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POVERTY AND CLIMATE CHANGE IN DEVELOPING COUNTRIES: AN ASSESSMENT

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Abstract

The present research investigates the impact of climate change on poverty, namely by understanding if CO2 emissions, temperature, precipitation, and forest area have an effect on poverty in developing countries, here assumed in absolute terms (poverty headcount ratio). This is a very relevant field of research as many countries suffer from severe poverty situations and climate change is becoming a growing threat to humanity, with poor people being the most harmed by it. To explore this relationship, we estimate a two-way fixed effects panel OLS econometric model for a sample of 76 low- and middle-income countries between 1998 and 2014, using information available in the World Bank's and University of East Anglia's databases. We find that, for the full sample, CO2 emissions and temperature significantly impact poverty (negatively and positively, respectively) and that forest area positively impacts poverty, but only in the baseline model. This demonstrates that temperature is a real concern, as an additional degree Celsius is estimated to increase absolute poverty in 1.17 percentage points. At the same time, CO2 emissions are important to reduce poverty, which means that some additional extent of climate degradation might be needed for these countries to achieve a certain threshold of development. To understand if regional differences affect the way climate change impacts poverty, we divide the sample in four subsamples and estimate both cross-section fixed and random effects models. We find that Africa is the only region where neither of the climatic variables significantly impact poverty, reinforcing the need in this continent for urgent development and structural change. CO2 emissions negatively impact poverty in Asia and Europe while forest area significantly affects poverty negatively in Europe and positively in Latin America and the Caribbean. This shows that the way climate interacts with poverty differs at the macro-level and that, depending of the level of development and location of each country it can translate into heterogeneous outcomes.

JEL-codes: I30, O15, Q54.

Keywords: Poverty, Climate Change, Developing Countries, Sustainable Development.

Resumo

Este estudo pretende investigar o impacto das alterações climáticas na pobreza, procurando perceber se as emissões de CO_2, temperatura, precipitação e área florestal estão correlacionadas com a pobreza nos países em desenvolvimento. Este é um campo de investigação relevante visto que vários países enfrentam graves situações de pobreza e, ao mesmo tempo, as alterações climáticas estão a tornar-se uma ameaça cada vez mais real para a humanidade, sendo que os mais pobres e vulneráveis são os mais prejudicados com este fenómeno. Nós estimamos um modelo econométrico OLS, com efeitos fixos seccionais e temporais, utilizando dados em painel para estudar esta relação, recorrendo a uma amostra de 76 países de baixo e médio rendimento, entre 1998 e 2014, usando para o efeito informação disponível na base de dados do Banco Mundial e da Universidade de East Anglia. Descobrimos que, na amostra total, as emissões de CO_2 e a temperatura afetam significativamente a pobreza (negativa e positivamente, respetivamente), e que a área florestal afeta positivamente a pobreza, mas só no modelo base. Estes resultados demonstram que o aumento da temperatura é motivo de preocupação já que se estima que um grau Celsius adicional aumenta a pobreza absoluta em 1.17 pontos percentuais. Ao mesmo tempo, as emissões de CO_2 são importantes para reduzir a pobreza, o que significa que a degradação ambiental pode ser necessária para que estes países possam atingir um certo patamar de desenvolvimento. Para perceber se as diferenças regionais influenciam a forma como as alterações climáticas afetam a pobreza dividimos a amostra principal em quatro subamostras e estimámos modelos com dados seccionais fixos e aleatórios. Concluímos que África é a única região onde nenhuma das variáveis climáticas afeta significativamente a pobreza, reforçando a necessidade urgente de, neste continente, se promover o desenvolvimento e a transformação estrutural. As emissões de CO_2 afetam a pobreza negativamente tanto na Ásia como na Europa, enquanto que a área florestal afeta a pobreza de forma negativa na Europa e positiva na América Latina e Caraíbas. Estes resultados mostram que a forma como as alterações climáticas interagem com a pobreza varia ao nível macro e que o nível de desenvolvimento e localização de um país pode levar a resultados bastante heterogéneos nesta relação.

Códigos-JEL: I30, O15, Q54.

Palavras-chave: Pobreza, Alterações Climáticas, Países em Desenvolvimento, Desenvolvimento Sustentável.

