controls	(1)	(2)	(1)	(2)
First 2 years	0.340***	0.071	0.012***	0.003
	(0.099)	(0.111)	(0.004)	(0.004)
Years 3-4	0.372**	-0.075	0.013*	-0.002
	(0.135)	(0.158)	(0.005)	(0.006)
Years 5-6	0.346*	-0.358	0.013*	-0.012
	(0.160)	(0.223)	(0.006)	(0.008)
Years 7-8	0.464	-0.513	0.016	-0.017
	(0.245)	(0.333)	(0.009)	(0.012)
Years 9-10	0.633*	-0.931*	0.019	-0.034
	(0.317)	(0.467)	(0.013)	(0.018)
	Deforestation		Emissions	
Panel B: With controls	(1)	(2)	(1)	(2)
First 2 years	0.225	-0.156	0.011	-0.006
	(0.253)	(0.286)	(0.009)	(0.010)
Years 3-4	0.300	-0.297	0.013	-0.011
	(0.264)	(0.287)	(0.010)	(0.010)
Years 5-6	0.277	-0.579	0.013	-0.021
	(0.261)	(0.312)	(0.009)	(0.011)
Years 7-8	0.416	-0.734	0.018	-0.026
	(0.334)	(0.390)	(0.012)	(0.014)
Years 9-10	0.600	-1.138*	0.021	-0.042*
	(0.377)	(0.460)	(0.015)	(0.017)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country*time	No	Yes	No	Yes
Observations	1,836	1,836	1,836	1,836

Note: Columns (1) do not include country-specific linear trends while columns (2) do. Covariates include real GDP growth, population growth, trade openness, agricultural exports, share of rural population, employment in agriculture, share of agricultural land and share of arable land. Standard errors in parentheses are bootstrapped with 1000 replications. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

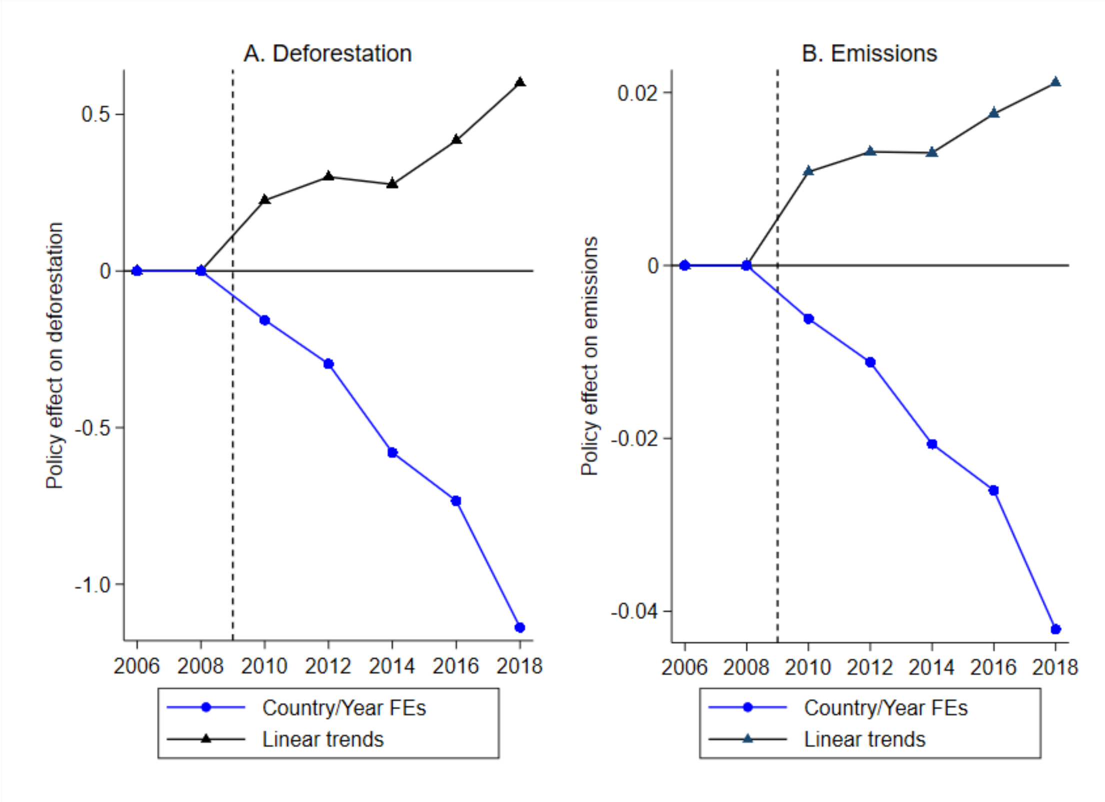

Figure 3.3: Policy effects on deforestation and emissions overtime

With the exception of years 9-10 estimates, the estimates in the other years shown in Table 3.2-**Panel B**: columns (2) are not statistically significant even at 10%, but their magnitude is not very small. Obviously, controlling for country-specific trends, along with other fixed effects, has affected the precision of the estimates, thus leading to low t-statistic values despite the estimates themselves being relatively large. Considering the magnitude of these estimates, we see that the first 2 year estimated impact of the programme are -0.156 on deforestation and -0.006 on emissions, and both are insignificant. These estimates translate to an annual average reduction of deforestation about 15,600 hectares and emissions about 6 megatonnes in adopting countries in the first 2 years of the programme adoption. The 15,600 hectares reduction of deforestation, although not statistically significant, represent a substantial reduction if compared to the pre-programme period average deforestation of 90,300 hectares of tree cover loss per year. The reduction of both deforestation and emission have accelerated enormously after 10 years of the programme adoption. In particular, years 9-10 programme estimated impact deepens to -1.138 on deforestation and -0.042 on emissions and both are significant at 10% nominal level. A -1.138 estimated impact on deforestation represent an annual average reduction of deforestation about 113,800 hectares in adopting countries after 10 years of programme adoption, while a -0.042 estimated impact on emission represent an annual average reduction of emissions about 42 megatonnes in adopting countries after 10 years of programme adoption. These results suggest that the longer a country is exposed to the UN-REDD programme, the stronger the programme effect is. As such, the belief that over the years, the UN-REDD programme incentives might have overridden transaction costs to deliver a positive policy effect (Libecap, 2014) is supported.

As discussed previously in (3.3.3)-(3.3.4), years 9-10 estimates is a useful benchmark measure compared to other years estimators. Indeed, for any country, the comparison in years 9-10 estimation is between potential outcomes for adoption prior to or at year 10 and potential outcomes for not adoption the UN-REDD programme at all. For this, years 9-10 estimates reflects more on the effect of having adopted the UN-REDD programme than any other years interval estimates. Therefore, the fact that years 9-10 estimated impact of UN-REDD on both deforestation and emissions are significant at 10% nominal level and large in magnitude suggests that the UN-REDD programme is relatively successful in reducing both deforestation and carbon dioxide emissions in adopting countries.

The UN-REDD programme was available for adoption by all developing countries since its inception in 2009. As such, differences in the time of programme adoption should therefore be independent of the UN-REDD programme availability, and it should rather be a decision made by the individual adopting country. From our estimation in Table 3.2, the favorable programme effect is seen over longer time periods and as number of countries adopting the programme grows. Therefore, it is possible that if all the countries had adopted the programme in 2009, we may have observed earlier signs of the positive programme effect rather than waiting for 9-10 years before the effect manifests clearly.

Controlling for country-specific linear trends appears crucial in identifying the impact of the UN-REDD programme on both deforestation and emissions, as their exclusion leads to misspecify the deforestation patterns and camouflages the variation induced by the UN-REDD programme. Clearly, assuming constant country-level deforestation propensities – when they are actually trending– biases the estimates. In this case, the estimated intercepts reflect the average of the trend instead of the true intercept. From a methodological viewpoint, we formally test the presence of country-specific linear trends in the deforestation and emissions data. We find that the F-test of the hypothesis that country-specific linear trends are jointly zero is strongly rejected by the data. These test results are presented in column (2) of Table B.10 in the Appendix for deforestation, and column (2) of Table B.11 for emissions. The test also indicates that once country-specific linear trends are controlled for, country individual fixed effects are no longer significant. This suggests that country-specific time varying unobserved factors are more important in explaining their deforestation and emissions policies, rather than do their time-invariant unobserved factors. Unobserved determinants of deforestation and emissions, such as weather, climate, quality of governance and government policies, often trend over time, thus the inclusion of country individual fixed effects only capture a small variation of them. Clearly, presuming that these unobserved factors are either constant within a country over the 18-years covered in our study or changing over time but uniformly across countries imposes restrictions on the regression parameters. While country-year interactions are completely unrestricted, they are often not feasible (Friedberg, 1998), thus the use of country-specific linear trends provide a feasible alternative, and more importantly their inclusion allows the unobserved country factors of deforestation and emissions to have a linear trend that varies across countries.

Our results also indicate that the REDD programme impact on deforestation and emissions accelerates substantially over the ensuing decade. The estimated impact of the programme change does not appear smaller for late adopters, thus suggesting that anticipatory effects are not particularly important. Furthermore, the strengthening of the programme effect over time suggests that its benefits might have overridden its transaction costs. Therefore, we conclude that the

UN-REDD programme has been relatively effective in reducing deforestation and emissions, therefore can be seen as a promising guardian of tropical forests.

Table 3.3 reports aggregated policy estimated effect where a single dummy is used for the whole adoption period, thus ignoring the timing of individual country REDD programme adoption. From the estimation perspective, this is simply the standard DID setting. As in Table 3.2, columns (1) of Table 3.3 differ from columns (2) only through the inclusion of country-specific linear trends in the latter. A χ^2-test indicates the importance of controlling for these trends in the specification of each outcome variable (deforestation and emission) data; see Table B.12 for deforestation and Table B.13 for emissions in the Appendix. Focusing on the estimates in columns (2) in Table 3.3 that control for country-specific linear trends, we see that the programme estimated impact has the correct sign, although not significant. Aside this statistical significance, the results suggest that deforestation and emissions have reduced by 22,900 hectares and 5 megatonnes, respectively in adopting countries. These results seems to have washed out the estimated programme impact found in the staggered DID setting (see Table 3.2). Clearly, the use of a single indicator for adoption year, while this not the case in the data, fails to capture the full adjustment process of the programme. In contrast, accounting for heterogeneous adoption years shows discernible changes in programme effects over time.

Table 3.3: Estimates of aggregate policy effect

	Deforestation		Emissions	
	(1)	(2)	(1)	(2)
$REDD \times POST$	0.446	-0.229	0.021	-0.005
	(0.337)	(0.436)	(0.012)	(0.016)
Covariates	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country*time	No	Yes	No	Yes
Adjusted R^2	0.896	0.908	0.880	0.897
Observations	1,836	1,836	1,836	1,836

Note: Columns (1) do not include country-specific linear trends while columns (2) do. Covariates include real GDP growth, population growth, trade openness, agricultural exports, share of rural population, employment in agriculture, share of agricultural land and share of arable land. Standard errors in parentheses are bootstrapped with 1000 replications. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

3.5.2 Regional differences

Simonet et al. (2019) and Jayachandran et al. (2017) argue that program of payments for ecosystem services often have heterogeneous impact across regions. In particular, the assessment of such schemes on deforestation demonstrates the existence of substantial variation in deforestation across regions (Jayachandran et al., 2017, Libecap, 2014, Robalino and Pfaff, 2013, Scullion et al., 2011). Contextual factors and policy design are vital in determining payments for environmental services schemes outcomes (Börner et al., 2017). Low levels of pre-programme compliance, low opportunity cost of participation and well-established property rights are some of the contextual factors that ensure payments for environmental services schemes success. In this section, we investigate whether such regional differences prevail after 10 years of the UN-REDD programme adoption. For this, we regroup developing countries in our sample into three main regions– Africa (46 countries), Asia-Pacific (34 countries), and Latin America and the Caribbean (22 countries); see Tables B.4 & **??** and Figure B.2 in the Appendix.

Table 3.4 shows the results for both deforestation (first part of the table) and emissions (second part of the table) specification, with country-specific linear trends controlled for. This table is complemented by the plots in Figure 3.4 depicted the trends in the estimates over time. As seen, the programme effect on both deforestation and emissions varies across regions and over time.

Considering first deforestation, we see that statistically significant negative effects are observed only in the Latin America and the Caribbean region. For the Africa region, the results are statistically insignificant and mixed, with the first 2 years to years 7-8 of programme adoption showing an insignificant negative estimates (insignificant reduction of deforestation and emission) while years 9-10 estimate are positive but insignificant as well (increase in deforestation). In the Asia-Pacific, with the exception of years 5-6 and 9-10 of programme adoption where statistically insignificant estimates are shown, the programme estimated impacted is positive but insignificant for the the other years. These heterogeneous trends in the UN-REDD programme impact are clearly illustrated in the right-hand side (RHS) subfigure in Figure 3.4, where only the Latin America and the Caribbean region has seen a deep decrease in policy estimates over time (blue curve with dot-markers). This region has seen an annual average about 200,400 hectares reduction of deforestation in UN-REDD programme adopting countries from the first 2 years of adoption to a stunning annual reduction of about 579,900 hectares in 10 years after the programme adoption. This means that the longer countries in this regions are exposed to the UN-REDD programme, the larger the programme impact on deforestation.

Now, looking at the emission results, we see similar patterns as in the case of deforestation, with the exception that most estimates are now significant in all regions. More specifically, Africa region has seen a significant increase in emissions over time in adopting countries, whereas there is a significant reduction of emissions in adopting Latin American and the Caribbean countries. Regarding the Asia-Pacific region, there has been a significant increase of emissions in programme adopting until years 7-8 of the programme adoption, and then a drop in years 9-10. Again, these heterogeneous impacts are clearly evidenced in the RHS subfigure in Figure 3.4, the Latin America and the Caribbean region shows a sharp decrease in policy estimates over time (blue curve with dot-markers), while that of the Africa region trend upward in the positive territory. Again, the Asia-Pacific region depicts mixed results.

Undoubtedly, there is evidence of UN-REDD programme success in the Latin America and the Caribbean region. In 2011, two yeas into the UN-REDD programme adoption, 90% of the countries in the Latin America and the Caribbean region sample had adopted the UN-REDD policy, compared to about 70% in Asia-Pacific and 50% in Africa. The heterogeneous impact of the programme across regions is explained by cross-region variations in forest composition, as well as the rates and drivers of deforestation propensities. Although the Asia-Pacific (0.6%) has on average the highest rate of deforestation, Latin America and the Caribbean region (5.1 million hectares) record the largest area of forest cover cleared per year, followed by the Asia-Pacific (3.4 million hectares) and Africa (2.3 million hectares) (see Table 3.1). Agricultural land expansion, dominated by commercial

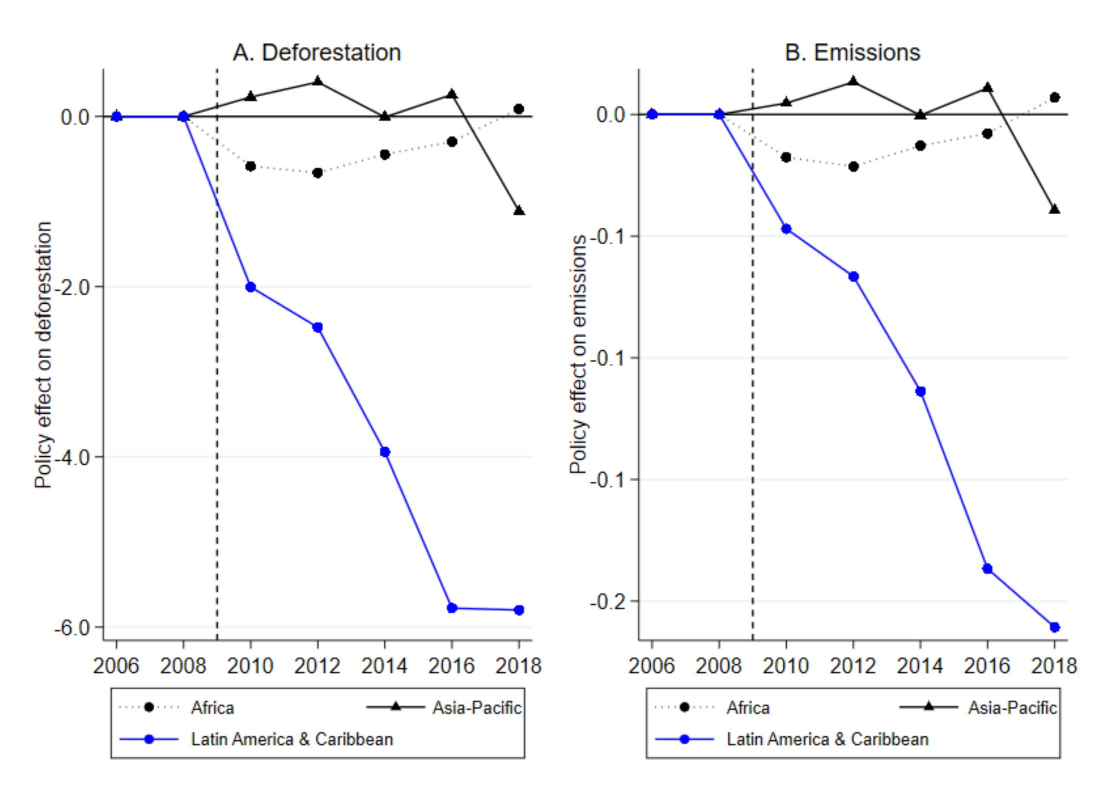

Figure 3.4: Estimated UN-REDD programme effects over time– Regional differences

agriculture, is the main driver of deforestation in both the Latin America and the Caribbean and the Asia-Pacific regions (Leblois et al., 2017). For Africa, it is GDP per capita. Better institutions and political environment play a critical role in patterns of deforestation across countries (Bhattarai and Hammig, 2001, Culas, 2007). The majority of tropical countries are rich in natural resources and use them heavily in their development process. It is institutions and policies that matter in whether or not resource-based development will be successful in the long-run. Improvements in institutions towards secure property rights and better environmental policies halt deforestation without impeding the path for economic development (Culas, 2007). The Latin America and the Caribbean region has comparatively better functioning institutions compared to developing Africa and Asia-Pacific regions. The complementary between institutional factors and forest sector polices may have reduced deforestation in Latin America and the Caribbean region. This analysis is consistent for the carbon dioxide emissions too. It is also possible that the success of the UN-REDD programme in Latin America and the

Caribbean region compared to Africa and the Asia-Pacific be a direct result of the financial incentives of the programme. We cannot also ignore the fact that the accumulation of multiple policies, domestic and global, must have led to the positive feedback in the Latin America and the Caribbean region.

Table 3.4: Impact of UN-REDD on deforestation and emissions across regions over time

	Africa	Asia–Pacific	Latin America & the Caribbean
Deforestation			
First 2 years	-0.583	0.228	-2.004
	(0.472)	(0.430)	(1.385)
Years 3-4	-0.661	0.404	-2.477
	(0.447)	(0.376)	(1.551)
Years 5-6	-0.445	-0.008	-3.942*
	(0.432)	(0.427)	(2.000)
Years 7-8	-0.298	0.257	-5.777*
	(0.478)	(0.434)	(2.459)
Years 9-10	0.088	-1.113	-5.799*
	(0.500)	(0.688)	(2.253)
R^2	0.938	0.938	0.919
Emissions			
First 2 years	-0.018	0.005	-0.047
	(0.018)	(0.016)	(0.047)
Years 3-4	-0.021	0.013	-0.067
	(0.017)	(0.014)	(0.052)
Years 5-6	-0.013	-0.000	-0.114*
	(0.016)	(0.015)	(0.068)
Years 7-8	-0.008	0.011	-0.187**
	(0.018)	(0.015)	(0.080)
Years 9-10	0.007	-0.039	-0.211***
	(0.019)	(0.025)	(0.077)
R^2	0.943	0.942	0.903
Covariates	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes
Country*time	Yes	Yes	Yes
Observations	828	612	396

Note: Regressions control for year fixed effects (FEs), country FEs, and country-specific linear trends (Country*time). Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

3.5.3 Heterogeneity across income levels

Low income economies often have competing needs between preserving the environment and achieving economic prosperity. Bhattarai and Hammig (2001) and Ota (2017) argue that the impacts of economic growth on environment degradation are generally larger for countries with lower income. Due to almost nonexistent environmental policies in low income countries, pursuing economic prosperity through increased income often triggers the introduction of environmental regulations at varying degrees. As such, one expects that any environment policy should have heterogeneous effects across economic development levels. In this section, we investigate whether such heterogeneous effects are observed with the UN-REDD programme.

Table 3.5, along with Figure 3.5, show the estimates of the UN-REDD programme effect on deforestation and emissions across income levels over time. The table shows, for each outcome variable (deforestation or emissions) and a given income level (Low, Lower-middle, Upper-middle, and High), the estimated UN-REDD programme over time. The classification of countries into the above four income groups was taken from the World Economic Situation Prospects 2019 report. Table B.3 in the Appendix summarises the regional classification (Africa, Asia-Pacific, Latin America and the Caribbean) of the countries in our sample into these four groups. Of the 102 countries in the sample, 30 are low income, 36 are lower-middle income, 28 are upper-middle income, and 8 are high income countries. For both the deforestation and emissions models, the results in Table 3.5 and Figure 3.5 indicate sizeable heterogeneous programme impacts over time and across income levels.