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Chapter 1. Introduction

Climate Change is a driver of great concern, claiming more attention around the world as time goes by. It is a fact that the temperatures and CO2 emissions in the atmosphere are growing (Hertel and Rosch, 2010), which shows that climate change is a problem that we need to deal with today.

Of particular concern is the effect of climate change on the poor. Even though extreme poverty is decreasing, it is still very present in many regions and countries (Campagnolo and Davide, 2019). Currently, the eradication of poverty in all its forms is the first Sustainable Development Goal, with world leaders agreeing to work together to accomplish this objective by 2030 (United Nations, 2017)[1] .

Climate change may impact the poor worsening their living conditions. As Kelly and Adger (2000) note, the poor are more vulnerable to climate variability and change, as they find it difficult to access resources and tend to be marginalized. Many poor live in weak conditions and depend of activities directly related to the environment, which means that the temperature increase, the rise of the sea levels and natural disasters can entail situations such as malnutrition, higher incidence of diseases, destruction of housing and jeopardize activities such as agriculture, fishery and forestry (Heller and Manni, 2002).

This dissertation aims to understand and measure the impact of climate change on poverty in less developed countries using several climatic variables such as CO2 emissions, temperature, precipitation, and forest area, and considering poverty in absolute terms, measured with the headcount ratio (number of people living with less than $1.90 a day, on 2011 prices at PPP). We investigate and test this relationship both for the sample of developing countries as a whole and, also, allowing for regional differences by dividing the sample in four subregions (Africa, Asia, Europe, Latin America and the Caribbean).

Our research goals are the following: first, to give a portrait of poverty and climate change around the world; second, to describe the mechanisms through which climate change impacts the poor; third, to measure the impact of climate change on poverty, after controlling for other variables, exploring this relationship in developing countries; fourth, to understand if regional differences affect the way climate change translates to poverty levels. Therefore,

[1] United Nations, Ministerial declaration of the high-level segment of the 2017 session of the Economic and Social Council & Ministerial declaration of the 2017 high-level political forum on sustainable development, convened under the auspices of the Economic and Social Council, https://sustainabledevelopment.un.org/?menu=1300 (accessed on 3/10/2019).

we pretend to answer the following questions: How are the poor (in absolute terms) affected by climate change in developing countries? Do regional differences influence the way climate change impacts poverty?

We estimate a two-way fixed effects panel OLS econometric model for a sample of 76 low- and middle-income countries between 1998 and 2014 in order to find how climate change, assessed by CO2 emissions, temperature increase, forest area or precipitation, impacts absolute poverty, after controlling for other variables typically considered in the literature. We also allow for regional differences, by estimating cross-section fixed/random OLS panel for four sub-samples: Africa, Asia, Latin America and the Caribbean, and Europe.

Although the topics of poverty and climate change are widely investigated, this research and results contribute to the academic community. Indeed, to the best of our knowledge, the impact of climate change on poverty is a recent topic of research and with sparse analysis, most of them focusing in specific regions and countries and frequently adopting a case study approach. By aggregating a set of developing countries, this study allows to take more broad conclusions that might be helpful for policy making and future investigation. Moreover, as noted by Stern (2007), the impacts of climate change can be catastrophic if nothing is done and the poor and vulnerable will always be the most harmed. For this reason, this is an important field of research that needs to continue to be explored and developed.

Our research find its roots in the work made by Azzarri and Signorelli (2020), that explore how long-term climatic conditions and extreme weather shocks impact poverty and welfare in Sub-Saharan Africa. The authors find that, for a set of twenty-four African countries between 1950 and 2014, different types of climatic conditions and weather shocks have heterogeneous impacts on poverty and welfare when considering the full sample or the sub-regions inside Sub-Saharan Africa. The present dissertation assumes a similar objective but extends the analysis to a wider sample that includes countries from different continents, allowing to test the way climate change impacts poverty and if it is affected by regional characteristics. We also consider a different estimation method, type of data (Azzarri and Signorelli (2020) use microdata), and climatic variables.