Considering first the deforestation specification (first part of Table 3.5), statistically significant estimates are only observed for upper-middle income countries, while that of the other income levels appear insignificant although their magnitude is relatively large. The non statistical significance stems probably from the large standard error estimates, which may be the result of the small number of observations due to the disaggregation at income levels. For example, only 8 countries are classified as high income countries in our sample, leading to about 144 observations in the regressions of this income group. Looking at the plots in the RHS graph of Figure 3.5, there is a deep downward trend in the estimated policy effect on deforestation spanning the negative territory for upper-middle income countries (blue solid curve with triangle-markers). Meanwhile, the programme effect has seen an upward positive trend in low income countries (dark solid curve with dot-markers). Clearly, while upper-middle income countries have seen a significant reduction of deforestation over time after adopting the UN-REDD programme, the adopting low income countries have seen an opposite effect. The reduction of deforestation in adopting upper-middle income countries has nearly doubled within 10 years, from on average 181,800 hectares per year the first 2 years of adoption to 331,100 hectares after 10 years of adoption (see first part of Table 3.5). Aside statistical significance, both lower-middle and high income countries depicts mixed results as shown the RHS graph in Figure 3.5. In particular, adopting lower-middle income countries on average have increased their deforestation up to years 7-8 after programme adoption, whereas in adopting high income countries deforestation has trended upward in the positive territory until years 3-4 after programme adoption. Then, both income level countries have seen a downward trend in policy estimates after the last positive peak onward, i.e., from years 7-8 for adopting lower-middle income countries and from years 3-4 for adopting high income; see the dark dashed curve with dot-markers (for lower-middle income countries) and the blue dashed curve with triangle-markers (for high income countries) in the RHS graph of Figure 3.5.

Regarding emissions (second part of Table 3.5), we first see that the estimated programme effects are statistically significant in low income countries (over the entire period) and upper-middle income countries (from years 7-8 after programme adoption), whereas in both adopting lower-middle and high income countries the estimates are insignificant over time. Nevertheless, both upper-middle and high income countries policy estimates have a negative sign over time, which indicates the reduction of emission over time. Meanwhile, only sporadic negative numbers are shown in both adopting low income (in years 3-4) and lower-middle income (in years 5-6, 9-10) countries. The left-hand side (LHS) graph in Figure 3.5 illustrates clearly this heterogeneous policy response. More specifically, while a steady downward trend is observed in adopting upper-middle and high income countries, adopting low income countries policy estimates have trended slightly upward in the positive territory and adopting lower-middle income countries policy estimates do not show a clear trend, although most estimates remain positive over time. Overall, adopting upper-middle (respectively high income) countries have reduced their emissions on average from 3 megatonnes per year (respectively 1 megatonne per year) in the first 2 years of UN-REDD programme adoption to 62 megatonnes per year (respectively 16 megatonnes per) in the 10 years after the programme adoption. Meanwhile, adopting low income countries have increased their carbon dioxide emissions on average from 10 megatonnes per year in the first 2 years of adoption to 48 megatonnes per year after 10 years of adoption. This result for low income countries mirrors very well the one found in deforestation specification for this group of countries.

Overall, our results confirm the environmental Kuznets curve (EKC) theory. The EKC stipulates that environmental degradation is inevitable during the early stages of development but as income increases, the quality of the environment should improve. In most low income nations, deforestation mostly is not accompanied by forest replacement, or if a replacement occurs, it is often lower than the harvest rate. However, growing income countries invest more in forest conservation as their level of income brings changes in their economic structures, thus yielding alternative sources of energy, which in turn reduces deforestation and increases their valuation of the ecosystem services. This may explain why in both the deforestation and emissions specifications, we observed quite opposite programme effects between low income and upper-middle income countries. For example, 10 years after the UN-REDD programme adoption, deforestation has reduced significantly on average by 331,100 hectares per year in adopting upper-middle income countries, while it has risen by 130,900 hectares per year in adopting low income countries. These trends are also evidenced in the model for carbon dioxide emissions. Even adopting lower-middle income countries have not seen a strong policy

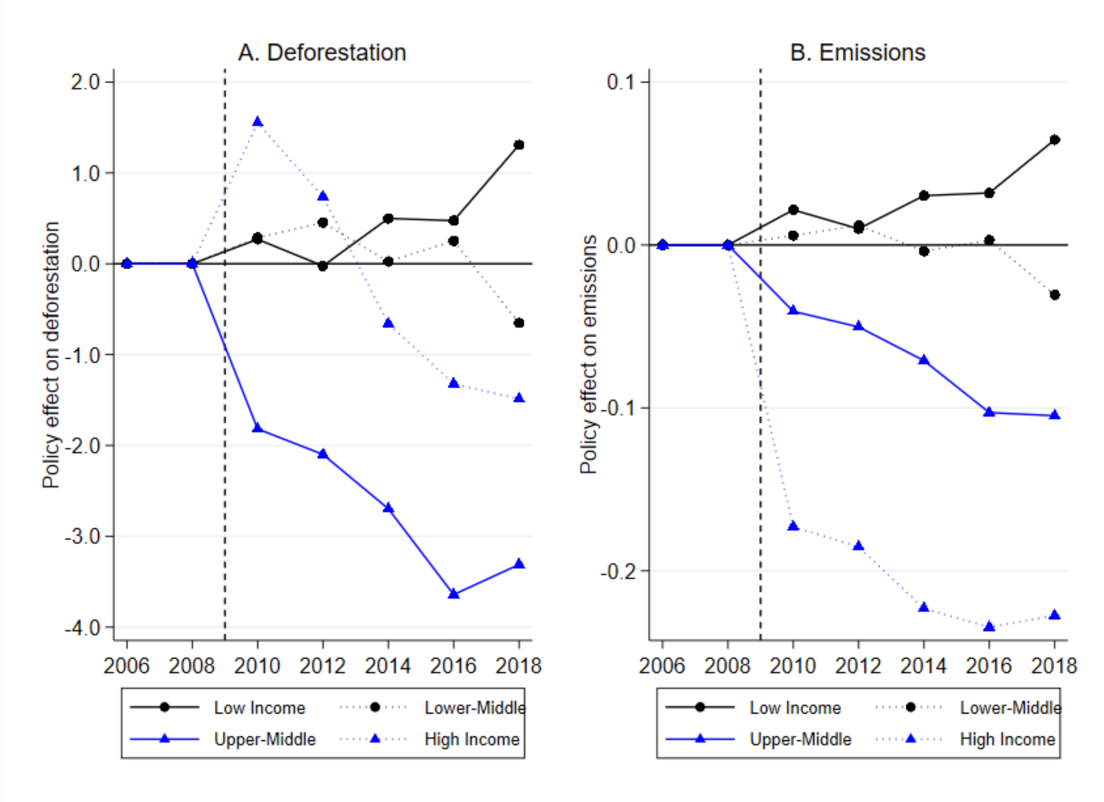

Figure 3.5: Estimated UN-REDD programme effects over time– Heterogeneity across income levels

impact compared to upper-middle income group. In particular, after 10 years of the UN-REDD programme adoption, the reduction of deforestation (respectively emissions) in adopting upper-middle countries is roughly 5.1 (respectively 2.6) times larger than the ones observed in adopting lower-middle income countries.

The EKC theory suggests an economic growth threshold over which a country can change the path of its forest transition by slowing down deforestation. The question, however, is whether most deforesting developing nations can achieve enough per capita income to reach this turning point. Researchers such as **?** have discussed the necessity of such a threshold. He argues that tunnelling through the EKC can help developing countries avoid the need to achieve a higher per capita income in order to reach the turning point. For example, an adequate use of the financial incentives provided by the UN-REDD programe can help to curb deforestation. Financial incentives from the UN-REDD programme may have helped, at least, the upper-middle to high developing income countries to tunnel through the EKC. However, more unified approaches could make the UN-REDD programme more successful in adopting low income countries, thereby the UN-REDD programme will fulfil its role as the guardian of tropical forests and becomes a forerunner in climate change mitigation.

Table 3.5: Impact of UN-REDD on deforestation and emissions across income levels over time

Income levels	Low	Lower-middle	Upper-middle	High
Deforestation				
First 2 years	0.269	0.287	-1.818	1.551
	(1.058)	(0.438)	(1.150)	(6.202)
Years 3-4	-0.024	0.453	-2.099	0.738
	(1.057)	(0.412)	(1.194)	(5.986)
Years 5-6	0.500	0.025	-2.697*	-0.660
	(1.080)	(0.453)	(1.356)	(5.797)
Years 7-8	0.475	0.253	-3.642*	-1.321
	(1.183)	(0.471)	(1.690)	(5.832)
Years 9-10	1.309	-0.651	-3.311*	-1.487
	(1.219)	(0.554)	(1.433)	(5.590)
R^2	0.945	0.929	0.918	0.915
Emissions				
First 2 years	0.022	0.006	-0.041	-0.173
	(0.042)	(0.016)	(0.038)	(0.203)
Years 3-4	0.010	0.012	-0.050	-0.185
	(0.042)	(0.015)	(0.038)	(0.196)
Years 5-6	0.030	-0.004	-0.071	-0.223
	(0.043)	(0.016)	(0.045)	(0.190)
Years 7-8	0.032	0.003	-0.103*	-0.235
	(0.048)	(0.017)	(0.054)	(0.193)
Years 9-10	0.065	-0.031	-0.105**	-0.227
	(0.049)	(0.020)	(0.049)	(0.184)
R^2	0.949	0.936	0.902	0.895
Covariates	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes
Country*time	Yes	Yes	Yes	Yes
Observations	540	648	504	144

Note: Regressions control for year fixed effects (FEs), country FEs, and country-specific linear trends (Country*time). Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

3.6 Robustness checks

3.6.1 Placebo test

The econometric strategy employed to identify the effect of the UN-REDD programme on both deforestation and emissions relies on the underlying assumption that there are no confounding factors during the study period that could actually affect deforestation and emissions in adopting countries other than the programme itself, once we control for the observed determinants (covariates) of both outcome variables, the country-specific unobserved fixed effects, and the country-specific linear trends. To explicitly check the validity of this assumption, we undertake a placebo test with the fictitious year 2008 as a falsification strategy. That is, we use 2008 as the initial year of programme implementation and test the effect of the UN-REDD on deforestation and emissions. If deforestation and emissions in adopting countries were significantly increasing or decreased as compared to the non-adopting countries, then the UN-REDD programme effect would be wrongly attributed. As such, we expect this pseudo programme to have no significant effect on deforestation and emissions. Table 3.6 and Figure 3.6 present the results, where we also show the baseline 2009 starting adoption year. As seen, none of the 2008 estimates is significant over time for both deforestation and emissions, thus validating our identification strategy.

Table 3.6: Placebo test

	Deforestation		Emissions	
	2009	2008	2009	2008
First 2 years	-0.156	-0.153	-0.006	-0.007
	(0.286)	(0.281)	(0.010)	(0.010)
Years 3-4	-0.297	-0.237	-0.011	-0.010
	(0.287)	(0.277)	(0.010)	(0.010)
Years 5-6	-0.579	-0.403	-0.021	-0.016
	(0.312)	(0.337)	(0.011)	(0.012)
Years 7-8	-0.734	-0.501	-0.026	-0.019
	(0.390)	(0.395)	(0.014)	(0.014)
Years 9-10	-1.138*	-0.540	-0.042*	-0.024
	(0.460)	(0.461)	(0.017)	(0.017)
Covariates	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes
Country*time	Yes	Yes	Yes	Yes
Adjusted R^2	0.908	0.908	0.898	0.897
Observations	1,836	1,836	1,836	1,836

Note: 2008 is the falsification (fictitious) year and 2009 is the year the programme was first impleted. Regressions control for year fixed effects (FEs), country FEs, and country-specific linear trends (Country*time). Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

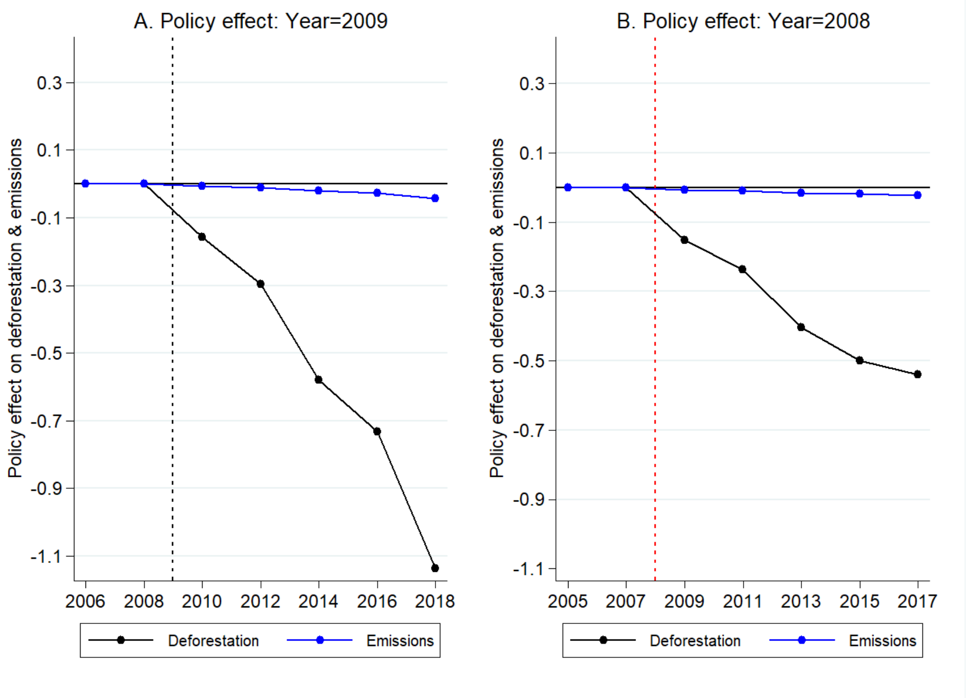

Figure 3.6: Placebo test

3.6.2 Other robustness checks

Since the early 90s, many developing countries have adopted several global environmental policies other than the UN-REDD programme. The goal of many of global environmental policies is to support the REDD+ efforts in adopting countries. For example, the Bonn challenge (BONN) launched in 2011 and recognised by 38 countries aims to regain ecological functionality and enhance human well-being across deforested or degraded forest landscapes. The Forest Investment Programme (FIP) that became operational in 2009 and recognised by 23 countries aims to provide scaled-up financing for readiness reforms and public/private investments. And the Global Environment Facility (GEF) established in 1992 provides funds to 99 developing countries in order to meet the objectives of the international environmental conventions and agreements. It is therefore possible that the impact of the UN-REDD programme found in the main analysis is biased because it may also be driven by these other environmental policies. In this section, we conduct two robustness checks that support our main analysis in Section 3.5.

First, wee look at whether controlling for the above three global environmental policies alter the estimated impact the UN-REDD programme found in our main analysis in Section 3.5. For this, we simultaneously include all the BONN, FIP and GEF policies variables along with the UN-REDD programme variable in our regressions. The estimated impact of the UN-REDD programme over time from these regressions are presented in Table 3.7 for both the deforestation and emissions. As shown in the last three columns of this table, only the BONN and FIP policies appear marginally significant (First 2 years and years 5-8 for BONN; years 5-6 for FIP), and both policies unexpectedly increase deforestation and emissions in UN-REDD adopting developing countries. While the GEF policy is clearly not statistically significant over time, a negative sign is nonetheless observed from years 7-8 after the UN-REDD programme adoption. Interestingly, in both the deforestation and emissions models, the signs and magnitudes of the estimated effects of the UN-REDD policy are identical to the ones obtained from the baseline regressions in Part B, columns (2) of Table 3.2.

Second, it is argued in the literature (see, e.g., Andam et al., 2008, Dewi et al., 2013, Nelson and Chomitz, 2009) that the presence of protected areas help to reduce deforestation. Therefore, failing to control for these policies could lead to overestimate the impact of the UN-REDD programme on deforestation and emissions in adopting countries. The International Union for Conservation of Nature (IUCN) classifies the protected areas around the world into six categories. These six categories differ mainly through their management objectives and protection levels, as shown in Table B.14. To control for these policies in the UN-REDD programme impact evaluation, dummy variables ($PA_j,\ j = 1, 2, \ldots 6$) indicating the presence of each type of protection are created in a given country and added to the baseline specification (3.3.1).

Table 3.8 contains summarised results, where the estimated effect of protected areas along the UN-REDD programme impact estimated over time are shown for the deforestation and emissions regressions. Although not statistically significant, we see that the estimated effect of all type of protections have a positive sign in both the deforestation and emissions model. Interestingly, the estimated impact of the UN-REDD programme on deforestation and emissions is larger compared to the baseline estimates in Section 3.5. This suggests that not controlling for the presence of protected areas underestimates the UN-REDD programme effect, but not the other way around.

Brazil has been receiving the REDD+ incentives since 2007, although the country did not formally adopt the UN-REDD programme. As such, we estimate the policy effects placing Brazil in the treated country group. We find qualitatively similar results[7] to those reported in Section 3.5. We also express the deforestation variable firstly as a percentage of forest area, and secondly as a percentage of total arable land, we find qualitatively similar results to those reported in Section 3.5.

[7]These results are not reported here in order to shorten the presentation but are available under request.

Table 3.7: UN-REDD versus other global environmental policies

Policies	UN-REDD	BONN	FIP	GEF
Deforestation				
First 2 years	-0.156	0.903*	0.187	0.053
	(0.286)	(0.441)	(0.419)	(0.094)
Years 3-4	-0.297	0.346	1.223	0.054
	(0.287)	(0.305)	(0.868)	(0.121)
Years 5-6	-0.579	0.708*	4.744*	0.036
	(0.312)	(0.326)	(2.316)	(0.134)
Years 7-8	-0.734	0.734*	2.343	-0.070
	(0.390)	(0.358)	(1.771)	(0.151)
Years 9-10	-1.138*			-0.130
	(0.460)			(0.182)
Adjusted R^2	0.908	0.909	0.915	0.908
Emissions				
First 2 years	-0.006	0.031*	0.001	0.003
	(0.010)	(0.015)	(0.016)	(0.003)
Years 3-4	-0.011	0.026	0.037	0.005
	(0.010)	(0.015)	(0.033)	(0.004)
Years 5-6	-0.021	0.034**	0.158*	0.006
	(0.011)	(0.013)	(0.077)	(0.005)
Years 7-8	-0.026	0.028*	0.134	0.002
	(0.014)	(0.013)	(0.084)	(0.005)
Years 9-10	-0.042*			0.001
	(0.017)			(0.006)
Adjusted R^2	0.898	0.899	0.905	0.897
Covariates	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes
Country*time	Yes	Yes	Yes	Yes
Observations	1,836	1,836	1,836	1,836

Note: Regressions control for year fixed effects (FEs), country FEs, and country-specific linear trends (Country*time). Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

Table 3.8: Effect of protected areas on deforestation

PA categories	PA1	PA2	PA3	PA4	PA5	PA6
Deforestation						
PA	0.264	0.245	0.005	0.213	0.243	0.203
	(0.216)	(0.204)	(0.195)	(0.143)	(0.267)	(0.161)
$REDD \times POST$						
First 2 years	-0.189	-0.281	-0.158	-0.285	-0.282	-0.251
	(0.267)	(0.266)	(0.245)	(0.260)	(0.213)	(0.259)
Years 3-4	-0.331	0.422	-0.298	-0.424	-0.423	-0.391
	(0.271)	(0.264)	(0.245)	(0.265)	(0.223)	(0.272)
Years 5-6	-0.617*	-0.707*	-0.581*	-0.711*	-0.706**	-0.679*
	(0.297)	(0.303)	(0.278)	(0.303)	(0.257)	(0.300)
Years 7-8	-0.774*	-0.863*	-0.736*	-0.867*	-0.861*	-0.838*
	(0.379)	(0.389)	(0.369)	(0.392)	(0.358)	(0.386)
Years 9-10	-1.173*	-1.263**	-1.139*	-1.265**	-1.256**	-1.239**
	(0.461)	(0.472)	(0.455)	(0.467)	(0.460)	(0.466)
Adjusted R^2	0.908	0.908	0.908	0.908	0.908	0.908
Emissions						
PA	0.012	0.009	0.0002	0.008	0.009	0.008
	(0.008)	(0.008)	(0.007)	(0.005)	(0.009)	(0.006)
$REDD \times POST$						
First 2 years	-0.008	-0.011	-0.006	-0.011	-0.011	-0.010
	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Years 3-4	-0.013	-0.016	-0.011	-0.016	-0.016*	-0.015
	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.010)
Years 5-6	-0.022*	-0.025*	-0.021*	-0.026*	-0.025**	-0.025*
	(0.010)	(0.010)	(0.010)	(0.011)	(0.009)	(0.011)
Years 7-8	-0.028*	-0.031*	-0.026*	-0.031*	-0.031*	-0.030*
	(0.013)	(0.013)	(0.013)	(0.014)	(0.012)	(0.014)
Years 9-10	-0.044*	-0.047**	-0.042*	-0.047**	-0.046**	-0.046**
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)
Adjusted R^2	0.898	0.897	0.897	0.897	0.897	0.898
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country*time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,836	1,836	1,836	1,836	1,836	1,836

Note: Regressions control for year fixed effects (FEs), country FEs, and country-specific linear trends (Country*time). Columns (PA1)-(PA6) contain the estimates of the six protection categories, along with the UN-REDD programme effects over time. Standard errors in parentheses are bootstrapped with 1000 replications. ***, **, and * indicate statistical significance at 1%, 5% and 10% nominal level, respectively.

3.7 Discussions and concluding remarks

The development goal of the the United Nations UN-REDD programme is to enhance carbon stocks in tropical forests through the provision of results-based payments to member countries for their efforts in decreasing deforestation. The UN-REDD programme was first launched in 2008 and developing countries started the implementation of the programme since 2009. To date, there is no comprehensive evaluation of the programme success using policy evaluation econometric techniques. In this study, we employ a novel econometric technique, the staggered difference-in-differences approach, to show that the UN-REDD programme has been successful in curbing deforestation and emissions over time in developing countries. While smaller policy impacts on deforestation and emissions are observed in the first few years of the policy adoption, much larger effects are evidenced over time. Clearly, the longer a country is exposed to the UN-REDD programme, the stronger the resulting effect is. This finding supports the belief that as time evolves, the UN-REDD programme incentives might have overridden its transaction costs to deliver a positive impact (Libecap, 2014).