The remaining text is organized as follows: in chapter 2 we show a literature review of the impact of climate change on poverty as well as main concepts and historical framework. Chapter 3 displays the methodology adopted to study the impact of climate change on poverty and describes the model and variables used as well as the data. Chapter 4 develops how poverty is impacted by climate change, with the model estimation and the main results discussion. Chapter 5 concludes.

Chapter 2. Poverty and climate change: research background

In this chapter we start by presenting the definitions and historical framework of poverty and climate change as well as some of the most important research contributions in both areas. We then proceed to analyse some relevant works that cross poverty and climate change.

2.1 Poverty

Poverty is a cornerstone in many research areas but there is not a generally accepted definition or measure to it. Misturelli and Heffernan (2010) applied a synchronic analysis to 159 definitions of poverty on a thirty-year period and concluded that the concept of poverty changes through time based on the way actors apply it. According to the authors, poverty can be seen in an individual or collective view, focused on the lack of material assets or in a multidimensional perspective. This study clearly shows that, since the 70s, a collective approach to poverty gained momentum, as well as a clearer direction towards a more multidimensional view of its concept. In the same line, Mabughi and Selim (2006) state that poverty is a plural concept with all their dimensions being surfaces of the same prism, interrelated and complementary, meaning that all are relevant and should be considered when defining and measuring poverty.

Generally, we can identify poverty in absolute or relative terms. One of the precursors on absolute poverty, Seebohm Rowntree, in a study published in 1901 named *Poverty: A Study of Town Life*, referenced it "as subsistence below a minimum, socially acceptable living condition, established based on nutritional requirements and other essential goods", that could be measured as the "equivalent sum of money required to attain minimum desired nutrition" (*apud* Mabughi and Selim, 2006 p. 184). A good and recent example of this approach is the World Bank's International Poverty Line, that was set in October 2015 at 1.90 dollars a day, using prices of 2011 in PPP (purchasing power parity). A person living below this level is in a situation of extreme poverty[2]. A very common measure of absolute poverty is the headcount ratio (H), that can be obtained by dividing the number of individuals whose income falls below a given poverty line for the total population. Although being very useful, the headcount ratio has some limitations. For example, it weights equally the individuals living below the poverty line, neglecting the distribution inside the interval between having no

[2] https://www.worldbank.org/en/topic/poverty/brief/global-poverty-line-faq (accessed on 15/10/2019).

income and being just beneath the line (Todaro and Smith, 2015).

Individuals are said to face relative poverty when “they lack the resources to obtain the types of diet, participate in the activities and have the living conditions and amenities which are customary, or are at least widely encouraged or approved, in the societies to which they belong” (Townsend, 1979 p. 30). In accordance with this notion, Ravallion and Chen (2019) state that it is common to use the mean or median to generally define relative poverty lines, with a person being considered relatively poor if their household income is less than fifty or sixty percent of the mean or median household income in the country they live. Relative poverty lines also have some limitations. One of them is how to weight the various levels of income when calculating the mean or median, as weighting equally the income of all members of a given population may perceive the idea that poverty is intensifying when, for example, the number of rich people increase, all other things being equal (Mabughi and Selim, 2006; Ravallion and Chen, 2019).

The 1998 Nobel laureate in Economics, Amartya Sen, proposed the Capability Approach to offer a broader sense to the notion and livelihood of poverty, complementing the more materialistic interpretation of its concept. According to him, “the central feature of well-being is the ability to achieve valuable functionings” (Sen, 1985 p. 200). Functionings are a set of dimensions that determine what a person is or can be (Sen, 1997 *apud* Mabughi and Selim, 2006). They can be elementary (*e.g.* being well nourished; escaping avoidable diseases) or complex (*e.g.* participating in the community life; not being ashamed of public participation) (Sen, 1985). A capability is the set of functioning vectors within the reach of a given individual (Sen, 1985). This approach directly refers to the notion of well-being as freedom, with the capability set “reflecting the person’s freedom to live one type of life or another” (Sen, 1992 *apud* Mabughi and Selim, 2006 p. 191), noting the positive freedoms one can have (ability “to do this” or “to be that”) (Sen, 1985).

Amartya Sen was also a centrepiece in adapting the notion of human development to the concept of poverty (Mabughi and Selim, 2006). Human development can be defined as the expansion of people choices, the ability to enlarge what a person can do and be (Mabughi and Selim, 2006). From this definition it is possible to follow two approaches: (i) the “conglomerative perspective”, which weights all members in a community when dealing with development; (ii) the “deprivation perspective”, which focuses specifically in the individuals that are deprived and poor (Sen and Anand, 1997). To adapt human development to poverty the second approach is the one of interest, and to do so, a proper measure must be used: the HPI (Human Poverty Index). The HPI assumes poverty in a multidimensional perspective. As Sen and Anand (1997) note, poverty is the worst form of deprivation, as it concentrates both the lack of material deprivation as well as the scarce opportunity to live an acceptable life. To measure it, the focus cannot be income-based only, as a person may face deprivation in many ways (it can be materially deprived, illiterate, prone to premature mortality, have lack of access to clear water, etc.) and in many levels (one can be illiterate but have material opulence or be well educated but without access to clear water) (Sen and Anand, 1997). To build the index, deprivation is measured in three dimensions, all equally weighted: living a long and healthy life (measured by the probability of not living until the age of forty), knowledge (measured by the percentage of illiterate adults) and lack of economic well-being (measured by the average population without access to safe water and the percentage of children under five that are underweight) (Mabughi and Selim, 2006). In 2010 the global Multidimensional Poverty Index (MPI) replaced the HPI as the main indicator of multidimentional poverty. It was developed by the Oxford Poverty & Human Development Initiative (OPHI) along with the United Nations Development Program (UNDP). It has three main dimensions (health, education, and standard of living) with multiple subdimensions each[3].

Generally, we can identify poverty as the "inability of an individual or a family to command sufficient resources to satisfy basic needs" (Fields, 1994 p. 88). We explored various views of poverty: it can be seen in absolute or relative terms, following a monetary approach or a multidimensional view, as in the Capability Approach. As stated by Misturelli and Heffernan (2010), there is a clear movement to a more multidimentional view of poverty, but, as presented by Mabughi and Selim (2006) all its views and interpretations are essential to fully comprehend the poverty phenomena, which indicates that they all are complementary and have an important role in the academic investigation and, thus, should not be forgotten.

2.2 Climate change and economic development

According to Todaro and Smith (2015) climate change can be defined as the lasting alteration of climate and it can occur in various forms such as increased average temperature, decreased annual precipitation or greater occurrence and intensity of droughts and natural

[3] For a more detailed information on MPI, please see https://ophi.org.uk/multidimensional-poverty-index/ (accessed on 15/10/2019).

disasters (storms, floods, etc.). Related to this concept is the notion of global warming that can be defined as the average increase of air and ocean temperatures, with climate change being used many times as a reference to this phenomenon (Todaro and Smith, 2015).

Climate change and economic development: academic contributions

Climate change impacts countries and populations in various ways. Winkler, Boyd, Torres Gunfaus and Raubenheimer (2015) state that there is an interdependency between climate change, development, and economic growth, with all these realities impacting one another, which makes it essential to clearly present them. It is therefore pertinent to clarify the concepts of economy growth and economic development. Simon Kuznets (1974 p. 247) defines a country's economic growth as the "long-term rise in capacity to supply increasingly diverse economic goods to its population, this growing capacity based on advancing technology and the institutional and ideological adjustments that it demands. All three components of the definition are important". Development can be seen as the "problem of accounting for the observed pattern, across countries and across time, in levels and rates of growth of per capita income" (Lucas, 1988 p. 3) or following the human development notion, that we already presented in the previous subchapter, and is characterized by Mabughi and Selim (2006) as the ability to expand the set of individuals choices, lifting the constraints one can face through life such as being illiterate, having lack of health, having poor access to resources, and struggling with scarce civil and political freedoms. The balance between climate change, economic growth and development directly points to the notion of sustainable development, that is displayed by Thirlwall (2011) as the ability to satisfy the present generation needs without jeopardizing the necessities of the world's future generations.