Despite these common patterns among countries, heterogeneous policy effects are also observed across regions and economic development levels. In particular, while the UN-REDD programme has been relatively successful in the Latin America and the Caribbean region, developing countries in Africa and Asia-Pacific have not seen the same impact. Similarly, upper-middle and high income countries are better off compared to lower-middle and low income countries. By emphasizing on these heterogeneous policy effects across regions and income levels, our study clearly shows that the impact of the UN-REDD programme is not uniform across economic development levels and geographical locations. As such, incorporating this heterogeneity in the decision making process is paramount to amplifying the global efforts to protect tropical forests.

Our results on regional differences corroborate the literature on payments for environmental services (PES) schemes on deforestation, which demonstrates the existence of substantial variation in deforestation across regions (Jayachandran et al., 2017, Libecap, 2014, Robalino and Pfaff, 2013, Scullion et al., 2011). This may be due to variation in transaction costs that are often higher for less developing countries (Alston and Andersson, 2011), low level of pre–programme compliance, low opportunity cost of participation and poorly-established property rights. Scullion et al. (2011) suggest that the inclusion of risk-integrated payments, robust monitoring and enforcement programmes will ensure environmental policy effectiveness. Also, PES schemes such as the REED programme are different from traditional policy instruments that are abide by legal regulations, sanction mechanisms or taxes (Börner et al., 2017), therefore their effectiveness is not often guaranteed.

Our finding on heterogeneous UN-REDD programme effects across economic development levels is similar to that of the literature on economic growth impact on income inequality and environmental degradation (Ota, 2017). Indeed, low income economies often have competing needs over conservation and economic/social welfare. Economic growth impacts on environmental degradation are generally larger for countries with lower income. Environmental policies are almost non-existent in many low income countries, and some developing nations in their quest to economic prosperity through increased income often triggers the introduction of environmental regulations at varying degrees. This may explain why deforestation and emissions have reduced in UN-REDD programme adopting upper-middle and high income countries but have increased in UN-REDD programme adopting lower-middle and low income countries. One of the policy implications of environmental Kuznets curve (EKC) is that the development process should not exceed the ecological threshold. The financial incentives provided by the UN-REDD can be used by developing countries to tunnel through the EKC. Restructuring the development process to achieve sustainable development is thus encouraged for developing countries in order to flatten the EKC curve (Bhattarai and Hammig, 2001). From policy perspective, it is vital for developing economies to avoid the same level of environmental damage caused by industrialised nations during their initial growth stages, without hindering economic development. In this context, global environmental policies play a major role. The negative impacts of development policies could be restrained within the limits of ecological thresholds by employing prudent environmental policies. Seeing the success of UN-REDD programme in upper-middle and high income countries, lower-middle and low income economies will benefit from using this policy to combat deforestation while partaking in a sustainable growth process.

The success of UN-REDD could have led the development path of developing countries towards positive forest cover changes by shortening the forest transition period. The heterogeneous policy effect provides guidance for decision makers at global and national levels. Financial incentives and other technical assistance must be focused on country requirements. Accounting for this heterogeneity in the decision making process could help to anticipate changes toward achieving environment protection in a more sustainable way. Considering the importance of the socio-economic environment, improvements to agricultural and forestry sector policies at the national level are also encouraged.

Appendix B

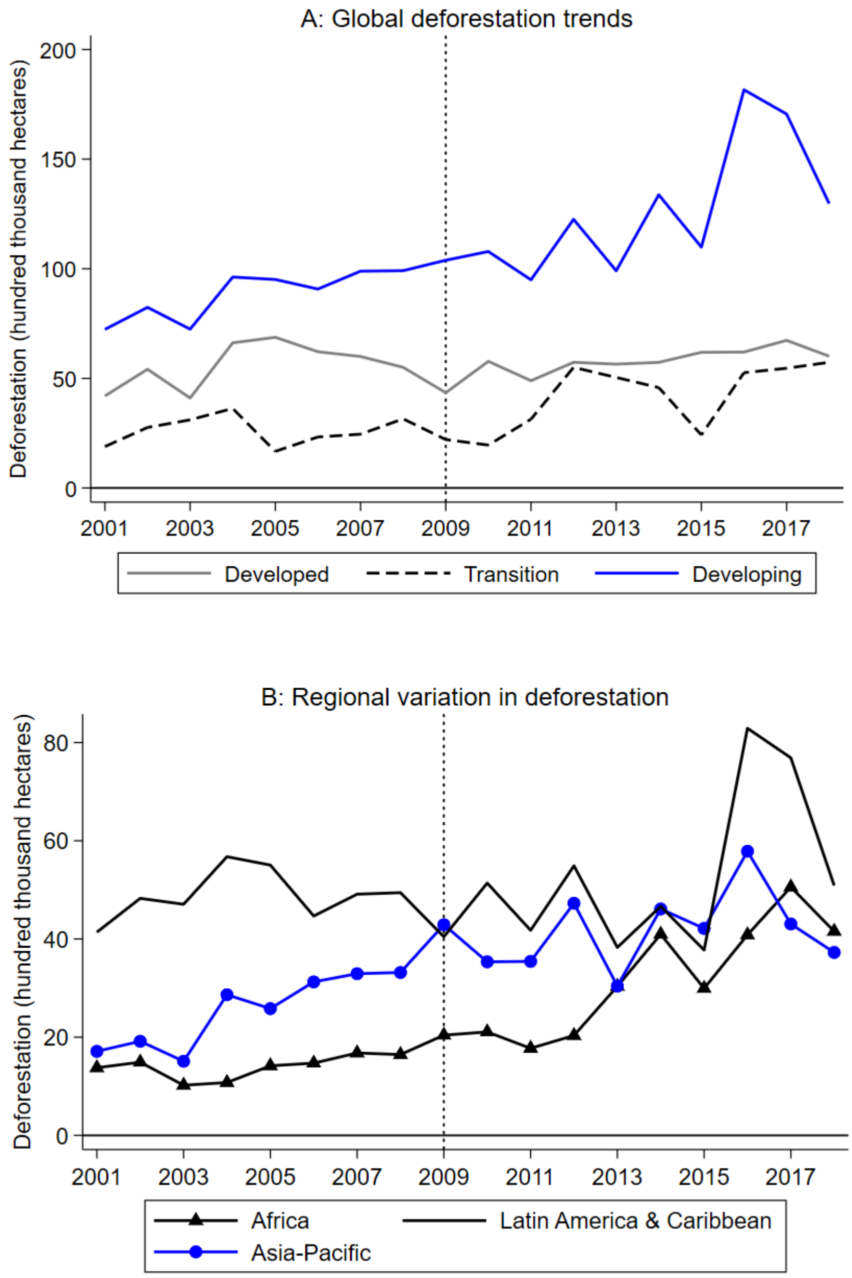

Figure B.1: Global and regional deforestation trends

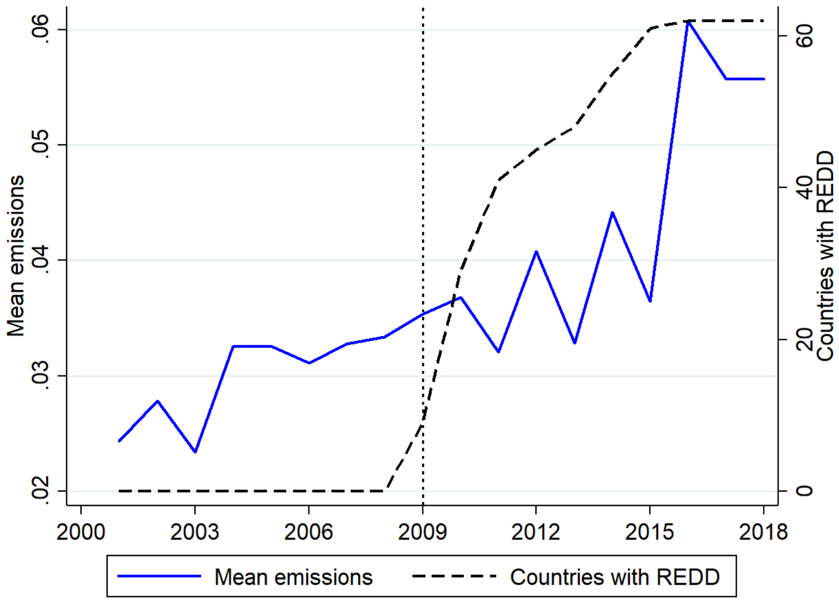

Figure B.2: Tropical emission trends in UN-REDD policy adoption

<u>**Note**</u>: Figure shows the average emissions against the number of developing countries that have adopted the UN-REDD policy, 2009-2018. The average emissions expressed in gigatonnes of carbon dioxide emissions.

Table B.1: Treated and control countries by region

Africa		Asia–Pacific		Latin America & Caribbean	
Control	Treated	Control	Treated	Control	Treated
Algeria	Benin	Afghanistan	Bangladesh	Brazil	Argentina
Angola	Burkina Faso	Brunei	Bhutan	Cuba	Bolivia
Botswana	Cameroon	China	Cambodia	Haiti	Chile
Burundi	Central African Rep.	Iran	Fiji	Nicaragua	Colombia
Djibouti	Chad	Iraq	India	Uruguay	Costa Rica
Egypt	Congo, Dem. Rep.	Jordan	Indonesia	Venezuela	Dominican Rep.
Eritrea	Congo, Rep.	Korea, Dem.	Lao PDR		Ecuador
Eswatini	Cote d'Ivoire	Korea, Rep.	Malaysia		El Salvador
Gambia	Equatorial Guinea	Lebanon	Mongolia		Guatemala
Mali	Ethiopia	Oman	Myanmar		Guyana
Mauritania	Gabon	Syria	Nepal		Honduras
Mozambique	Ghana	Timor-Leste	Pakistan		Mexico
Namibia	Guinea	Turkey	PNG		Panama
Niger	Guinea-Bissau	UAE	Philippines		Paraguay
Rwanda	Kenya	Yemen	Solomon Islands		Peru
Sao Tome & Principe	Liberia		Sri Lanka		Suriname
Senegal	Madagascar		Thailand		
Sierra Leone	Malawi		Vanuatu		
South Africa	Morocco		Vietnam		
	Nigeria				
	Sudan				
	Tanzania				
	Togo				
	Tunisia				
	Uganda				
	Zambia				
	Zimbabwe				

Note: The sample consists of 102 developing countries. Of which, control (C) and treated (T) countries are 40 and 62 respectively, located in Africa (46 countries in total; C=19, T=27), Asia-Pacific (34 countries in total; C=15, T=19) and Latin America and the Caribbean(22 countries in total; C=6, T=16).

Table B.2: UN-REDD programme adoption by country, 2009-2018

Adoption Year :	Africa	Asia–Pacific	Latin America & Caribbean
2009 : (9)	Demo. Republic of Congo	Indonesia	Bolivia
	Tanzania	Papua New Guinea	Panama
	Zambia	Vietnam	Paraguay
2010 : (20)	Central African Republic	Bangladesh	Argentina
	Congo, Rep.	Bhutan	Colombia
	Gabon	Cambodia	Costa Rica
	Kenya	Nepal	Ecuador
	Nigeria	Philippines	Guatemala
	Sudan	Solomon Islands	Guyana
		Sri Lanka	Mexico
2011 : (12)	Benin	Mongolia	Chile
	Cameroon	Myanmar	Honduras
	Cote d'Ivoire	Pakistan	Peru
	Ethiopia		Suriname
	Ghana		
2012 : (4)	Morocco	Lao PDR	
	Uganda	Malaysia	
2013 : (3)	Madagascar		
	Tunisia		
	Zimbabwe		
2014 : (7)	Chad	Fiji	
	Equatorial Guinea		
	Guinea Bissau		
	Liberia		
	Malawi		
	Togo		
2015 : (6)	Burkina Faso	India	Dominican Republic
	Guinea	Vanuatu	El Salvador
2018 : (1)		Thailand	
Total: 62	**27**	**19**	**16**

Note: Three countries (South Sudan, Samoa, and Jamica) were omitted from the sample due to lack of data. South-Sudan adopted the UN-REDD programme in 2011, while it was adopted in 2015 in both Samoa and Jamaica. Numbers in parenthesis indicate the number of countries that adopted the programme that year.

Table B.3: Regional classification of countries by income level

Regions	Africa		Asia-Pacific		Latin America & Caribbean	
Income levels	Control	Treated	Control	Treated	Control	Treated
Low (30)	Burundi	Benin	Afghanistan	Nepal	Haiti	
	Eritrea	Burkina Faso	Korea, Dem.			
	Gambia	Central African Rep.	Syria			
	Mali	Congo, Dem. Rep.	Yemen, Rep.			
	Mozambique	Ethiopia				
	Niger	Guinea				
	Rwanda	Guinea-Bissau				
	Senegal	Liberia				
	Sierra Leone	Madagascar				
		Malawi				
		Chad				
		Togo				
		Tanzania				
		Uganda				
		Zimbabwe				
Lower-middle (36)	Angola	Cote d'Ivoire	Timor-Leste	Bangladesh	Nicaragua	Bolivia
	Djibouti	Cameroon		Bhutan		Honduras
	Egypt	Congo, Rep.		Indonesia		El Salvador
	Mauritania	Ghana		India		
	Sao Tome & Principe	Kenya		Cambodia		
	Eswatini	Morocco		Lao PDR		
		Nigeria		Sri Lanka		
		Sudan		Myanmar		
		Tunisia		Mongolia		
		Zambia		Pakistan		
				Philippines		
				PNG		
				Solomon Islands		
				Vietnam		
				Vanuatu		
Upper-middle (28)	Botswana	Gabon	China	Fiji	Brazil	Colombia
	Algeria	Equatorial Guinea	Iran	Malaysia	Cuba	Costa Rica
	Namibia		Iraq	Thailand	Venezuela	Dominican Rep.
	South Africa		Jordan			Ecuador
			Lebanon			Guatemala
			Turkey			Guyana
						Mexico
						Peru
						Paraguay
						Suriname
High (8)			UAE		Uruguay	Argentina
			Brunei			Chile
			Korea, Rep.			Panama
			Oman			

Source: World Economic Situation Prospects 2019. Country in red color are non-adopters of the UN-REDD programme. Numbers in parenthesis indicate the number of countries in each income category.

Table B.4: Classification of countries by institutional quality

Moderately Free		Mostly Unfree		Repressed	
Control	Treated	Control	Treated	Control	Treated
Botswana	*Chile	Afghanistan	Argentina	Algeria	Bolivia
Brunei	Colombia	Angola	Bangladesh	Burundi	Central African Republic
Jordan	Costa Rica	Brazil	Benin	Cuba	Congo, Dem. Rep.
*Korea, Rep.	Cote d'Ivoire	China	Bhutan	Eritrea	Equatorial Guinea
Namibia	Dominican Rep.	Djibouti	Burkina Faso	Iran	Liberia
Oman	El Salvador	Egypt	Cambodia	Iraq	Sudan
Rwanda	Fiji	Eswatini	Cameroon	Korea,Dem.	Suriname
Turkey	Guatemala	Gambia	Chad	Syria	Zimbabwe
*UAE	Indonesia	Haiti	Congo,Rep.	Timor-Leste	
Uruguay	*Malaysia	Lebanon	Ecuador	Venezuela	
	Mexico	Mali	Ethiopia	Yemen	
	Mongolia	Mauritania	Gabon		
	Morocco	Mozambique	Ghana		
	Panama	Nicaragua	Guinea		
	Paraguay	Niger	Guinea-Bissau		
	Peru	Sao Tome & Principe	Guyana		
	Philippines	Senegal	Honduras		
	Tanzania	Sierra Leone	India		
	Thailand	South Africa	Kenya		
	Vanuatu		Laos		
	Vietnam		Madagascar		
			Malawi		
			Myanmar		
			Nepal		
			Nigeria		
			Pakistan		
			PNG		
			Solomon Islands		
			Sri Lanka		
			Togo		
			Tunisia		
			Uganda		
			Zambia		

Note: Using the Index of Economic Freedom, all countries categorized into three categories: 1. Moderately Free; 2. Mostly Unfree; and 3. Repressed (Heritage, 2021) . *In our sample the four countries - Chile, Republic Korea, Malaysia and United Arab Emirates - belong to 'Mostly Free category' have been placed in the 'Moderately Free category' due to low prevalence of countries with high economic freedom.

Table B.5: List of variables

Variable	Description	Source
Outcome variables		
Deforestation (*df*)	Tree cover loss at national level by 30% canopy cover, in hundred thousand hectares per year	GFW
Emissions (*emi*)	CO_2 emissions from above ground biomass loss at national level by 30% canopy cover, in gigatonnes	GFW
Explanatory variables		
GDP growth (Δgdp)	Real GDP growth rate, in annual %	WDI
Population growth (*gpop*)	Population growth, in annual %	WDI
Trade openness (*open*)	Sum of exports and imports, in % of GDP	WDI
Agricultural exports (*agexp*)	Agricultural raw materials exports, in % of merchandise exports	WDI
Rural population (*rpop*)	Rural population, in % of total population	WDI
Employment in agriculture (*emp*)	Employment in agriculture, in % of total employment	WDI
Agricultural land (*agland*)	Agricultural land, in % of land area	WDI
Arable land (*arable*)	Arable land, in % of land area	WDI

Note: GFW ≡ Global Forest Watch; WDI ≡ World Development Indicators of the World Bank

Table B.6: Descriptive statistics

Variable	Mean	Std. dev.	Min.	Max.
Before Policy ($N = 1364$)				
Outcome variables				
Deforestation	0.903	3.731	0	53.788
Emissions	0.031	0.123	0	1.765
Controls				
Real GDP growth	4.337	6.934	-99.670	64.081
Population growth	2.039	1.388	-4.537	15.177
Trade openness	73.618	39.019	0	351.110
Agricultural exports	5.498	11.753	0	79.536
Rural population	50.195	22.217	4.666	91.540
Employment in agriculture	40.215	23.758	0.550	92.548
Agricultural land	41.944	22.204	0.450	85.490
Arable land	13.310	12.919	0.043	63.786
After Policy ($N = 472$)				
Outcome variables				
Deforestation	1.545	2.972	0	24.221
Emissions	0.055	0.113	0	0.850
Controls				
Real GDP growth	4.572	3.589	-36.040	17.291
Population growth	1.860	0.863	-0.267	4.172
Trade openness	73.506	36.059	0.200	200.380
Agricultural exports	6.461	12.333	0	98.947
Rural population	52.054	20.959	8.130	87.020
Employment in agriculture	40.996	20.353	0.059	81.706
Agricultural land	37.298	20.408	0.470	79.050
Arable land	12.988	12.881	0.333	59.853

Note: Data are from 102 countries covering 2001-2008 (pre-programme period) and 2009-2018 (adoption period). Deforestation is measured by hundred thousand hectares of tree cover loss per year. Emissions measure is in gigatonnes of carbon dioxide emissions per year. GDP per capita is in constant 2010 US Dollar. Real GDP growth and population growth are given as annual percentages. Trade openness is the sum of exports and imports as a percentage of GDP. Agricultural exports is the agricultural raw material exports as a percentage of merchandise exports. Employment in agriculture is given as a percentage of total employment. Agricultural land and arable land are expressed as a percentage of land area.

Table B.7: Correlation matrix, deforestation

	df	*Δgdp*	*gpop*	*open*	*agexp*	*rpop*	*emp*	*agland*	*arable*
df	1.0000								
Δgdp	0.0799*	1.0000							
gpop	0.0650*	0.6589*	1.0000						
open	0.0526*	0.6481*	0.7585*	1.0000					
agexp	-0.0125	0.2846*	0.4323*	0.3651*	1.0000				
rpop	0.0516*	0.7309*	0.8324*	0.7949*	0.4508*	1.0000			
emp	0.0649*	0.6850*	0.8719*	0.7350*	0.4510*	0.9405*	1.0000		
agland	0.0476*	0.6708*	0.7672*	0.6400*	0.2275*	0.7494*	0.7055*	1.0000	
arable	0.0160	0.5565*	0.5699*	0.4706*	0.2202*	0.6859*	0.5863*	0.8066*	1.0000

Note: *Denotes statistical significance at 10% level.

Table B.8: matrix, emissions

	emi	*Δgdp*	*gpop*	*open*	*agexp*	*rpop*	*emp*	*agland*	*arable*
emi	1.0000								
Δgdp	0.0916*	1.0000							
gpop	0.0768*	0.6589*	1.0000						
open	0.0649*	0.6481*	0.7585*	1.0000					
agexp	-0.0095	0.2846*	0.4323*	0.3651*	1.0000				
rpop	0.0641*	0.7309*	0.8324*	0.7949*	0.4508*	1.0000			
emp	0.0812*	0.6850*	0.8719*	0.7350*	0.4510*	0.9405*	1.0000		
agland	0.0425*	0.6708*	0.7672*	0.6400*	0.2275*	0.7494*	0.7055*	1.0000	
arable	0.0170	0.5565*	0.5699*	0.4706*	0.2202*	0.6859*	0.5863*	0.8066*	1.0000

Note: *Denotes statistical significance at 10% level.

Table B.9: Programme effect on Deforestation and Emissions– preliminary analysis

	Before Policy		After Policy		DID
	Treated	Controls	Treated	Controls	
Developing countries					
Deforestation	2.821	0.719	1.481	1.044	-1.665
	(0.467)	(0.118)	(0.138)	(0.244)	
CO_2 emissions	0.101	0.024	0.053	0.035	-0.059
	(0.018)	(0.004)	(0.005)	(0.008)	
Africa					
Deforestation	1.886	0.166	1.190	0.265	-0.795
	(0.404)	(0.017)	(0.181)	(0.032)	
CO_2 emissions	0.074	0.006	0.043	0.008	-0.033
	(0.018)	(0.001)	(0.043)	(0.002)	
Asia–Pacific					
Deforestation	3.922	0.298	2.192	0.365	-1.797
	(1.138)	(0.050)	(0.385)	(0.068)	
CO_2 emissions	0.153	0.012	0.084	0.015	-0.072
	(0.043)	(0.002)	(0.014)	(0.003)	
Latin America & Caribbean					
Deforestation	1.511	1.712	1.483	2.020	-0.336
	(0.246)	(0.457)	(0.134)	(0.547)	
CO_2 emissions	0.040	0.054	0.041	0.062	-0.007
	(0.006)	(0.015)	(0.004)	(0.017)	

Note: Standard errors are in parentheses.

Table B.10: Estimates of policy effects on deforestation over time (χ^2 test)

	(1)	(2)
First 2 years	0.225	-0.156
	(0.253)	(0.286)
Years 3-4	0.300	-0.297
	(0.264)	(0.287)
Years 5-6	0.277	-0.579
	(0.261)	(0.312)
Years 7-8	0.416	-0.734
	(0.334)	(0.390)
Years 9-10	0.600	-1.138*
	(0.377)	(0.460)
Covariates	Yes	Yes
Year fixed effects	$\chi^2(17)$=30.84 (p-value=0.021)	$\chi^2(17)$=20.14 (p-value=0.267)
Country fixed effects	$\chi^2(101)$=3,761.39 (p-value=0.000)	$\chi^2(101)$=5,581.57 (p-value=0.000)
Country*time	No	$\chi^2(101)$=672.91 (p-value=0.000)
Adjusted R^2	0.895	0.908
Observations	1,836	1,836

Note: Column (1) controlling for year fixed effects and country fixed effects; and column (2) controlling for year fixed effects, country fixed effects and country-specific linear trend. Standard errors in parentheses are bootstrapped with 1000 replications. Finally, ***, **, and * indicate statistical significance at nominal level 1%, 5% and 10%, respectively.

Table B.11: Estimates of policy effects on emissions over time (χ^2 test)

	(1)	(2)
First 2 years	0.011	-0.006
	(0.009)	(0.010)
Years 3-4	0.013	-0.011
	(0.010)	(0.010)
Years 5-6	0.013	-0.021
	(0.009)	(0.011)
Years 7-8	0.018	-0.026
	(0.012)	(0.014)
Years 9-10	0.021	-0.042*
	(0.015)	(0.017)
Covariates	Yes	Yes
Year fixed effects	$\chi^2(17)$=27.67 (p-value=0.049)	$\chi^2(17)$=17.76 (p-value=0.404)
Country fixed effects	$\chi^2(101)$=3,403.25 (p-value=0.000)	$\chi^2(101)$=5,623.01 (p-value=0.000)
Country*time	No	$\chi^2(101)$=822.97 (p-value=0.000)
Adjusted R^2	0.880	0.898
Observations	1,836	1,836

Note: Column (1) controlling for year fixed effects and country fixed effects; and column (2) controlling for year fixed effects, country fixed effects and country-specific linear trend. Standard errors in parentheses are bootstrapped with 1000 replications. Finally, ***, **, and * indicate statistical significance at nominal level 1%, 5% and 10%, respectively.

Table B.12: Aggregate DID estimates– Deforestation (χ^2-test)

	(1)	(2)
$REDD \times POST$	0.446	-0.229
	(0.337)	(0.436)
Covariates	Yes	Yes
Year fixed effects	χ^2(17)=33.56 (p=0.010)	χ^2(17)=21.44 (p=0.207)
Country fixed effects	χ^2(101)=3,912.24 (p=0.000)	χ^2(101)=6,411.32 (p=0.000)
Country*time	No	χ^2(101)=765.65 (p=0.000)
Adjusted R^2	0.896	0.908
Observations	1,836	1,836

Note: Column (1) controlling for year fixed effects and country fixed effects; and column (2) controlling for year fixed effects, country fixed effects and country-specific linear trend. Standard errors in parentheses are bootstrapped with 1000 replications. Finally, ***, **, and * indicate statistical significance at nominal level 1%, 5% and 10%, respectively.

Table B.13: Aggregate DID estimates– Emissions (χ^2-test)

	(1)	(2)
REDD*POST	0.021	-0.005
	(0.012)	(0.016)
Covariates	Yes	Yes
Year fixed effects	χ^2(17)=34.88 (p=0.007)	χ^2(17)=18.89 (p=0.335)
Country fixed effects	χ^2(101)=3,664.42 (p=0.000)	χ^2(101)=6,496.60 (p=0.000)
Country*time	No	χ^2(101)=956.76 (p=0.000)
Adjusted R^2	0.880	0.897
Observations	1,836	1,836

Note: Column (1) controlling for year fixed effects and country fixed effects; and column (2) controlling for year fixed effects, country fixed effects and country-specific linear trend. Standard errors in parentheses are bootstrapped with 1000 replications. Finally, ***, **, and * indicate statistical significance at nominal level 1%, 5% and 10%, respectively.

Table B.14: Protected area classification

Type of protection	**Description**
PA1 (Ia). Strict Nature Reserve	Protected areas that are strictly set aside to protect biodiversity and also possibly geological/geomorphological features, where human visitation, use and impacts are strictly controlled and limited to ensure protection of the conservation values. Such protected areas can serve as indispensable reference areas for scientific research and monitoring.
PA1 (Ib). Wilderness Area	Protected areas that are usually large unmodified or slightly modified areas, retaining their natural character and influence, without permanent or significant human habitation, which are protected and managed so as to preserve their natural condition.
PA2. National Park	Large natural or near natural areas set aside to protect large-scale ecological processes, along with the complement of species and ecosystems characteristic of the area, which also provide a foundation for environmentally and culturally compatible spiritual, scientific, educational, recreational and visitor opportunities.
PA3. Natural Monument or Feature	Protected areas set aside to protect a specific natural monument, which can be a land-form, sea mount, submarine cavern, geological feature such as a cave or even a living feature such as an ancient grove. They are generally quite small protected areas and often have high visitor value.
PA4. Habitat/Species Management Area	Protected areas aiming to protect particular species or habitats and management reflects this priority. Many category 4 protected areas will need regular, active interventions to address the requirements of particular species or to maintain habitats, but this is not a requirement of the category.
PA5. Protected Landscape/Seascape	A protected area where the interaction of people and nature over time has produced an area of distinct character with significant ecological, biological, cultural and scenic value; and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values.
PA6. Protected area with sustainable use of natural resources	Protected areas that conserve ecosystems and habitats, together with associated cultural values and traditional natural resource management systems. They are generally large, with most of the area in a natural condition, where a proportion is under sustainable natural resource management and where low-level non-industrial use of natural resources compatible with nature conservation is seen as one of the main aims of the area.

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Chapter 4
On the Effectiveness of Kyoto's Clean Development Mechanism for Emissions Reduction: Evidence from Developing Economies

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Statement of Authorship

Title of Paper	On the Effectiveness of Kyoto's Clean Development Mechanism for Emissions Reduction: Evidence from Developing Economies
Publication Status	☐ Published ☐ Accepted for Publication ☐ Submitted for Publication ☒ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	

Principal Author

Name of Principal Author (Candidate)	Warnakulasooriya Lakmini Priyanthi Fernando		
Contribution to the Paper	This paper is completely written by myself, including planning, data collection, proposing the methodology, estimation and interpretation of results.		
Overall percentage (%)	100%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	07.10.2020

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Abstract

This paper investigates the effectiveness of Kyoto's Clean Development Mechanism (CDM) on emissions reduction in developing countries. Using a quantile difference–in–differences approach on a balanced panel of 104 developing countries over the period 1996–2016, we find that the CDM has a strong impact only at low quantiles of the distribution of greenhouse gas (GHG) emissions. In particular, low–emitting countries show a significant 10% reduction in emissions, whereas countries with high emissions experience an insignificant, but 9% increase in emissions over the post–policy period. In addition, decomposition across GHG types and sectoral emissions suggests that CDM is not effective in reducing emissions for carbon dioxide or for the energy sector. Heterogeneity of the policy effect is observed across regions. In particular, compared to Africa and the Asia–Pacific, the CDM successfully reduced emissions in the Latin America and the Caribbean region. The policy, however, shows no significant effect in higher income developing economies. Reforms in the design and implementation of the CDM are therefore, necessary to receive anticipated policy outcomes.

Keywords: CDM; Emissions; difference–in–differences estimation; Quantiles; Climate change

JEL classification: O19, Q54, Q55, Q56

4.1 Introduction

The actions against climate change need to be collective and follow a credible international approach (Frankel, 1999, Kolstad and Toman, 2005, Olmstead and Stavins, 2006). In this context, the Clean Development Mechanism (CDM), pledged under the Kyoto Protocol of the United Nations Framework Convention on Climate Change, has been designed to engage developing economies in climate change mitigation while also promoting sustainable development. The CDM provides greenhouse gas (GHG) emission credits for developed economies through projects implemented in those countries.

Assessment of the success of the CDM is vital in framing an effective international policy architecture on climate change (Banuri and Gupta, 2000). Most of the existing empirical analyses assessing the CDM's success have employed mean–type regression analysis (Dechezleprêtre et al., 2008, He et al., 2014, Huang and Barker, 2012, Zhang and Wang, 2011), and thus cannot capture the effect of the policy along the distribution of emission measures. As countries show a tendency to implement CDM projects differently (Flues, 2010, Silayan, 2005, Winkelman and Moore, 2011), it is important to assess its heterogeneous effects, taking into account the distribution of emissions across countries. Another shortfall is that the majority of the studies consider the impact of the CDM only on carbon dioxide emissions, whereas approximately 30% of GHG emissions consist of methane, nitrous oxide and fluorinated gases. Each of these gases has a different lifetime (period it remains in the atmosphere) and radiative efficiency (the ability to absorb energy). Further, the Paris Climate Accord binds only the developed countries who had historically high emissions whereas the developing countries have no commitment to emission reduction targets when ratifying, despite having high emissions in the recent past (Figure C.2).

A successful emission reduction strategy needs to be holistic and addresses heterogeneities across all sectors and types of emissions. Therefore, our study fill this gap by using the CDM to examine the impact of international climate policies in developing economies. As such, this study mainly evaluates whether the implementation of CDM projects has triggered a reduction of GHG emissions in developing countries, and whether countries have responded differently to the policy.

Using a quantile treatment effect approach in a difference–in–differences setting, we find notable heterogeneous effects for the CDM across the GHG emissions distribution of developing countries. In particular, improvement in emissions reduction is observed only at the lower tail of the emissions distribution, whereas the policy has resulted in an increase in GHG emissions in the middle and high quantiles of the emission variables. This indicates that although the CDM may not have benefited the medium– to high–emitting countries, it does benefit low–emitting developing countries. On the other–hand, we find very strong evidence for reduced carbon intensity over the entire distribution of CDM host countries during the post–policy period. Policy adoption has therefore triggered favourable responses not in net emissions, but in carbon intensities. In high–emitting countries, the CDM was successful in reducing only fluorinated gases. Moreover, the policy has a significant heterogeneous effect across sectors of the economy. At the upper tail of the emissions distribution, the CDM has been a success for the agricultural and industrial sectors, although it is failed to reduce emissions in the energy, land—use change and forestry (LUCF) and waste sectors. In addition, policy response in developing countries exhibit regional and income–based heterogeneities. In particular, compared to the rest of the developing world, the policy was effective in reducing GHG emissions in the region of Latin America and the Caribbean. However, we do not find strong evidence across income levels. Specifically, we have seen GHG emissions reduction only for low–income economies, but the policy effect shows no significant improvement in emissions reduction above the median quantile for other income categories.

Our findings are in line with the Weitzman price–quantity theorem on the best policy to reduce GHG emissions. According to this theorem, the prevailing technological uncertainty makes taxes (price–based approaches) more effective than cap–and–trade (quantity–based approach) policies (Pizer, 1997). The Kyoto Protocol has followed the tradable quantity–type approach, and this could be a reason for its failure as an emissions abatement policy. In a price–type policy, the structure of costs and damages in climate change is important (Nordhaus, 2006). In a climate policy, the benefits are the stock of GHGs, and the costs are the flow of GHG emissions. Therefore, the marginal cost of emission reduction is related to the level of reduction, whereas the marginal benefit of emission reduction is invariant to the current level of emissions. When the damages are caused by stock externalities, the damage function in terms of current emissions is likely to be linear. On the other hand, abatement costs are a non–linear function of emissions. When there is uncertainty, emission taxes are therefore considered a more efficient solution for climate change than quantitative targets. Another advantage of the tax mechanism is its importance as a revenue–generating mechanism in the fiscal policy stance. This effect is explained as the 'double burden' where inefficiency losses of the overall tax system increase due to the increase in price and reduction in real income.

Our study contributes to the literature firstly by identifying the causal effect of the CDM as a global climate policy while addressing the ambiguity of its success in the extant literature. To the best of our knowledge, this is the first study that employs quantile difference–in–differences regression analysis to evaluate the impact of a global climate policy. The results confirm and even strengthen earlier results, indicating the high likelihood of CDM failure for high–emitting countries if the policy continues in the same manner. Secondly, the current study adds a new dimension by investigating the impact of the CDM at various disaggregations of types and sector–wise emissions. Therefore, we have employed a holistic approach in our analysis, without limiting it to carbon dioxide emissions. We have included emissions of four major GHG component gases and five sectors in investigating the differential policy response. Thirdly, we carry out region– and income–based heterogeneity analyses, which may aid in advancing the existing knowledge on the CDM's effectiveness in developing countries.

The rest of the paper is structured as follows. Section, 4.2, briefly outlines the GHG emission trends and the background of Kyoto's Clean Development Mechanism. Section 4.3 describes the data used, followed by the empirical strategy in Section 4.4. Section 4.5 reports the results across all heterogeneous specifications and Section 4.6 discusses the empirical findings. Section 4.7 presents some robustness checks. Section 4.8 shares the conclusion.

4.2 GHG emissions and the Clean Development Mechanism

Climate change intensifies and fabricates new risks for natural and human systems (Pachauri et al., 2014). In general, these risks are distributed unevenly and detrimental for developing economies. The severity of climate change depends on the growth of anthropogenic emissions – the primary cause of climate change – and is driven by population size, economic activity, technology and climate policy.

Historically, it is the developed countries that have been most responsible for climate change. Their wealth has been achieved from heavy industry and energy use leading to stockpiling of emissions in the atmosphere, but now, slowly, the process has begun to decouple. While developed countries still produce large amounts of carbon emissions, increasingly developing countries are doing so as well (Figures C.1 and C.2 in the Appendix). In 2016, developing countries produced 66% of the annual emissions whereas developed and economies in transition produced only 26% and 8%, respectively (Table C.1 in the Appendix). Conversely, annual average emissions are always highest for the developed countries and lie above the world averages. In developing countries, the Asia–Pacific region and upper–middle income category record the highest emissions. Carbon dioxide is the leading greenhouse component gas and the energy sector produces the most emissions of any sector (Figure C.3 in the appendix).

The Kyoto Protocol of the United Nations Framework Convention on Climate Change (UNFCCC) is a framework for reducing global GHG emissions. Participating countries are grouped as Annex I and Non-Annex I parties, corresponding to developed and developing nations. Whereas developing countries are not restricted in their GHG emissions, developed countries are bound to GHG reduction targets that must be met primarily through national measures. In addition, three market–based mechanisms have been introduced to meet the emission commitments: Emission Trading, Joint Implementation and Clean Development Mechanism. These flexibility mechanisms create 'carbon markets', where reduced carbon dioxide emissions are considered as commodities to be traded on the market. The CDM is the only mechanism of the Kyoto Protocol that involves developing countries[8]. By using the CDM, industrialised nations can meet their emission commitments in developing countries where no binding targets are recorded in the Kyoto Protocol[9]. The expectation of the CDM is to assist the industrialised nations to reduce their GHG abatement costs while helping developing countries to achieve emission reduction and sustainable development.

The CDM, established in 1997 and fully operational in late 2004, is the first global project–based offset mechanism for GHG abatement transfers from developing to developed countries. Currently, there are more than 7,600 registered projects with substantially uneven project distribution. More than 75% of the projects are implemented in only three countries: China, India and Brazil. More advanced developing countries with greater abatement potential host more CDM projects while least developed countries remain under–represented in the CDM (Cosbey et al., 2006). Apart from its unequal distribution, the market–based environmental policy instruments (i.e. taxes, cap–and–trade systems) typically include offset mechanisms to allow for cost–effective abatement (OECD, 2006, Stavins, 2003). However, compared to direct government regulations, their performance is not as anticipated. Design failures and institutional and technological limitations coupled with poor political interest, remain major obstacles in effective implementation.

[8]Eligibility to host a CDM project requires that developing countries first ratify the Kyoto Protocol and establish a Designated National Authority within the country to manage and supervise the CDM registration process.

[9]The CDM allows emission reduction (or emission removal) projects in developing countries to earn certified emission reductions (CERs), each equivalent to one tonne of CO_2. These CERs can be traded and sold, and used by industrialized countries to meet a part of their emission reduction targets under the Kyoto Protocol.

The success of the CDM as a global climate policy has been questioned due to its environmental integrity. From forward–looking research, Banuri and Gupta (2000) argue that the adoption of less GHG–intensive technologies has not only reduced emissions but created additional benefits for developing countries. This idea is supported by He et al. (2014) and Huang and Barker (2012) in their cross–country impact assessments of the CDM. By contrast, Schneider (2008) and Schneider et al. (2007) argue that the CDM has not achieved the emission reduction targets as the carbon market functions depend considerably on the presence of caps for CDM credit issuance. According to Wara and Victor (2008), failure to reflect the actual CDM–provoked emission reductions calls for an immediate introduction of comprehensive design and functional reforms to carbon markets. Such reforms may further aid in avoiding unanticipated price fluctuations of the emission permits. Despite the high expectations of the global community, unresolved design failures and accounting responsibilities of the participating countries create much ambiguity around the CDM's credibility in global climate governance.

The CDM receives criticism for allowing developed countries to choose to invest in favorable, low–cost reduction options and leaving developing countries with the most expensive options for their own reductions (Stahlke, 2020). This is referred to as the 'low–hanging fruit' issue,[10] because the CDM is placing developing countries at a higher level on their marginal abatement cost curve while developed countries receive emission credits for tapping the cheapest abatement costs (Banuri et al., 2001, Narain and van't Veld, 2008). By characterising the low–hanging fruit problem as compensation for the forgone opportunity costs of CDM projects, Narain and van't Veld (2008) suggest mandating a 'virtual option' clause in CDM projects. Accordingly, developing countries would be compensated for immediate project costs and for the forgone option value. Further, the host–country governments should not approve CDM projects unless full compensation is received. The authors do however, show their concern that political and practical obstacles could influence mandating such a virtual option for the CDM.

[10]This is also called the 'sold-out hypothesis', the 'cherry-picking' or the 'cream-skimming' problem.

On a positive note, Castro (2012) found that although the low-hanging fruits problem does exist in some sectors and countries, its effect would dissipate in future. Technological progress and the transfer of knowledge and information are some co-benefits of the CDM that prevent the low-hanging fruit problem from occuring (Dechezleprêtre et al., 2008, Popp, 2011). As technology transfers reduce marginal abatement costs, the risk on future abatement options is minimised, making CDM a more appealing policy choice for developing countries. CDM is however, not instrumented for technology transfer, nor does it guarantee the successful adaptation of foreign technology to local conditions. For this reason, Hübler (2015) stresses the importance of introducing an integrated multidimensional funding mechanism that overcomes the aforementioned limitations of the CDM.

Reversing or halting the impact of climate change is a daunting task. Economists have repeatedly questioned the feasibility of achieving the climate targets set by the UNFCCC. Nordhaus (2018) shows that even with reasonable technology and ambitious abatement strategies, combating climate change may be unfeasible owing to projected rapid economic growth in developing countries. In this context, the prospects of strong policy measures appear to be dimming rather than brightening. There is substantial uncertainty about the path of climate change and its impacts – future emissions, concentrations and damages. However, this does not reduce the urgency of adopting climate change policies today. We understand that policy failures are unavoidable, and the best practice is to learn from the mistakes and develop a new system. The need for credible policies to slow climate change is more pressing and therefore early action is always preferred.

4.3 Data

In this empirical investigation, we use a balanced panel of 104 developing countries in the regions of Africa (47), the Asia–Pacific (32) and Latin America and the Caribbean (25) over the period 1996–2016. Long term strategies are essential to halt climate change as 'greening' economic activities includes implementing multidimensional policy reforms. Policy evaluation on climate change thus requires considerable pre- and post- policy time spans. Our analysis focuses on the period 1996-2016, which includes a considerable pre-treatment period. This observation of the historical pattern of emissions is crucial in emission reduction assessments.

The data on the CDM projects are sourced from the project pipeline available on the UNFCCC website (UNFCCC, 2020). The CDM project cycle comprises of different stages - project activities that should be completed before issuing certified emission reduction (CERs): project identification; project design document development; host country approval; validation; registration; implementation and monitoring; verification and certification; and CER issuance. The year of first policy adoption is considered as 2005 and only the projects at the registration stage are included in the analyses. After the registration phase, CDM projects take time to show the effect. After 2010, only four countries adopted the CDM policy (2011: Bhutan and Liberia; 2012: Kenya and Ethiopia). Therefore, we have considered 2010 as the cut–off year of policy adoption. In our sample, 48 countries with approximately 7,600 registered CDM projects are placed in the treated group. The remaining developing countries, with no registered projects or with projects registered beyond 2010 are placed in the control group. The CDM is therefore, an indicator variable taking the value 1 in the year in which a country has a CDM project registered during 2005-2010 and in all years afterwards for the period from 1996–2016, and 0 otherwise.

We use GHG emissions and carbon intensity as the main outcome variables. Data for GHG emissions were extracted from the Climate Analysis Indicators Tool (CAIT) developed by the World Resource Institute (WRI, 2017). The CAIT aids mainly in the decisions made by the UNFCCC and other forums on national and global progress on climate change. The significance of this data set lies in its completeness and relative accuracy, as country data sets are produced by applying a consistent methodology. The CAIT provides comprehensive emissions data at both aggregated and disaggregated levels. We use country–level total GHG emissions in the main analysis. This is supplemented with the estimations on four other GHG component gases: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and fluorinated gases (*F-Gas*). The main component gas, carbon dioxide, contributes to more than 73% of the total emissions followed by methane (18%), nitrous oxide (7%) and fluorinated gases (2%). All emissions are expressed in metric tons of CO_2 equivalents (MtCO_2.e) and the logarithm of the emissions is used in the estimations.