The Environmental Kuznets curve (EKC) is frequently used to explore the relation between climate change and economic growth in the literature. The EKC states that the relationship between income and environmental damage is inversely u-shaped, meaning that, in the beginning, as income increases, environmental damage also increases but there is a turning-point henceforth environmental damage decreases with economic growth (Stern, Common and Barbier, 1996). This theoretical framework came into existence in the 90s and directly arises from the Kuznets Curve hypothesis[4], as the evidence of a similar relationship

[4] The Kuznets Curve hypothesis postulates that *per capita* income and income inequality have an inverse U-shaped relationship, with income inequality growing in early stages of economic growth and, after a turning point is achieved, it then starts to decrease as economic growth continues to perpetuate (Dinda, 2004). It is important to note that the Kuznets Curve hypothesis is an "observed empirical phenomenon" (Dinda, 2004 p. 431) that is not questioned academically. For more information about the Kuznets Curve please see the original study of the relation of income inequality with economic growth (Kuznets, 1955).

between environmental degradation and income per capita began to be noted in this period (Dinda, 2004).

Literature on the validity of EKC is abundant. Of particular interest is Acheampong (2018) that examines the relationship between economic growth, CO2 emissions and energy consumption between 1990 and 2014 and finds evidence for the EKC at a global level, but the results for some specific regional areas, such as Latin America and the Caribbean, are against this theoretical formulation. Also, Churchill, Inekwe, Ivanovski, and Smyth (2018) study the EKC hypothesis for CO2 emissions from 1870 to 2014 and found evidence to it for the sample as a whole and for nine of the twenty countries in the sample.

Even though the theoretical foundation behind the EKC is solid and there are multiple empirical investigations that confirm the implied relationship, there are still many limitations that deserve attention. Dinda (2004) points some of these weaknesses which include, for example, that results of the EKC application depend of the methodology used in the investigation; that the EKC validity is observed for specific types of pollutants but many others have N-shaped or monotonic relations with income growth; and that the EKC, as suggested by its theoretical foundation, might not be permanent, which obliges nations to re-link their throughput with economic growth or apply “end-of-the-pipe” solutions for some pollutants to validate the underlying nexus (Dinda, 2004).

The EKC has a wide range of applications in the literature and is clearly an interesting approach to study the relation between environmental damage and economic growth, but its results must always be seen with caution, as it has several limitations (Dinda, 2004) that might give an inaccurate representation of the world.

The institutional approach to climate change and economic development

Along with a significant effort made by the academia regarding climate change, several institutions and governmental agencies worldwide also have an important role in investigating and responding to the main concerns around this phenomena.

A very good example of the institutional effort made to counter and understand climate change is the United Nations Framework Convention on Climate Change (UNFCCC), an international environmental treaty adopted at the Rio Earth Summit in 1992. Every year, since 1994, a Conference of Parties with all the UNFCCC country-members (as of today they are 197) takes place in order to discuss and prevent an unbalanced interference of human activity in the environment, mainly by reinforcing the need to stabilize the GHG (greenhouse gas) emissions.[5]

Most notably, there are two UNFCCC Conference of Parties that deserve special attention. The first one occurred in 1997 and was responsible for the adoption of the "Kyoto Protocol", an international agreement to which several industrialized developed countries committed in order to reduce GHG emissions. It was implemented in 2005 and had two commitment periods: one from 2008 to 2012 and a second one from 2013 to 2020, promoted by the Doha Amendment to the Kyoto Protocol. In the first period of execution the reduction of GHG emissions targeted an average decrease of five percent against 1990 levels. In the second period of execution the target was set to reduce GHG emissions eighteen percent below 1990 levels. We must note that the composition of countries in each of the periods is different from one another.[6]

The second one took place in 2015 and was responsible for the adoption of the "Paris Agreement", which reinforces, for the first time, a collective effort to tackle climate change.[7] The three main objectives of the Agreement are: (i) maintaining the global average temperature increase below 2ºC, in regard to pre-industrial levels, aiming, particularly, to an increase of 1.5ºC; (ii) to increase the capacity of countries to better adapt to climate change and overcome its negative impacts; (iii) mobilizing and facilitating income flows to achieve mitigation and adaptation objectives (Campagnolo and Davide, 2019). To accomplish them, each country-member committed to NDCs (Nationally Determined Contributions), a set of plans specific to each country that are autonomously determined and directly target climate change, coming into force in 2020 (Campagnolo and Davide, 2019).