The decomposition of GHG emissions comprises five main sectors: energy, industrial processes, agriculture, land-use change and forestry (LUCF) and waste (WRI, 2017). Energy sector emissions includes emissions from five sub–sectors: electricity/heat, manufacturing/construction, transportation, other fuel combustion and fugitive emissions. Energy sector emissions are partly due to carbon dioxide emitted from the fossil fuel combustion and partly from methane and nitrous oxide. The industrial processes sector includes emissions from cement manufacture, adipic and nitric acid production and other non-agriculture industries. Agriculture sector emissions cover the emissions from livestock, rice cultivation, agricultural soils and other agricultural sources (eg: crop residues and savanna). The LUCF includes net emissions and removals due to land use changes. Waste sector emissions are a result of landfills, wastewater treatment, human sewage and other waste. According to the reporting framework used by the UNFCCC, international bunkers is another main sector; however, the emissions from international bunkers (aviation and marine bunkers) are not included as a sector in the CAIT national GHG emissions.

Carbon intensity is measured in kilograms of CO_2 per unit of GDP (measured in international dollars in 2011 prices). The data on carbon intensity were extracted from the "Our World in Data" web platform (OWD, 2020). These data have been compiled using three sources: carbon dioxide emissions data from the Global Carbon Project and the Carbon Dioxide Information Analysis Centre (Le Quéré et al., 2014) and long-term GDP data from the Maddison Project Database (Bolt and Van Zanden, 2014).

The control variables, GDP per capita, GDP per capita squared, population, trade openness and world governance indicators are obtained from the World Bank's World Development Indicators (WDI, 2020) and financial openness is expressed by the Chinn-Ito index (KAOPEN) (Chinn and Ito, 2006). A brief description of all the variables used in our analyses are shown in Table C.2 in the Appendix.

The choice of explanatory variables reflects the literature on Environmental Kuznets Curve (Cole et al., 1997, Dasgupta et al., 2002, Dinda, 2004, Huang and Barker, 2012, Stern, 2004). Our study, therefore includes the logarithm of GDP per capita and its squared term. The logarithm of GDP and population is used as a proxy for overall economic demand. Trade share, the sum of total exports and imports of goods and services as a percentage of GDP, is used to denote trade openness. Financial openness is expressed using the Chinn-Ito index (KAOPEN) which measures a country's degree of capital account openness. World governance indicator control for the quality of governance. It is derived averaging six dimensions of governance: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law and control of corruption.

Our empirical strategy involves examining the effect of CDM projects implemented in Non-Annex I developing countries (host countries) compared with non-host developing countries. This is implemented within a difference–in–differences quantile treatment effects setting as described in Section 4.4. The Non-Annex I, developing countries with CDM projects registered before 2010 are in the treated group and non–host developing countries are in the control group. We allow the CDM policy to show its effect over a six year period and therefore, countries who adopt the policy after 2010 are placed in the control group.

Our identification assumption is that pre–treatment trends and changes in outcome variables in both treated and control countries are the same in the pre–policy period. Figure 4.1 and Figure 4.3 for emissions and carbon intensity show that, visually the pre–existing trends are quite similar for treated and control groups. Figures 4.2 and 4.4 show the emissions and carbon intensity before and after the policy, respectively. After CDM implementation, there is a slight increase in emissions, but the carbon intensity has fallen marginally. The distributions of the emissions and carbon intensity of the treated group show no significant difference after the policy was introduced. Table 4.1 shows the mean difference of two outcome variables in treated and control groups. The DID calculation shows a negative policy effect for both variables. Descriptive statistics of all the variables are presented in Table C.4 of the Appendix.

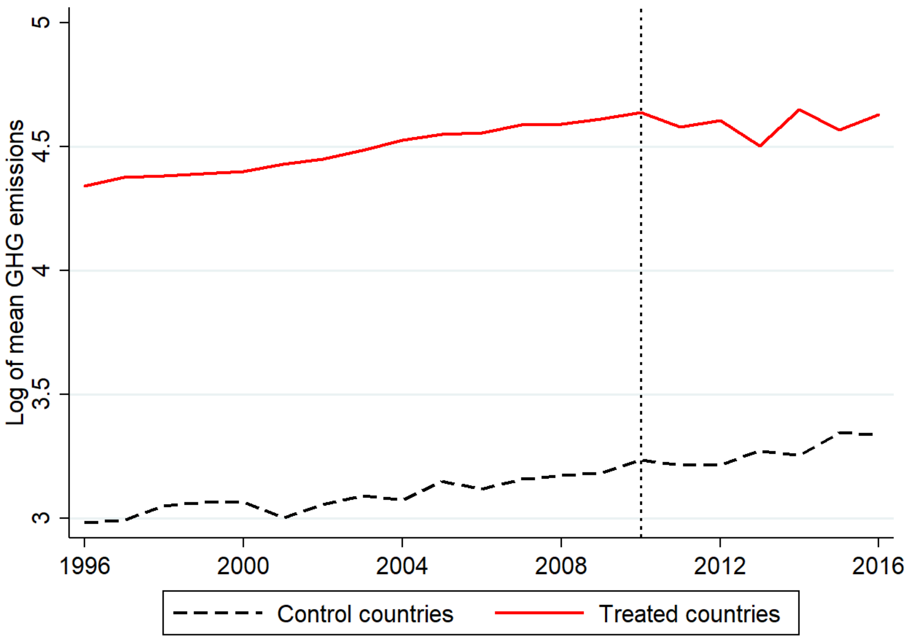

Figure 4.1: GHG emissions: control countries and treated countries

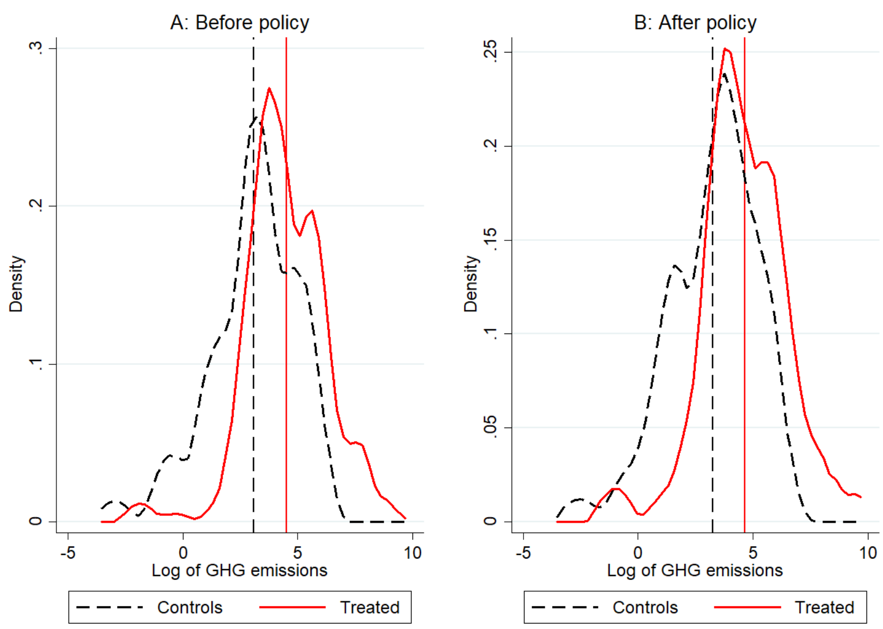

Figure 4.2: Distribution of GHG emissions

Note: The kernel is Epanechnikov. The vertical lines indicate control and treated country group means.

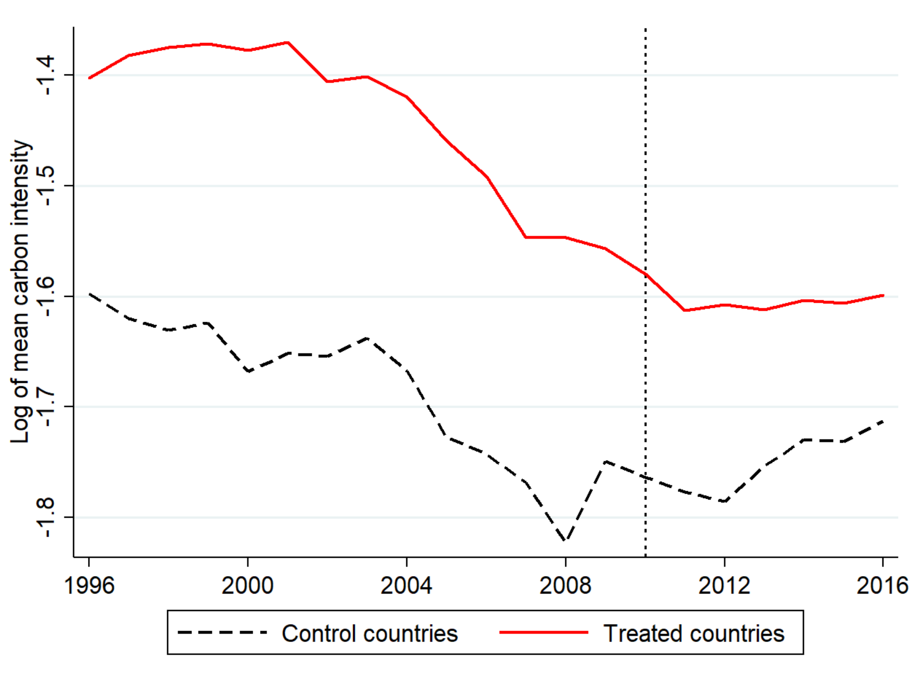

Figure 4.3: Carbon intensity: control countries and treated countries

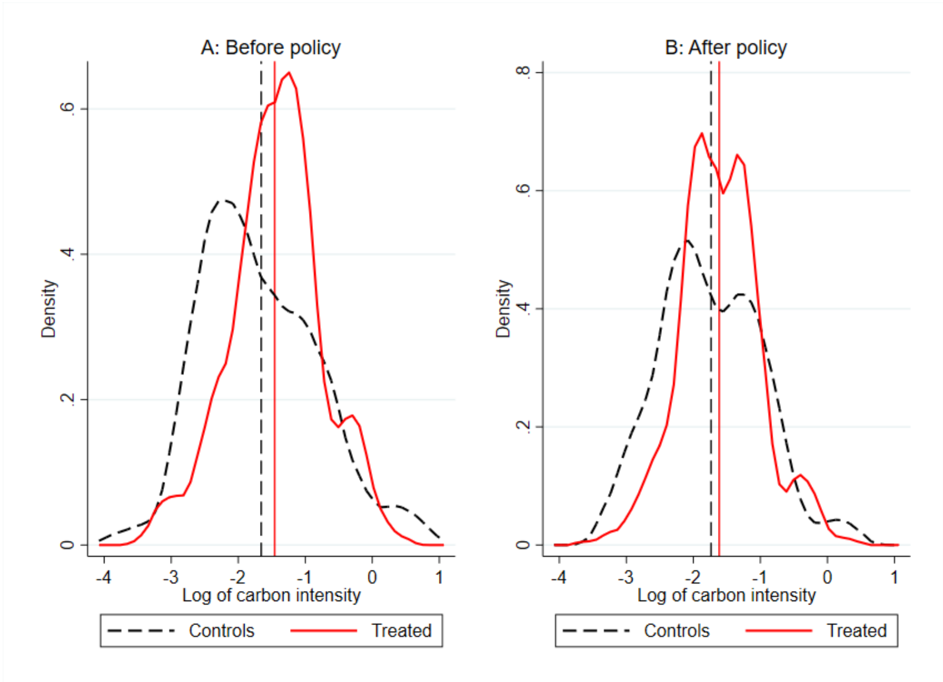

Figure 4.4: Distribution of carbon intensity

Note: The kernel is Epanechnikov. The vertical lines indicate control and treated country group means.

Table 4.1: Means of outcome variables by treatment

	Treated countries	Control countries	DID
Log of GHG emissions			
Before policy	4.517	3.073	-0.049
	(0.066)	(0.067)	
After policy	4.645	3.250	
	(0.100)	(0.093)	
Log of carbon intensity			
Before policy	-1.457	-1.658	-0.081
	(0.026)	(0.033)	
After policy	-1.615	-1.736	
	(0.032)	(0.040)	

Note: Estimates are the means of treated and control countries. Standard errors are shown in parentheses.

4.4 Empirical strategy

We employ the quantile treatment effects approach of Powell (2016) in a difference–in–differences framework to identify the policy effect. We closely follow two studies that uses the same approach: Ampofo and Doko Tchatoka (2019), who examine the effectiveness of wage policies in Ghana, and Smith (2017), who examines the impact of US school food programs on the distribution of child dietary quality. We specifically estimate the following specification:

$$Y_{it} = (CDM \times POST)'_{it}\beta(U_{it}) + X'_{it}\gamma(U_{it}) + \mu_i(U_{it}) + \eta_t(U_{it}) \qquad (4.4.1)$$

where Y_{it} refers to the outcome variables, log of GHG emissions or log of carbon intensity, of country i at time t; $(CDM \times POST)_{it}$ is the variable of interest, CDM_i captures the difference in the outcome variable between treated and control countries over the sample period and $POST_t$ shows the period after the policy adoption. The coefficient of interest, $\beta(U_{it})$, therefore captures the effect of the policy adoption on GHG emissions or carbon intensity for the treated countries.

X_{it} contains exogenous covariates: GDP per capita, GDP per capita squared, population, world governance indicators, trade openness and financial openness, and its coefficient $\gamma(U_{it})$ captures the effect of a change in these covariates on the log of GHG emissions or log of carbon intensity. $\mu_i(U_{it})$ and $\eta_t(U_{it})$ account for the country and year fixed effects (FE). Here, the error term, U_{it}, represents time–varying individual heterogeneity, which is defined as a function of time–invariant individual country characteristics, A_i and an idiosyncratic term, V_{it}; so that $U_{it} = f(A_i, V_{it})$. Therefore, our policy effect, $\beta(U_{it})$, is time–varying. The identification assumption for standard quantile regression (QR) is that the error term is distributed in a conditionally uniform way over the unit interval, $U_{it}|(CDM \times POST)_{it}, X_{it} \sim U(0,1)$. This is due to the possible correlation of A_i, which is embedded in U_{it}, with both Y_{it} and $(CDM \times POST)_{it}$. Thus, these omitted factors in U_{it} thus, can correlate with Y_{it} and $(CDM \times POST)_{it}$ inducing endogeneity.

The coefficients in quantile regression vary according to a nonseparable error term, known as the rank variable (Smith, 2017). The rank variable, U_{it}, defines the conditional quantiles over which estimation occurs – a high value of rank means the country is at the top of the conditional distribution, and likewise for a low value of rank. The ranking structure decides the interpretation of coefficients in quantile regression and to the definition of the counterfactual distribution. In our study, the counterfactual is the distribution of GHG emissions in the absence of policy adoption. In a potential outcomes framework, this counterfactual implies preserving rank such that low quantiles are defined by low–emissions and high quantiles by high–emissions. This ranking structure gives coefficient estimates the desirable interpretation for the research question, 'How does the CDM policy impact GHG emissions prone to countries with low GHG emissions separately from those with high GHG emissions'. In the identifying process, the quantile regression for panel data (QRPD) of Powell (2016), estimates the impact of CDM policy (treatment variable) on the outcome distribution (GHG emissions) using 'within' variation in the treatment variables. Powell's estimators contain nonadditive individual fixed effects in quantile regression and thus are not directly comparable to an additive approach.

The identifying assumption in Powell's model is that changes in $(CDM \times POST)_{it}$ and X_{it} are uncorrelated with changes in the conditional ranking structure $U_{it}|(CDM \times POST)_{it}, X_{it}$ once controlling for A_i (Chernozhukov et al., 2013). To the extent that endogenous characteristics are fixed over the sample period, the remaining change in the ranking structure should be idiosyncratic conditional on the choice of policy adoption and country fixed effects. Further, it is assumed that the ranking structure is 'conditionally stable' over the 21 year period from 1996–2016, $U_{i1}|(CDM \times POST)i1, X_{i1} \sim U_{i2}|(CDM \times POST)_{i2}, X_{i2}$. This suggests that a country with high GHG emissions in year 1 also has high GHG emissions in year 2.

There is no functional form placed on $f(A_i, V_{it})$ (Powell, 2016). As in OLS-FE, individual country fixed effects A_i are allowed to be arbitrarily correlated with $(CDM \times POST)_{it}$ and X_{it}. The estimator is consistent for a fixed T, so this will be the case in study as $T = 21$ years. The estimator is directly comparable to pooled quantile regression in terms of interpretation (Smith, 2017). This is because estimates vary with U_{it} in both models, but the pooled regression does not control for A_i.

There are two moment conditions in the QRPD of Powell (2016). The first sample moment highlights the 'within transformation' of the data. For simplicity, denoting $(CDM \times POST)$ by D_{it} and dropping X_{it}.

$$g_i(b) = \frac{1}{T}\sum_{t=1}^{T} D_{it}[1(Y_{it} \leq D'_{it}b) - \tau_i(b)] \tag{4.4.2}$$

where $\tau_i(b) = \frac{1}{T}\sum_{s=1}^{T} 1(Y_{is} \leq D'_{is}b)$. This moment shows the estimator uses within individual comparisons for identification by controlling for A_i without having to estimate each A_i. This approach is the same as the de–meaning approach of OLS fixed effects.

The second moment condition of QRPD ensures that $E[\tau_i(b)] = \tau$, a condition that also holds in standard/pooled quantile regression:

$$h(b) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} 1(Y_{it} \leq D_{it}^{'}b) - \tau. \tag{4.4.3}$$

The second moment condition maintains the rank of the counterfactual policy as described above by ensuring that, on average, the probability of the outcome being less than or equal to the quantile function is equal to τ.

Equation 4.4.2 shows that QRPD is directly comparable to pooled quantile regression: if we constrain $\tau_i(b) = \tau$, we arrive at the sample moment corresponding to the standard quantile regression (QR) of Koenker and Bassett Jr (1978),

$$l_i(b) = \frac{1}{T}\sum_{t=1}^{T} D_{it}[1(Y_{it} \leq D_{it}^{'}b) - \tau] \tag{4.4.4}$$

Our estimation strategy uses the Generalized Methods of Moments (GMM). As in Chernozhukov and Hong (2003), we maximise the following objective function:

$$L_N(b) = -\frac{1}{2}\left(\sum_{i=1}^{N} m_i(b)\right)^{'} W_N(b)\left(\sum_{i=1}^{N} m_i(b)\right) \tag{4.4.5}$$

where $m_i(b)$ is a set of moment conditions satisfying $E[m_i(b) = 0$, and the weighting matrix is defined as $W_N(b) = \left[\sum_i m_i(b)m_i(b)'\right]^{-1}$. To estimate QRPD, we use the two moment conditions found in equations 4.4.2 and 4.4.3 and follow the estimation procedure outlined in Powell (2016). Pooled QR can be estimated following Koenker and Bassett Jr (1978) and the moment condition of $l_i(b)$ from equation 4.4.4.

In the case of both QR and QRPD, the quadratic objective function $L_N(b)$ is highly non–convex with many local optima owing to its 'blocky' nature, but it does have a well–pronounced global optimum. Computation is further hindered by the dimension of the parameter set. Therefore, we follow Chernozhukov and Hong (2003) and use Markov Chain Monte Carlo (MCMC) algorithm to maximise equation 4.4.5. Inferences are then drawn from the posterior distribution.

We use the logarithm of the variables in the estimation except for shares (trade and financial openness) and indicators (world governance indicators). We bootstrap the standard errors with 1000 replications. The coefficient of interest, β, measures the impact of CDM policy on the GHG emissions of the treated countries. The identification of our parameter of interest is that changes in GHG emissions in the treated countries is post 2010 are the result of CDM policy adoption. This means that any difference in GHG emissions between the treated and control countries prior to policy adoption should be same or statistically insignificant.

The inclusion of country fixed effects and year fixed effects aids identification. Country fixed effects capture any economic development that may influence the countries' GHG emissions other than the reduced emissions made possible by the CDM policy. The year fixed effects account for any decisions that influence the emissions over the years. Not accounting for these factors may wrongly attribute their effects to the policy adoption.

4.5 Results

Estimates of the CDM effects are presented as aggregated effects (sub section 4.5.1) and decomposed effects: on type of emissions (sub section 4.5.2) and on sectoral emissions (sub section 4.5.3). Then region– and income–based heterogeneous policy effects are shown in sub sections 4.5.4 and 4.5.5, respectively.

4.5.1 Aggregated policy effects on emissions

Table 4.2 presents the estimates of the CDM policy effect on log of GHG emissions for two models: QRPD and Pooled QRs. For comparison, we include FE and OLS estimates in respective panels. The FE estimate shown in Panel A of Table 4.2 shows a statistically insignificant impact of CDM, on average. Across quantiles, significant negative policy effect is observed only at the lower tail of the emissions distribution. The low–emitting CDM–host countries show a 10.3% reduction in GHG emissions over the post–policy period. The policy effect then turns positive over the remainder of the distribution. The largest significant positive effect of a 6.5% increase in emissions is seen at the 75^{th} quantile. Figure 4.5 shows the graph of the estimates in Panel A of Table 4.2, with 95% confidence bands shaded.