One of most important investigation work on this topic with a significant impact in the academia but particularly at the political level is the report led by Nicholas Stern entitled *Stern review: the economics of climate change* that was published in 2006. Even though this report was written to be given to United Kingdom's prime minister of the time (Stern, 2007), the assessed topics and broad conclusions make it one of the most important works that explore the economic impacts on the environment. The main conclusions of the report are: (i) the occurrences of the near future will have a deep impact on climate in the second half of the present century and in the XXII century; (ii) if nothing is done to prevent these occurrences, their impacts may become irreversible; (iii) the cost to take action against these impacts can

[5] https://unfccc.int/process-and-meetings/the-convention/what-is-the-united-nations-framework-convention-on-climate-change (accessed on 9/12/2019).
[6] https://unfccc.int/kyoto_protocol (accessed on 26/12/2019).
[7] https://unfccc.int/resource/bigpicture/#content-the-paris-agreement (accessed on 9/12/2019).

account only 1% of global GDP per year (these costs will rise if delayed); (iv) it is necessary to give an international response against climate change since it is a global problem. Countries and institutions must work together; (v) CO_2 emissions must stabilize between 450 and 550 ppm (parts per million). If nothing is done, they could rise to more than 850 ppm at the end of the century; (vi) temperature can increase 2ºC/3ºC but a worst-case scenario points to an increase of 5ºC (Stern, 2007).

2.3 Poverty and climate change: main literature contributions

The impact of climate change on poverty has been investigated for some time but there is a growing effort to explore this relationship since the past decade. This happens mainly because the evidence around climate change is becoming stronger and its negative effects can utterly change the way the humanity live (Stern, 2007).

The mechanisms behind climate change and poverty

There are many channels through which climate change can affect poverty. Hallegatte, Bangalore, Bonzanigo, Fay, Narloch, Rozenberg, and Vogt-Schilb (2014) use the standard asset-based framework to represent poverty, income, and consumption at the household level. Accordingly, the instantaneous utility of a household is maximized for a level of income equal or higher than the vector of consumption multiplied by the price vector. The income each household has depends of the assets it owns and the capital returns from the different activities it can participate. From this model framework there are four main channels through which climate change can impact poverty: consumption, assets, productivity, and opportunities.

Leichenko and Silva (2014) review several articles and specify two channels through which climate change impacts poverty. Direct channels connect biophysical changes, market responses and poverty outcomes and translate mainly through food prices and agricultural productivity. Indirect channels include more complex relations between climate change and poverty, as the way the first affects the second may be specified by other factors (social, cultural, institutional, political, etc.), highlighting that "climate change overlaps, interacts with, and often compounds the effects of other social, economic, and environmental stressors" (Leichenko and Silva, 2014 p. 544). While the first channel focuses on the immediate impact climate change can have on poverty, the second one demonstrates the diversity of connections climate change can have with other factors to impact poverty.

Table 1 displays each of the channels of transmission presented by Hallegatte *et al.*

(2014), summarizing their main characteristics. It also divides each of them between direct and indirect channels following the research of Leichenko and Silva (2014).

Table 1 – Impact channels of climate change on poverty

Main Channel	Mechanism	Specific channels	Direct/ Indirect	Example
Consumption channel	A change in the price vector will provoke an increase/decrease in the vector of consumption.	Food prices	Direct Channel	A climate shock can increase food prices due to crop destruction. If not compensated by an increase in productivity, poverty will increase.
		Energy prices Land prices	Indirect Channel	
Asset channel	Households can lose assets both by destruction and forced liquidation.	Physical assets losses	Direct/Indirect Channel	Due to climate impacts on household's income, poor families may not have the ability to grant education and health services to their children, setting an intergenerational poverty trap.
		Human capital and health Social capital and conflict Natural capital and ecosystem services *Ex ante* impact and risk taking	Indirect Channels	
Productivity channel	Productivity is negatively affected by economic inefficiencies and changing economic and environmental conditions.	Agricultural productivity, profit, and wages	Direct Channel	If agriculture has a higher role than other sectors, the supply of labour to agriculture is less elastic, meaning wages will heavily decrease in response to a price shock, increasing poverty.
		Labour productivity and wages	Indirect Channel	
Opportunity channel	A household can increase its income by expanding its range of activities. Climate change can constrain the activities' expansion.	Economic growth Impact on structural change Migration	Indirect Channels	Economic growth is one of the drivers of poverty reduction. By affecting it, climate change is slowing down poverty alleviation due to this motor.