Table 4.2: CDM effect on log of GHG emissions

		Quantiles				
A: QRPD	FE	0.1	0.25	0.5	0.75	0.9
CDM $\times POST$	-0.083	-0.103***	0.029**	0.028***	0.065***	0.092
	(0.068)	(0.026)	(0.015)	(0.007)	(0.017)	(0.119)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165
B: Pooled QR	OLS	0.1	0.25	0.5	0.75	0.9
CDM $\times POST$	-0.037	-0.042	0.058	0.064	0.005	0.219**
	(0.089)	(0.093)	(0.114)	(0.065)	(0.078)	(0.093)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165

Note: The QRPD estimates with controls in Panel A and the pooled QR estimates with controls in Panel B. The individual control variables are GDP per capita, GDP per capita squared, population, trade openness, world governance indicators and financial openness. MCMC algorithm is used for Panel A and the bootstrapped standard errors with 1000 replications are shown in parentheses for Panel B. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

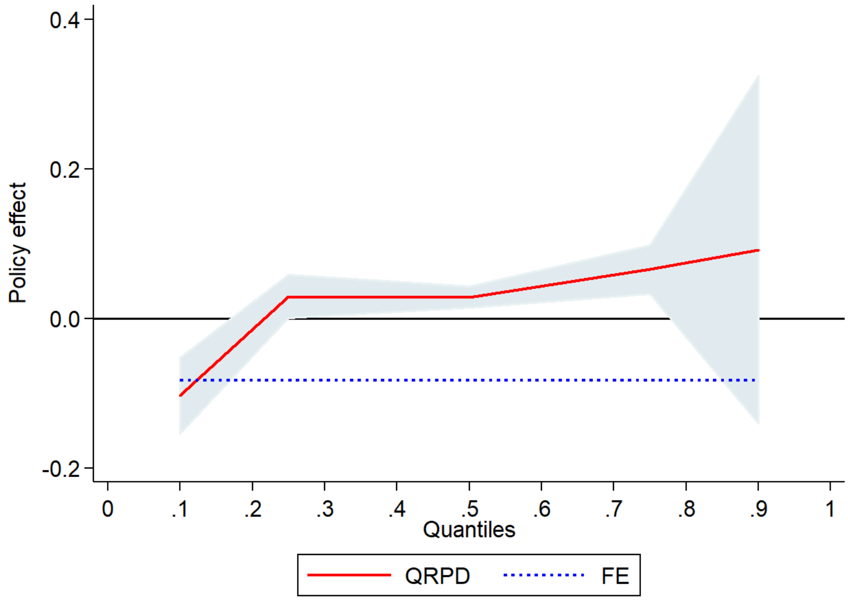

Figure 4.5: CDM effect on GHG emissions

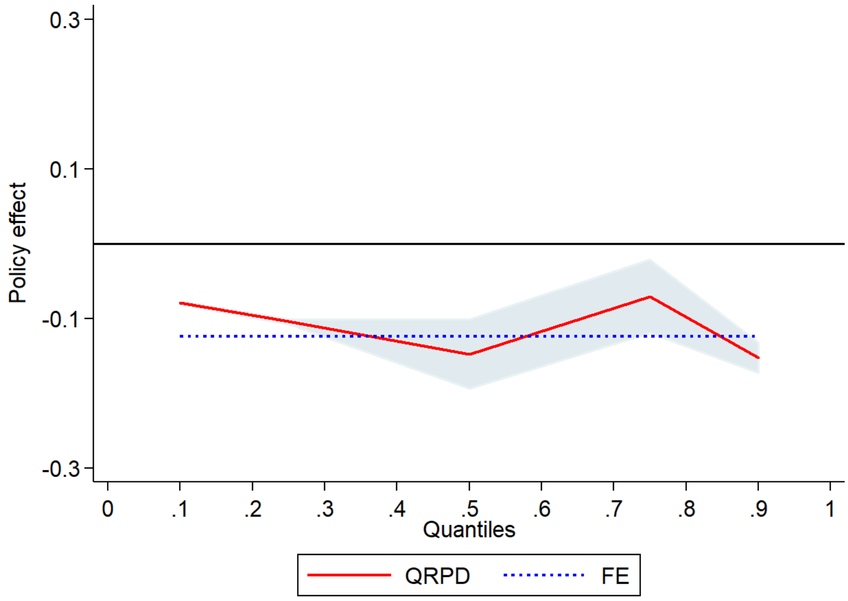

Figure 4.6: CDM effect on carbon intensity

In our analysis, the expected negative policy effect is seen only for countries at the lowest quantile. The statistical insignificance of the average estimate justifies the use of quantile regression approach in assessing the impact of CDM on GHG emissions in the host countries. The policy effect measured using pooled QR in Panel B are qualitatively similar to the QRPD estimates of Panel A of Table 4.2. However, note that their magnitudes differ from that of the QRPD estimates. Overall, our findings reveal that although CDM stimulates emissions reduction in low–emitting countries, we cannot rule out its ineffectiveness in high–emitting developing countries.

Table 4.3 presents the estimates using carbon intensity as the outcome variable. In contrast to the GHG results, we find very strong evidence for reduced carbon intensity over the entire distribution for CDM host countries during the post–policy period, see Figure 4.6.

The policy adoption has led to a 7.9% reduction in carbon intensity at the lower tail. The effect increases to a maximum of 15.2% reduction in carbon intensity at the upper tail. Comparing Tables 4.2 and 4.3, we conclude that the policy adoption has triggered heterogeneous responses in carbon intensities across CDM–host countries but it is not so for net GHG emissions.

Figures C.4 and C.5 in the Appendix show the full policy effects for emissions and carbon intensity, respectively across all quantiles. As we are not focusing on the monotonocity of the policy effect, only selected estimates at 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles are reported in the rest of our analyses.

4.5.2 Decomposed policy effects on type of emissions

Previous analysis focuses on the impact of CDM on emissions at the aggregate level. The effect of the CDM may vary across emission type, however. We thus, estimate equation (4.4.1) using QRPD for each greenhouse component gas. The results are presented in Table 4.4 and Figure 4.7.

The estimates in Table 4.4 reveal that, for high–emitters, with the exception

Table 4.3: CDM effect on log of carbon intensity

		Quantiles				
A: QRPD	FE	0.1	0.25	0.5	0.75	0.9
CDM $\times POST$	-0.124*	-0.079***	-0.104***	-0.148***	-0.071***	-0.152***
	(0.066)	(0.001)	(0.002)	(0.024)	(0.025)	(0.010)
B: Pooled QR	OLS	0.1	0.25	0.5	0.75	0.9
CDM $\times POST$	-0.125**	-0.074	-0.092*	-0.085	-0.106	-0.265**
	(0.052)	(0.089)	(0.053)	(0.056)	(0.075)	(0.132)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,057	2,057	2,057	2,057	2,057	2,057

Note: The QRPD estimates with controls in Panel A and the pooled QR estimates with controls in Panel B. The individual control variables are GDP per capita, GDP per capita squared, population, trade openness, world governance indicators and financial openness. MCMC algorithm is used for Panel A and the bootstrapped standard errors with 1000 replications are shown in parentheses for Panel B. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

of *F-Gas*, the CDM policy has not been successful in reducing any other type of emissions. In particular, the policy is associated with a significant increase in CO_2 (22.3%) and N_2O (10.3%) emissions for high–emitters. As the policy effect on CO_2 emissions is quite similar to that of the aggregate effect, CO_2 emissions must have driven it. This is anticipated, as CO_2 is the major constituent of GHG, contributing more than 70% to total GHG emissions. The strong policy effect on *F-Gas*, however, muted in the aggregate effect as it contributes to less than 2% of the total GHG emissions. The results thus confirm that the CDM is not effective in reducing GHG emissions except the *F-Gas* for high–emitting countries. It is, therefore, important that developing countries choose CDM projects based

Table 4.4: CDM effect on emissions, by type of emissions

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
All GHGs						
$CDM \times POST$	-0.083	-0.103***	0.029**	0.028***	0.065***	0.092
	(0.068)	(0.026)	(0.015)	(0.007)	(0.017)	(0.119)
CO_2 emissions						
$CDM \times POST$	-0.013	-0.077***	-0.297**	0.139***	0.061***	0.223***
	(0.084)	(0.011)	(0.125)	(0.008)	(0.019)	(0.016)
CH_4 emissions						
$CDM \times POST$	-0.018	0.189***	-0.059***	-0.080***	-0.007	0.029**
	(0.034)	(0.008)	(0.008)	(0.006)	(0.012)	(0.013)
N_2O emissions						
$CDM \times POST$	-0.041	0.073***	0.174***	-0.099***	-0.002	0.103***
	(0.032)	(0.009)	(0.005)	(0.006)	(0.008)	(0.014)
F-Gas emissions						
$CDM \times POST$	-0.034	-0.128***	-0.069**	-0.207***	0.113***	-0.082***
	(0.095)	(0.012)	(0.029)	(0.025)	(0.018)	(0.014)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

on their emissions composition, rather than accepting any CDM investment from a developed country.

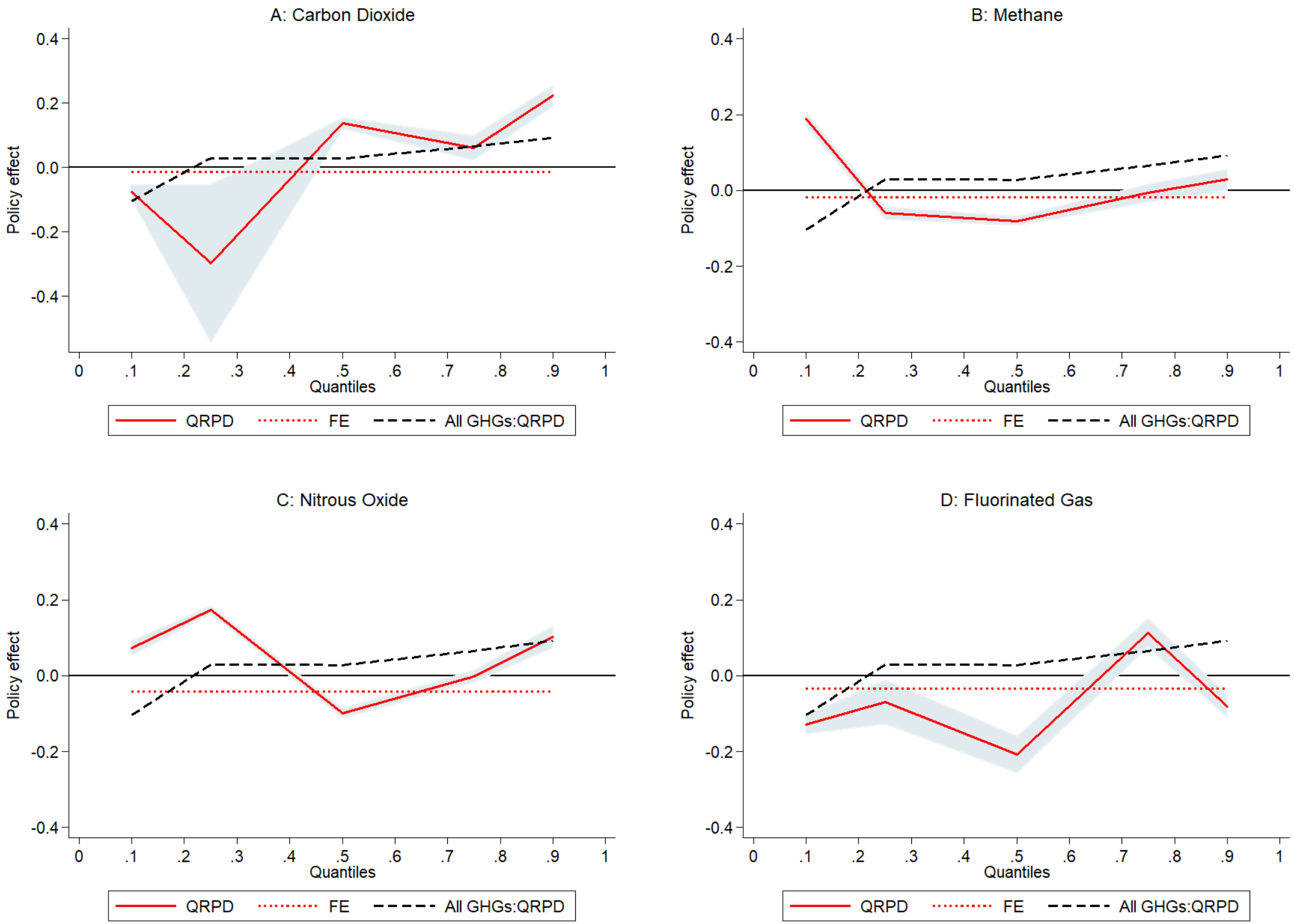

Figure 4.7: CDM effect on disaggregated emission groups

4.5.3 Decomposed policy effects on sectoral emissions

The estimates of equation (4.4.1) on sectoral decomposition of GHG emissions are presented in Table 4.5 and Figures C.6 and C.7 in the Appendix. There is substantial variation in policy response in each sector. Agriculture– and industry–related emissions show a significant reduction at the upper tail. Agriculture sector with only 3.2% and the industry sector with a large significant reduction of 33.6%.

One major role of the CDM is to boost transfers of clean, less polluting technologies to developing countries. CDM projects benefit big industries by employing such technologies in the manufacturing process. Our finding that the CDM has reduced industrial emissions of adopting countries over the entire distribution is similar to Schneider (2007), who shows that the CDM was successful in reducing emissions from industrial plants and landfills. He further argues that if concerns over the CDM are properly addressed, it would continue to be an important toll in climate change mitigation for developing countries.

On the other hand, energy, LUCF and waste sectors are the least to benefit from the CDM. Contributing more than 60% to total GHG emissions, both low and high–emitters in the energy sector show an 8.7% and a 17.5% increase in emissions over the post–policy period, respectively. Only the medium–emitters in the energy sector show emissions reduction: 11.1% at the $25th$ quantile, 7.3% at the median quantile, and 5.0% at the 75^{th} quantile. The LUCF sector shows emission reduction of 7.2% and 20.3% at the median and 75^{th} quantiles, respectively. Similarly, waste sector emissions are not responsive to policy adoption except at the 25^{th} quantile with 3.1% emission reduction.

The positive policy estimate seen at the upper quantiles of the emissions distribution in the energy sector could be a result of the link between CDM and carbon leakage (Figure C.7). Sijm et al. (2005) define carbon leakage as the ratio of policy–induced emission increase in non–abating country over the reduction of emissions by an abating country. According to Kallbekken (2007) and Bollen et al. (1999), the non–responsiveness of the energy sector to the CDM could have been driven by market leakages, which are transmitted through price fluctuations. For

Table 4.5: CDM effect on log of GHG emissions, by sector

		Quantiles				
Sector	FE	0.1	0.25	0.5	0.75	0.9
Energy						
CDM $\times POST$	-0.006	0.087***	-0.111***	-0.073***	-0.050***	0.175***
	(0.038)	(0.010)	(0.011)	(0.009)	(0.013)	(0.005)
Agriculture						
CDM $\times POST$	-0.018	-0.022	0.106***	-0.186***	-0.083***	-0.032
	(0.033)	(0.014)	(0.004)	(0.006)	(0.008)	(0.042)
LUCF						
CDM $\times POST$	-0.177	0.170***	0.063*	-0.072**	-0.203***	0.052***
	(0.144)	(0.049)	(0.038)	(0.028)	(0.030)	(0.013)
Industry						
CDM $\times POST$	-0.156	-0.486***	-0.259***	-0.321***	-0.215***	-0.336***
	(0.099)	(0.009)	(0.008)	(0.009)	(0.012)	(0.024)
Waste						
CDM $\times POST$	0.059	0.002	-0.031**	0.028***	0.098***	0.037
	(0.041)	(0.015)	(0.012)	(0.010)	(0.013)	(0.036)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

a single CDM project, such price fluctuation is insignificant and often neglected; however, the aggregate effects might be significant. The CDM investments could reduce the unit production costs of energy–intensive industries in host–countries. This can lead to an expansion of those industries at the cost of other countries' market share. As a result, the low–energy industries in developing countries end up having higher total energy use. Ultimately instead of lowering emissions, the CDM may even increase emissions to unprecedented levels in developing countries.

4.5.4 Heterogeneous effects across regions

Table 4.6 and Figure C.8 show the policy effect on GHG emissions by geographic region. The African region receives the fewest benefits from the CDM policy as estimates are positive across the entire distribution of GHG emissions. In contrast, the Asia–Pacific countries show negative policy estimates over the entire distribution of GHG emissions except at the 90^{th} quantile. This indicates that the CDM is effective in reducing emissions in low– to medium–emitters but not for high–emitters. We find a strong policy effect for the Latin America and the Caribbean region as we move across the GHG distribution. The emission reduction is as large as 100.3% at the lower tail and 24.1% at the upper tail.

The policy estimates are not compatible with the geographical distribution of CDM projects. The Asia–Pacific region owns the largest share, 85%, of the CDM projects (>6,000 projects) followed by 13% (>1,000 projects) in Latin America and the Caribbean and 2% (>100 projects) in Africa. Although the Asia–Pacific region owns the largest share of CDM projects, the policy is more effective in the Latin America and the Caribbean region. This indicates that geographical distribution of CDM projects has minimal impact, whereas other contextual factors (institutional quality, corruption, governance quality and political will, etc.) play a key role in the policy success. Having a level of emissions similar to the Latin America and the Caribbean region but with the fewest CDM project implementations, Africa reveals the importance of considering regional– and country–specific needs in policy designing and implementation. It is advisable not to compensate the country needs over global efforts in combating climate change.

Table C.5 in the Appendix shows the estimates for disaggregated regional emissions by emission type. Results reveal that CDM has reduced the carbon dioxide emissions along the entire distribution of emissions. African region shows reductions only in N_2O and *F-Gas* emissions. Further, all four GHG component gases show significant reduction in the upper tail for the Asia-Pacific region. These results are encouraging as the region houses the biggest emitters of the developing economies, China and India. Therefore, we can conclude that although the CDM

Table 4.6: CDM effect on log of GHG emissions, by region

		Quantiles				
Region	FE	0.1	0.25	0.5	0.75	0.9
Africa						
CDM $\times POST$	0.048	0.158***	0.104***	0.067***	0.105***	0.252***
	(0.048)	(0.014)	(0.006)	(0.007)	(0.037)	(0.011)
Observations	972	972	972	972	972	972
Asia–Pacific						
CDM $\times POST$	-0.089	-0.042***	-0.144***	-0.026	-0.170***	0.087***
	(0.089)	(0.016)	(0.010)	(0.019)	(0.014)	(0.011)
Observations	671	671	671	671	671	671
Latin America and the Caribbean						
CDM $\times POST$	-0.416*	-1.003***	-0.281***	-0.211***	-0.191***	-0.241***
	(0.219)	(0.139)	(0.031)	(0.049)	(0.028)	(0.011)
Observations	522	522	522	522	522	522
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

acts favorably, it requires major improvements in implementing country-specific projects to make effective contribution to combat climate change.

4.5.5 Heterogeneous effects across income levels

The heterogeneous policy effects across income levels[11] are shown in Table 4.7 and Figure C.9. As seen, for high–emitters, the policy effect is observed only for the low income category, with a marginal 1.2% emission reduction at the upper tail of the GHG distribution. Beyond the median quantile, the CDM shows no benefit for higher income developing countries (lower–middle income, upper–middle income and high income). Emission increases are as large as 33.3% and 10.5% for high–emitters in lower–middle and high income categories, respectively.

Looking at income groups, the poorest countries are responsible for only 5% of the emissions in developing countries and a marginal 3% of the global emissions. On the other hand, the medium income developing countries contribute to 86% and 57% of developing country and global emissions, respectively. The world's highest emerging country emitters, China, India and Brazil, are in this medium income category, which explains the reason for high emissions. In terms of population, the low income category includes only 9% of the developing countries' population[12], whereas the population share in medium–income categories is 88%[13]. We understand that an increase of a few billions in low income countries would therefore have a lesser impact on GHG emissions compared to that of the increasing population in medium-income countries.

[11]Aggregation by income is based on the total emissions of countries within each of the World Bank income groupings: low income, lower–middle income, upper–middle income and high income.

[12]Low income countries are home to a population of 0.6 billion.

[13]Lower-middle income and upper–middle income countries combined are home to a population of 5 billion.

Table 4.7: CDM effect on emissions, by income

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
Low Income						
CDM $\times POST$	-0.043	0.016	-0.038	-0.106***	0.039***	-0.012
	(0.086)	(0.010)	(0.045)	(0.009)	(0.009)	(0.044)
Observations	561	561	561	561	561	561
Lower–Middle Income						
CDM $\times POST$	0.004	-0.133***	0.117***	-0.044***	0.269***	0.333***
	(0.082)	(0.015)	(0.022)	(0.014)	(0.007)	(0.024)
Observations	683	683	683	683	683	683
Upper–middle Income						
CDM $\times POST$	-0.188	-0.053***	-0.303***	0.188***	0.168***	0.042
	(0.123)	(0.015)	(0.033)	(0.023)	(0.009)	(0.076)
Observations	588	588	588	588	588	588
High Income						
CDM $\times POST$	-0.419	-0.413***	-0.289***	-0.227***	0.077***	0.105***
	(0.369)	(0.019)	(0.016)	(0.017)	(0.014)	(0.005)
Observations	333	333	333	333	333	333
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Bootstrapped standard errors with 1000 replications in parenthesis for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

4.6 Discussion

Our results indicate that the CDM benefits the region of Latin America and the Caribbean the most compared to the rest of the developing world. This region probably satisfies the notion that the inflow of CDM projects is determined by the institutional and technological developments in host countries. According to Acemoglu et al. (2006), technological innovation is vital for high-tech countries, whereas for others it is technological adaptation that matters. As GHG abatement technology is comparatively advanced, more advanced developing countries generally attract more CDM projects. The least developed countries, therefore, may not benefit optimally from the CDM policy. This explains why the lagging African region benefits less from the CDM compared to the regions of Latin America and the Caribbean and the Asia–Pacific. The CDM project distribution for Latin America and the Caribbean and for Africa is 13% and 2%, respectively. However, countries may not benefit at all if they are left–out of the system. Therefore, it is the duty of the policy makers to create conducive environments to obtain the maximum benefits from global environmental policies while partaking effectively in combating climate change.

The CDM's top priority is to engage the highest–emitting developing countries in the emissions abatement process. This has already been accomplished with more than 75% of projects disbursed in China, India, Brazil and Mexico; however, as to the CDM's dual goal of emission reduction and promoting sustainable development, the latter is questionable, if the least developed countries are left out. Ultimately, the CDM should work in all development settings, not exclusively in emerging markets.

The CDM's capacity–building efforts are believed to aid developing countries in attracting more CDM investments (Winkelman and Moore, 2011); however, the CDM has not been successful in overcoming the existing predicaments of the least developed countries. It is not because these countries have fewer opportunities: A World Bank study by De Gouvello et al. (2008) reveals that the African region has the potential to implement 3,200 clean energy projects equivalent to an annual emission reduction of 740 million tonnes of CO_2.e. Therefore, the CDM clearly has not been an effective vehicle for incentivising CDM investments in a fair and equitable manner across developing countries.

With increasing emissions, extreme poverty has decreased in the Asia–Pacific whereas the opposite is observed in Sub-Saharan Africa (Goldstein, 2015). The reduction in emissions in Sub-Saharan Africa has increased the number of people living in poverty. However, Aden (2016) reports that 21 developing countries have decoupled emissions and economic growth successfully. This indicates that efforts towards carbon emission abatement must be determined by national circumstances. Although carbon-intensive industries are discouraged, the abatement efforts should not act as a deterrent to development potential in developing countries. Similarly, efforts need to differentiate between countries at different levels of development. Low income countries need to focus more on building technological capabilities, whereas high-income developing countries, which they already have the capability to address climate change, should invest in cooperative activities.

The International Energy Agency recognises renewable energy as the best option to support economic growth while reducing emissions (IEA, 2020). Africa has the richest solar resources but only 43% of Africans have access to a reliable power supply. Renewable energy delivers economic benefits with zero effects on climate change. Although decarbonisation is not a priority for developing countries compared to economic growth and poverty alleviation, investments in renewable energy would supplement both objectives while supporting global emissions abatement efforts. In this context, global climate governance should consider designing apt policies learning from the loopholes in the CDM.

4.7 Robustness checks

4.7.1 Placebo test

The validity of the identification strategy for the impact of CDM policy on outcome variables is determined by the parallel trend assumption. Using the year before the policy adoption, i.e. 2004, as the falsification year, we test the parallel trend assumption. The impact of the CDM policy is estimated by interacting the two indicator variables: the 2004 post–policy adoption variable and the treated (in our analysis, the CDM policy) country indicator.

Table 4.8: Placebo test

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
A: Log of GHG emissions						
CDM$\times POST_{2004}$	-0.048	-0.134***	0.115***	0.009	0.067	0.050
	(0.068)	(0.008)	(0.011)	(0.014)	(0.056)	(0.047)
Observations	2,165	2,165	2,165	2,165	2,165	2,165
B: Carbon intensity						
CDM$\times POST_{2004}$	-0.095	-0.072***	-0.132***	-0.089***	-0.005	-0.205***
	(0.066)	(0.007)	(0.001)	(0.006)	(0.018)	(0.005)
Observations	2,057	2,057	2,057	2,057	2,057	2,057
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

We presume to have estimates with no significant difference before policy implementation. If there is a significant difference, it is presumed to be in the same direction as the post–policy estimates. As shown in Table 4.8, we observe significant estimates at the lower tail only, but in the same direction for both outcome variables – GHG emissions and carbon intensity.

4.7.2 Different control group

The validity of the identification strategy for the impact of CDM policy on outcome variables depends on the pre-existing trends in treated and control country groups before the policy adoption. Although in our analysis we focus only on the developing countries, the CDM policy is designed to engage all Non-Annex I parties with the Kyoto Protocol in the emissions reduction process. This includes not only the developing countries, but economies in transition as well[14]. The choice of control group is vital. Although the treated and control groups are not equivalent, they need to be comparable in the DID setting prior to CDM policy adoption.

Therefore, we estimate the policy effect using the same treatment group but a different control, the transition economies, and report the results in Table 4.9. We observe qualitatively similar policy effects for GHG emissions, with the exception of the 25^{th} and median quantiles. However, the carbon intensity depicts opposite results to those generated in our main analysis. We conclude that our results are quite robust to the baseline when estimated with GHG emissions, but not when estimated with carbon intensity.

4.7.3 Different time of policy adoption

The impact of the CDM policy could be driven by the differences in the time of policy adoption. By decomposing the policy effect into extensive and intensive margins, based on the year of policy adoption, we observe whether such differences have any influence on the policy effect. Countries that adopted the policy in 2005 are considered the early adopters and other countries, which adopted the policy

[14] We classify all countries into three groups: developed countries, economies in transition and developing countries, based on the United Nations World Economic Situation and Prospects 2019 report (UN, 2019)

Table 4.9: Different control group

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
A: Log of GHG emissions						
CDM $\times POST$	-0.096	-0.375***	-0.213***	-0.166***	0.085***	0.185***
	(0.111)	(0.019)	(0.020)	(0.041)	(0.012)	(0.006)
Observations	1,172	1,172	1,172	1,172	1,172	1,172
B: Carbon intensity						
CDM $\times POST$	0.330***	0.134***	0.251***	0.336***	0.278***	0.609***
	(0.088)	(0.002)	(0.004)	(0.017)	(0.021)	(0.008)
Observations	1,176	1,176	1,176	1,176	1,176	1,176
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

after 2005, the late adopters. We then re-estimate the baseline model in equation (4.4.1) and display the results in Table 4.10.

The policy estimates for the early adopters are positive for the entire distribution of the GHG emissions. In contrast, the late adopters show a favourable response to the CDM, but with significant emission reductions only at the lower quantile (18%) and the median quantile (3%). Despite receiving benefits for a longer period of time, the early adopters are not responding favourably to the CDM. This indicates that the time of the policy adoption has no impact on the emissions reduction. We observe that the highest emitters of the developing country group – China, India, Brazil and Mexico – fall in the early adopter category. This explains why the CDM is less beneficial to early adopters.

Table 4.10: Different time of policy adoption

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
A: Log of GHG emissions						
CDM×*POST*	-0.083	-0.103***	0.029**	0.028***	0.065***	0.092
	(0.068)	(0.026)	(0.015)	(0.007)	(0.017)	(0.119)
Early adopters						
CDM×*POST*	-0.089	0.066***	0.002	0.050***	0.081***	0.007
	(0.117)	(0.014)	(0.010)	(0.011)	(0.024)	(0.080)
Late adopters						
CDM×*POST*	-0.028	-0.181***	0.008	-0.030	0.061*	0.045***
	(0.074)	(0.015)	(0.013)	(0.022)	(0.035)	(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

4.8 Policy implications and concluding remarks

Coping with climate change remains a daunting task for both scientists and economists. Amidst the adoption of various policies to slow climate change, improvement in emissions trends remains minimal. In this context, effective decarbonisation is recognized as being everyone's responsibility.

In this paper, we explored the impact of Kyoto's CDM on GHG emissions in developing countries. The CDM was designed to encourage developing country participation in reducing emissions and promoting sustainable development. Since 2005, developed countries have implemented emission reduction projects in developing countries and received CERs for the reduced emissions. Using a quantile treatment effect approach in a DID framework, we find improvement only at the lower tail of the emissions distribution. The CDM shows no benefit to high–emitting developing countries. The policy effect across emission types and sectors shows that the CDM has not benefited the key emission contributors: carbon dioxide and the energy sector. In addition, the region of Latin America and the Caribbean benefits the most from the CDM, but we did not see any success of the policy across income levels in developing countries.

Our results confirm the idea that the CDM alone is likely not sufficient to combat climate change. The success of a global climate policy depends on the widespread participation over a long time. These policies should not challenge national sovereignty, must be clear on the accountability of participating countries, and must be flexible and transparent for adopting countries.

Climate change puts both sustainable economic growth and good development outcomes at risk. Through climate action, countries can unlock new economic and employment potentials. Acting on climate change also allows countries to develop sustainably. Global climate governance should thus design policies that provide financial and technical competencies to combat climate change while ensuring the achievement of sustainable development in developing countries.

Appendix C

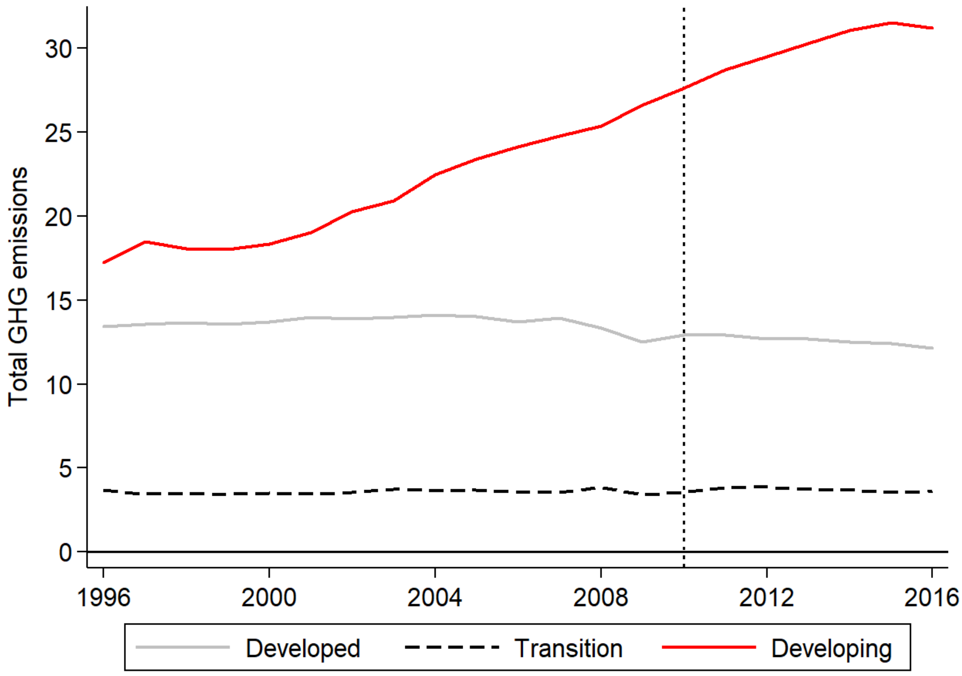

Figure C.1: Global total GHG emissions

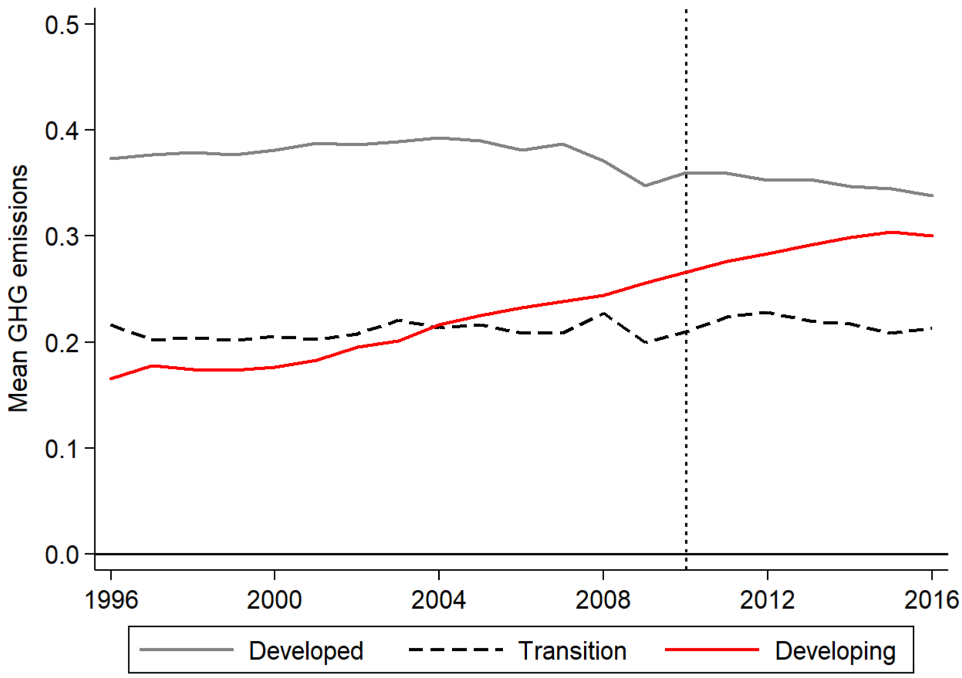

Figure C.2: Global mean GHG emissions

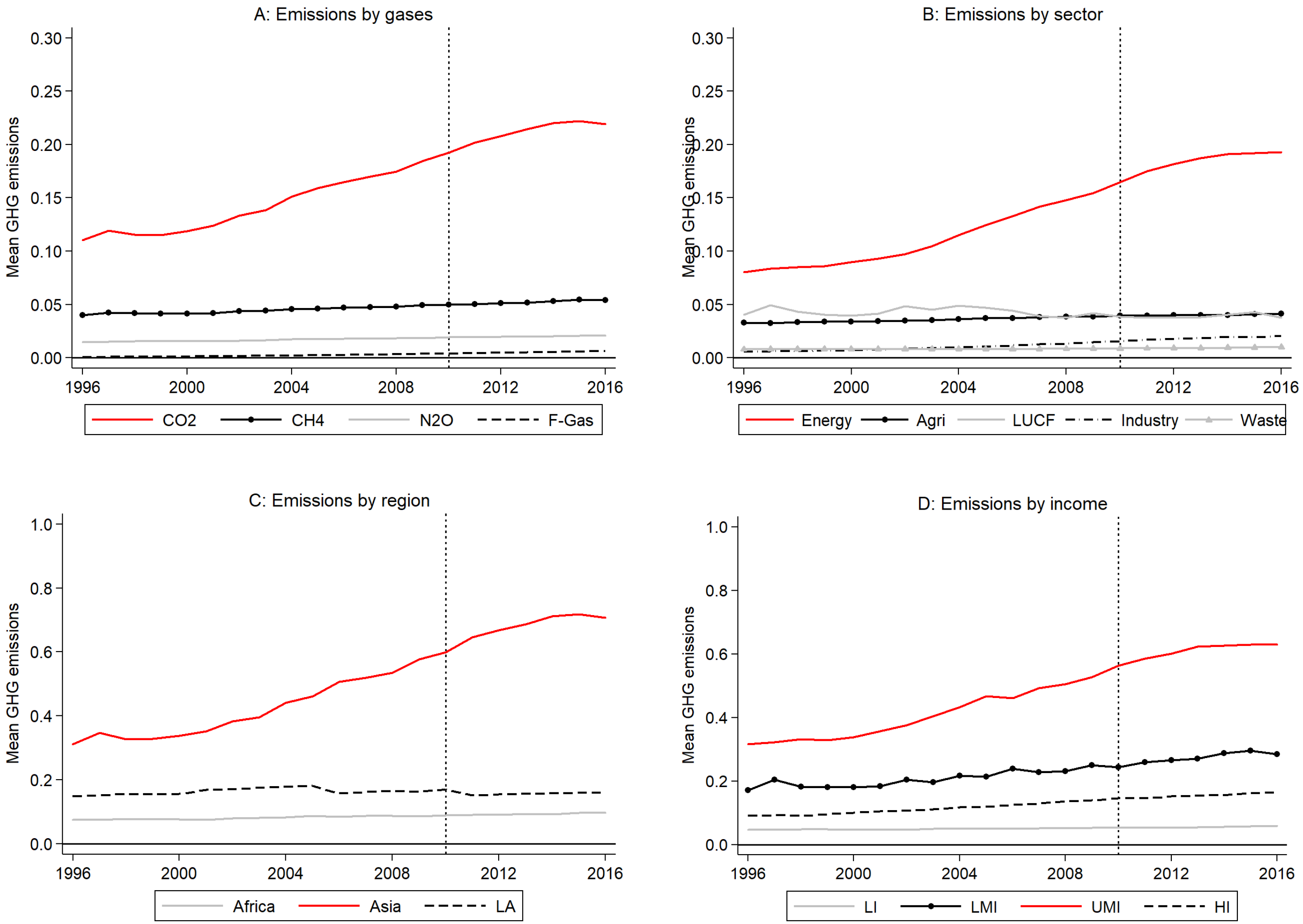

Figure C.3: Heterogeneities in emissions

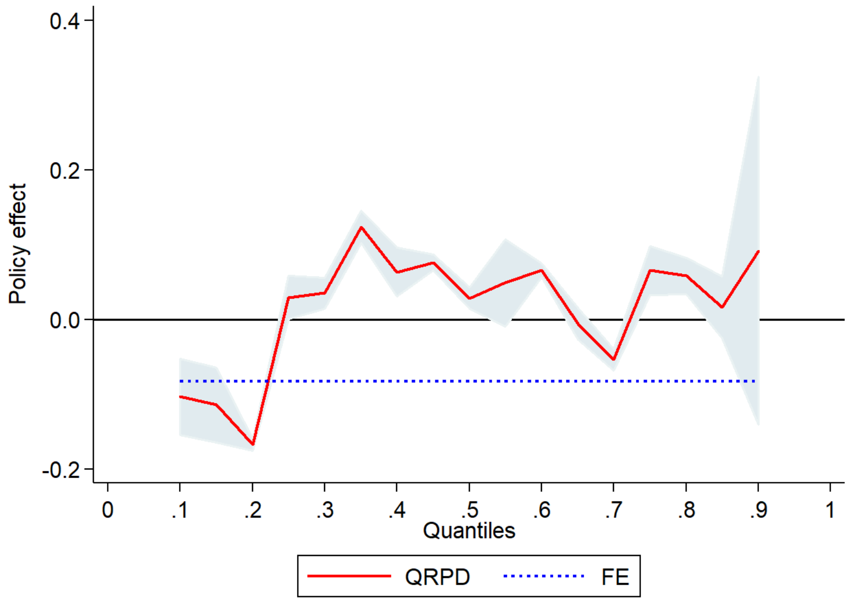

Figure C.4: Policy effect on GHG emissions

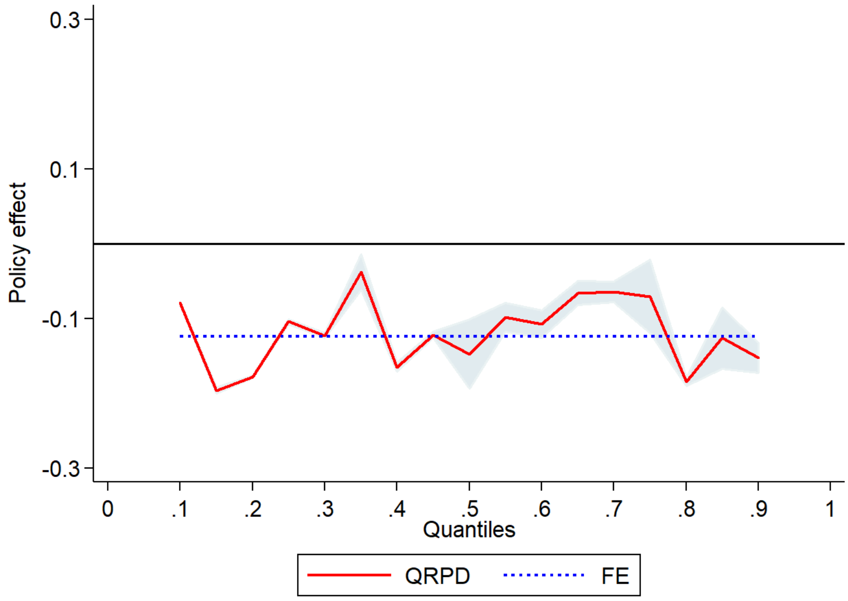

Figure C.5: Policy effect on carbon intensity

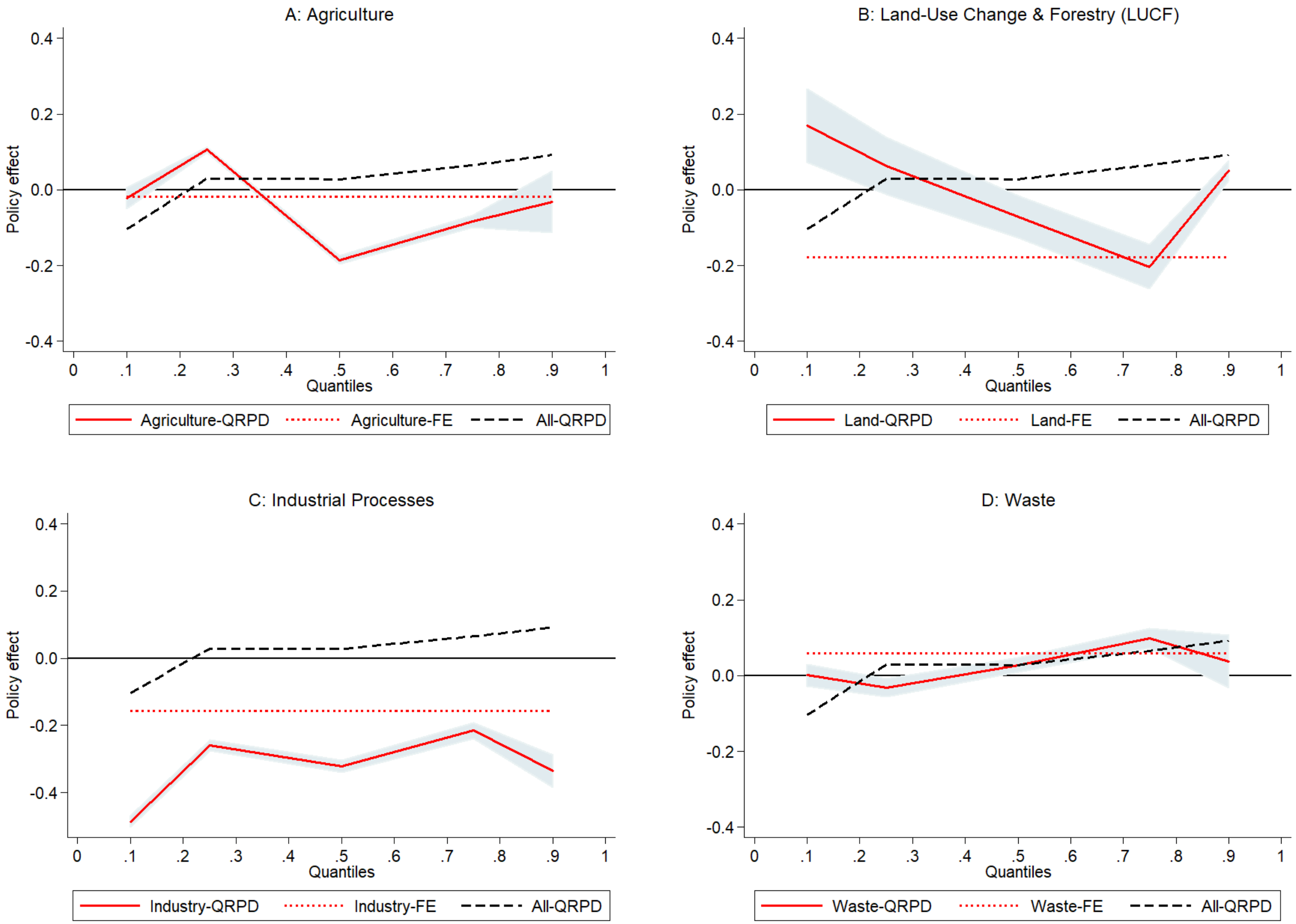

Figure C.6: CDM effect on sectoral emissions

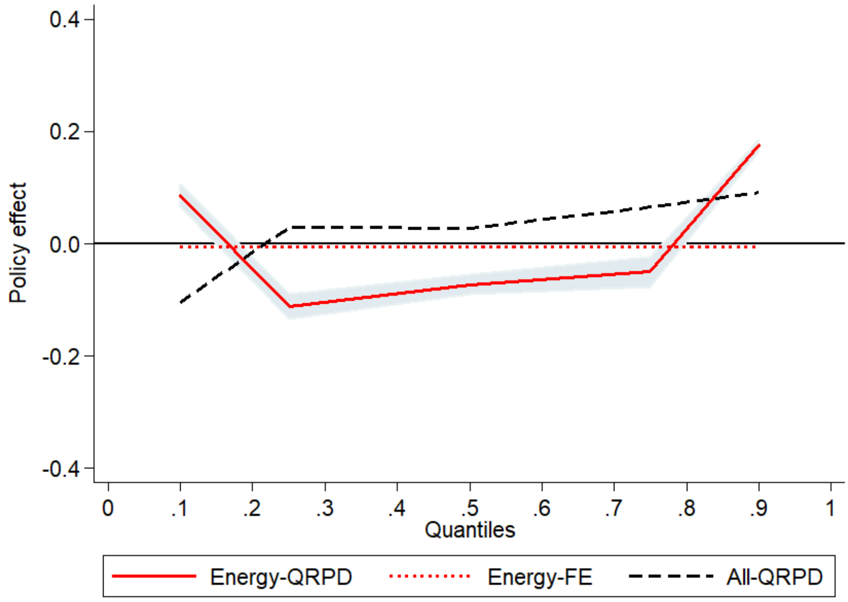

Figure C.7: CDM effect on GHG emissions in the energy sector

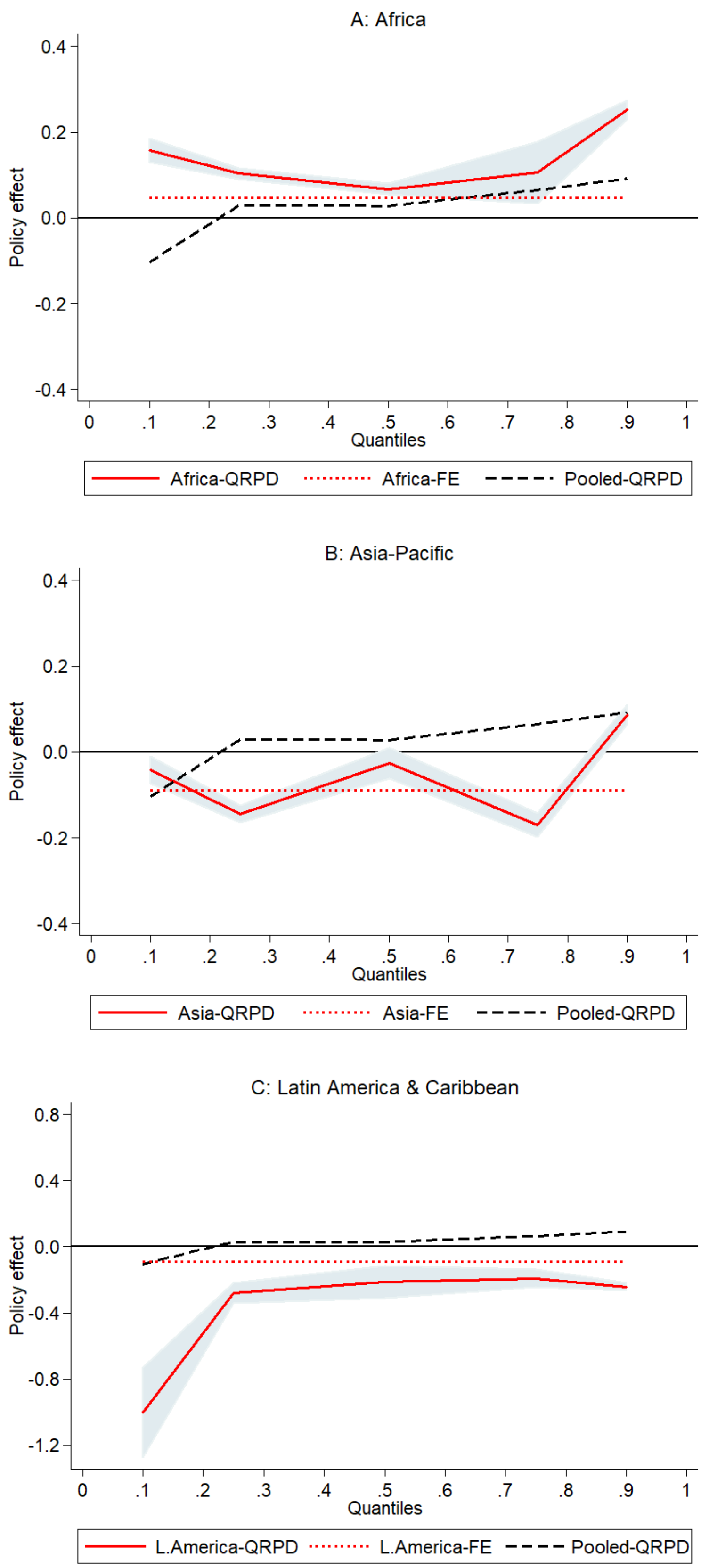

Figure C.8: Region–based CDM effect on emissions

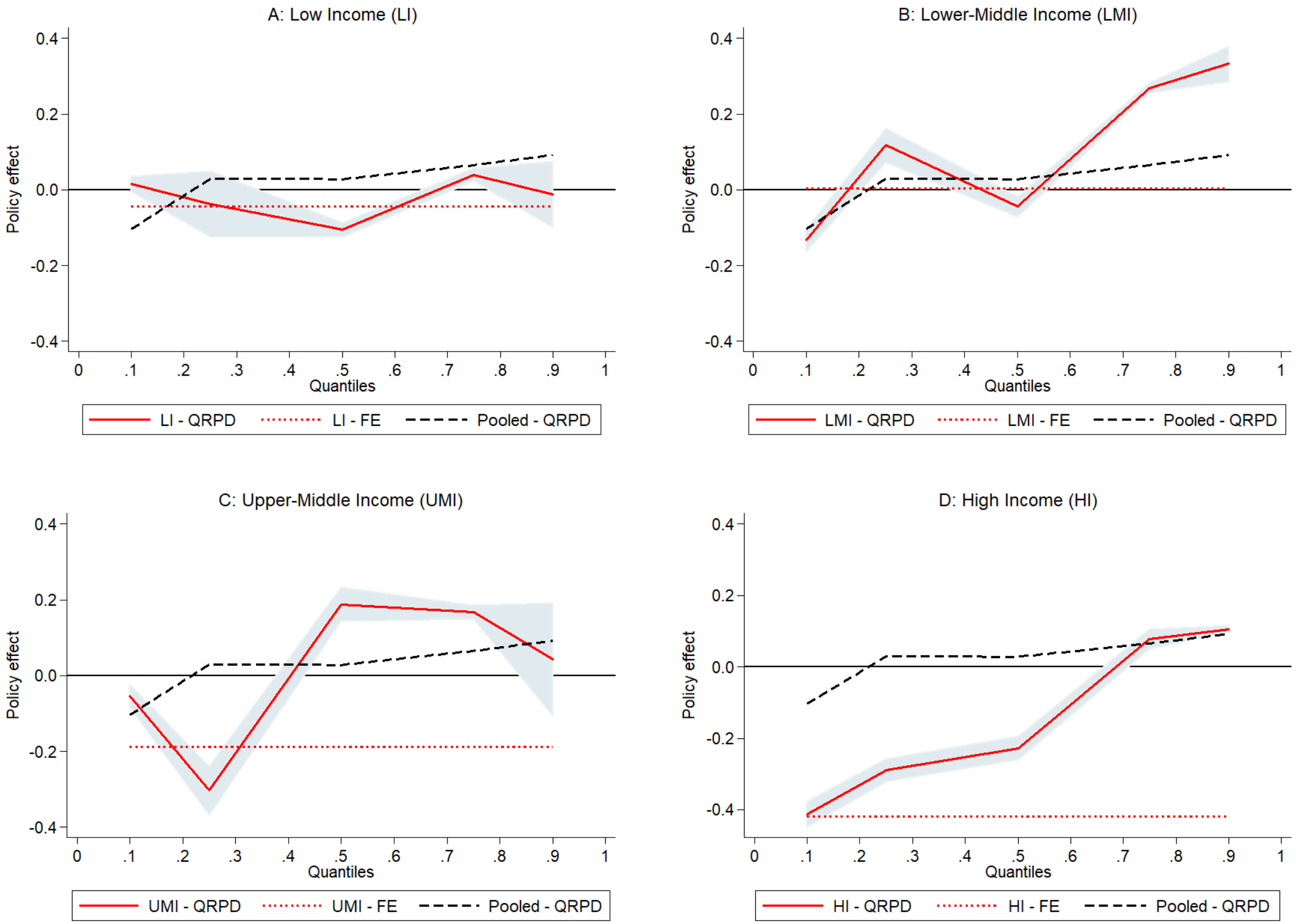

Figure C.9: Income–based CDM effect on emissions

Table C.1: Emissions trends

	Total emissions (Gt.CO_2.e)			Mean emissions (Gt.CO_2.e)			Change (%)			Share to total (%)
	1996	2006	2016	1996	2006	2016	1996–2006	2006–2016	1996–2016	2016
GLOBAL EMISSIONS										
World	34.35	41.43	47.00	0.25	0.27	0.28	20.62	13.44	36.83	100.00
Developed	13.43	13.73	12.16	0.37	0.38	0.34	2.18	- 11.43	- 9.50	25.86
Transition	3.68	3.55	3.62	0.22	0.21	0.21	- 3.47	2.03	- 1.52	7.70
Developing	17.24	24.16	31.23	0.17	0.23	0.30	40.12	29.25	81.11	66.43
DEVELOPING COUNTRIES										
By gases										
CO_2	11.48	17.13	22.78	0.11	0.16	0.22	49.22	32.97	98.42	72.94
CH_4	4.15	4.91	5.62	0.04	0.05	0.05	18.35	14.49	35.50	18.00
N_2O	1.54	1.84	2.18	0.01	0.02	0.02	19.39	18.37	41.31	6.98
F-Gas	0.07	0.28	0.65	0.00	0.00	0.01	291.29	133.91	815.26	2.08
By sector										
Energy	8.37	13.80	20.06	0.08	0.13	0.19	64.77	45.37	139.53	64.24
Agriculture	3.44	3.86	4.32	0.03	0.04	0.04	12.25	11.91	25.61	13.84
LUCF	4.20	4.60	3.90	0.04	0.04	0.04	9.71	- 15.38	- 7.16	12.48
Industry	0.58	1.21	2.11	0.01	0.01	0.02	107.49	73.81	260.65	6.74
Waste	0.84	0.86	1.04	0.01	0.01	0.01	3.36	20.84	24.89	3.34
By region										
Africa	3.57	3.98	4.58	0.08	0.08	0.10	11.38	15.16	28.26	14.66
Asia–Pacific	9.95	16.24	22.62	0.31	0.51	0.71	63.25	39.23	127.29	72.42
Latin America & Caribbean	3.72	3.94	4.03	0.15	0.16	0.16	5.86	2.34	8.34	12.91
By income										
Low Income	1.26	1.36	1.61	0.05	0.05	0.06	8.05	18.40	27.93	5.15
Lower-Middle Income	5.67	7.89	9.37	0.17	0.24	0.28	39.07	18.73	65.12	30.01
upper–middle Income	8.87	12.90	17.62	0.32	0.46	0.63	45.53	36.50	98.65	56.41
High income	1.44	2.01	2.63	0.09	0.13	0.16	38.91	31.35	82.46	8.44

Table C.2: List of variables

Variable	Description	Source
Outcome variables		
GHG emissions	Greenhouse gas emissions, metric tonnes of carbon dioxide equivalent (Mt$CO_2.e$)	WRI
CO_2 emissions	Carbon dioxide emissions, Mt$CO_2.e$	WRI
CH_4 emissions	Methane emissions, Mt$CO_2.e$	WRI
F-Gas emissions	Fluorinated gas emissions, Mt$CO_2.e$	WRI
N_2O emissions	Nitrous oxide emissions, Mt$CO_2.e$	WRI
Carbon intensity	Kilograms of CO_2 emissions per unit of GDP, PPP in 2011 prices	OWD
Controls		
GDP per capita	GDP per capita, constant 2010 thousand USD	WDI
Squared GDP per capita	Square of GDP per capita, constant 2010 thousand USD	WDI
Population	Total Population	WDI
WGI	Worldwide Governance Indicators for quality of governance, -2.5 (weak) to 2.5 (strong)	WDI
Trade	Trade openness, sum of exports and imports of goods and services, percentage of GDP	WDI
KAOPEN	Chinn-Ito index measures financial openness, 2.33 (most open) to -1.92 (least open)	Chinn and Ito (2006)

Note: OWD = Our World in Data sourced from Global Carbon Project, Carbon Dioxide Information Analysis Centre and Maddison Project Database; WDI = World Development Indicators of the World Bank and WRI = World Resource Institute

Table C.3: Control and treated country groups

Africa		Asia–Pacific		Latin America & Caribbean	
Control	Treated	Control	Treated	Control	Treated
Algeria	Congo, Dem.Rep.	Bahrain	Bangladesh	Bahamas	Argentina
Angola	Egypt	Kiribati	Cambodia	Barbados	Bolivia
Benin	Ghana	Kuwait	China	Belize	Brazil
Botswana	Madagascar	Lebanon	India	Guyana	Chile
Burkina Faso	Morocco	Maldives	Indonesia	Haiti	Colombia
Burundi	Namibia	Myanmar	Iran	Jamaica	Costa Rica
Cameroon	Nigeria	Oman	Israel	Paraguay	Dominican Rep.
Cape Verde	Senegal	Qatar	Jordan	Trinidad & Tobago	Ecuador
Central African Rep.	Sierra Leone	Saudi Arabia	Korea, Rep.	Venezuela	El Salvador
Chad	South Africa	Solomon Islands	Laos		Guatemala
Comoros	Tunisia	Turkey	Malaysia		Honduras
Congo	Uganda	Yemen	Mongolia		Mexico
Côte d'Ivoire			Nepal		Nicaragua
Equatorial Guinea			Pakistan		Panama
Ethiopia			Philippines		Peru
Gambia			Singapore		Uruguay
Guinea			Sri Lanka		
Guinea-Bissau			Thailand		
Kenya			UAE		
Lesotho			Vietnam		
Liberia					
Libya					
Malawi					
Mali					
Mauritania					
Mauritius					
Mozambique					
Niger					
Rwanda					
Sudan					
Swaziland					
Tanzania					
Togo					
Zambia					
Zimbabwe					

Note: In our sample, 48 countries are in the treated group. Another 56 non-host developing countries in the control group.

Table C.4: Descriptive statistics

Variable	Mean	Std. dev.	Min.	Max.	N
Before Policy					
Outcome variables					
Log GHG emissions	3.747	1.930	-3.219	9.104	1441
Log CO_2 emissions	3.251	2.072	-4.605	8.898	1385
Log CH_4 emissions	2.322	1.920	-3.912	6.933	1456
Log *F-Gas* emissions	-1.389	1.911	-4.605	5.124	1372
Log N_2O emissions	1.232	2.056	-4.605	6.171	1442
Log carbon intensity	-1.560	0.788	-3.930	0.922	1372
Controls					
Log GDP per capita	7.916	1.913	5.234	22.469	1456
Log Squared GDP per capita	66.323	46.227	27.393	504.835	1456
Log population	16.021	1.772	11.276	21.009	1456
WGI	-0.369	0.676	-2.100	1.528	1456
Trade	76.047	48.056	0.167	437.327	1456
KAOPEN	-0.017	1.484	-1.920	2.334	1455
After Policy					
Outcome variables					
Log GHG emissions	3.891	1.959	-2.526	9.358	725
Log CO_2 emissions	3.325	2.129	-2.996	9.172	698
Log CH_4 emissions	2.515	1.906	-3.912	7.143	728
Log *F-Gas* emissions	-0.349	1.901	-4.605	5.536	703
Log N_2O	1.432	2.032	-4.605	6.323	722
Log carbon intensity	-1.677	0.676	-3.526	0.415	686
Controls					
Log GDP per capita	8.157	1.926	5.393	22.948	728
Log Squared GDP per capita	70.244	48.869	29.089	526.600	728
Log population	16.245	1.745	11.542	21.044	728
WGI	-0.401	0.653	-1.887	1.608	728
Trade	79.653	44.138	0.200	379.099	728
KAOPEN	-0.024	1.521	-1.920	2.334	728

Table C.5: CDM effect on emissions, by regional emissions

		Quantiles				
	FE	0.1	0.25	0.5	0.75	0.9
Africa						
CO_2 emissions	0.112	0.804***	0.506***	0.139***	0.086***	0.268***
	(0.105)	(0.028)	(0.010)	(0.012)	(0.033)	(0.015)
CH_4 emissions	-0.005	-0.103***	-0.018	-0.091***	-0.057***	0.054***
	(0.053)	(0.006)	(0.019)	(0.015)	(0.018)	(0.005)
N_2O emissions	-0.017	0.144***	0.229***	-0.096***	-0.059***	-0.183***
	(0.044)	(0.005)	(0.005)	(0.004)	(0.010)	(0.024)
F-Gas emissions	-0.004	0.085***	-0.038***	-0.152***	0.029*	-0.131***
	(0.122)	(0.009)	(0.014)	(0.020)	(0.016)	(0.023)
Asia-Pacific						
CO_2 emissions	-0.106	-0.060***	-0.195***	-0.126***	-0.028	-0.023***
	(0.135)	(0.014)	(0.027)	(0.037)	(0.050)	(0.008)
CH_4 emissions	0.025	0.330***	0.313***	0.114***	0.251***	-0.067***
	(0.043)	(0.020)	(0.006)	(0.010)	(0.008)	(0.009)
N_2O emissions	-0.115	0.115***	0.077***	0.120***	-0.216***	-0.191***
	(0.071)	(0.029)	(0.011)	(0.007)	(0.068)	(0.005)
F-Gas emissions	-0.256*	-0.725***	-0.611***	-0.339***	-0.206***	-0.349***
	(0.146)	(0.030)	(0.093)	(0.029)	(0.010)	(0.028)
Latin America and the Caribbean						
CO_2 emissions	-0.255	-0.048***	-0.401***	0.023	-0.325	-0.236***
	(0.176)	(0.014)	(0.017)	(0.050)	(0.000)	(0.031)
CH_4 emissions	-0.040	0.090***	-0.191***	0.049***	0.257***	0.155***
	(0.077)	(0.002)	(0.003)	(0.005)	(0.011)	(0.008)
N_2O emissions	-0.091	0.050***	0.054***	-0.092***	0.107***	0.120***
	(0.068)	(0.006)	(0.007)	(0.010)	(0.021)	(0.038)
F-Gas emissions	-0.259*	-0.549***	-0.339***	-0.367***	-0.171***	0.037***
	(0.153)	(0.037)	(0.012)	(0.025)	(0.022)	(0.010)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,165	2,165	2,165	2,165	2,165	2,165

Note: Bootstrapped standard errors with 1000 replications are shown in parentheses for FE and the MCMC for QRPD. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

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Chapter 5
Concluding Remarks

Tackling the twin development crises, public debt and climate distress, is paramount to support developing countries pursue sustainable economic development. This thesis investigates the presence of debt thresholds and the effectiveness of global climate policies in emissions reduction in developing countries. The thesis contains three independent chapters, covering the public debt–growth nexus (first chapter) and climate policies (second and third chapters).

Results from the first chapter show debt threshold effects are not common across developing countries. Only Latin America and the Caribbean region have shown threshold effects. Heterogeneous threshold effects are also seen across countries with respect to income and governance quality levels, with only the lowest income and lowest governance quality countries showing a debt threshold effect. Furthermore, beyond the debt threshold, high debt does not impede growth for developing economies.

The second chapter examines the effectiveness of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (REDD) in conserving tropical forests for emissions reduction. The findings indicate that the policy effect takes time to materialise, i.e., the longer a country is exposed to the policy, the stronger the policy effect is. Countries in the Latin America and the Caribbean region and the low income group show stronger response to the REDD policy. Further, minimising the transaction costs seems critical to the success of the REDD policy.

The third chapter assesses the Kyoto's Clean Development Mechanism (CDM) for its efficiency in reducing emissions in developing countries. The results show that the CDM has not been very effective for reducing emissions in high–emitting developing countries. Although a positive policy response is seen for certain greenhouse gases and sectors, design and implementation changes are necessary to receive anticipated policy outcomes.