Source: own elaboration with information from Leichenko and Silva (2014) and Hallegatte *et al.* (2014).

As we can see in Table 1, each channel of transmission can affect the income of households in several ways, transmitting afterwards to poverty. The mechanisms and examples are set in a static way but, as Hallegatte *et al.* (2014) and Leichenko and Silva (2014) note, the channels often work connected, offering a dynamic view of the poverty phenomenon. Also, in Table 1, we can see that the view offered is focused on how climate change can harm or increase poverty. Hallegatte *et al.* (2014) and Leichenko and Silva (2014) also present situations through these channels where climate change can promote poverty alleviation. For example, through the opportunities channel (impact on structural change) the application of climate policies may destroy job positions in industrial companies but it will create job opportunities in greener ones. If the job creation more than compensates the job destruction, poverty will decrease (Morgenstern *et al.*, 2002, *apud* Hallegatte *et al.*, 2014).

Empirical research on poverty and climate change

We now present the empirical research gathered that explore the relationship between climate change and poverty (see Appendix 1 for a more detailed description). As seen by the previous examples given by Hallegatte *et al.* (2014) and Leichenko and Silva (2014), climate change can both positively and negatively impact the livelihoods of poor people. At the same time, due to the richness of this topic, there are several different methodologies and topic combinations that can be explored to understand how climate change and poverty relate. Based on this we divide the literature in different groups following their conclusions and variables used. We start by presenting the more general literature, focusing thereafter on each of the variables employed to estimate the impact of climate change on poverty in developing countries (CO2 emissions, temperature, precipitation, and forest area).

Starting from a more conceptual perspective, Barbier and Hochard (2018) identify two main vulnerable groups to climate change in the rural areas of less developed countries: people living in less-favoured agricultural areas (this includes agricultural lands with difficult terrain, poor soil quality or low level of precipitation, and agricultural lands with poor access to markets); people living in coastal areas with less than ten meters of elevation. Although the incidence of poverty in these two groups is not proved to be higher when compared to other rural areas (Barbier and Hochard, 2018), their particular characteristics make them ideal targets of poverty-environmental traps (Barbier 2010, 2015; Hallegatte *et al.* 2015 *apud* Barbier and Hochard, 2018). Using infant mortality as a proxy of poverty, they estimate that 586 million people with high infant mortality live in less-favoured agricultural areas and 85 million live in low elevation coastal zones. Although these population numbers have decreased between 2000 and 2010, the majority of them are located in low-income or lower middle-income countries (Barbier and Hochard, 2018).

Another interesting perspective, before analysing research around specific climatic variables, is given by Campagnolo and Davide (2019), that explore whether or not the NDCs each of the country-members of the UNFCCC committed as part of the Paris Agreement may jeopardize other Sustainable Development Goals, specifically the eradication of poverty. Using a panel of 130 developed and less developed countries for the period between 1990 and 2014, they find that the aggregate effect of the full implementation of the NDCs will increase the poverty headcount ratio in the world by 4.2% in 2030, compared to the baseline scenario. This result may be reversed by the introduction of an international climate fund, with some developing countries beneficing form an increase in GDP and a consequent poverty prevalence reduction. It is important to note that these results depend of the relative size of the received funds and the specific economic structure of each country (there are cases in which the resource allocation provoked by this dynamic to greener sectors and R&D from more productive sectors may hurt the overall economy of some less developed countries, increasing the poverty prevalence) (Campagnolo and Davide, 2019).

In terms of CO2 emissions, Dhrifi, Jaziri, and Alnahdi (2020) investigate the causality between foreign direct investment, CO2 emissions, and poverty (household's final consumption expenditure *per capita*) for a panel of 98 developing countries from Africa, Asia, and Latin America, between 1995 and 2017. They find that CO2 emissions increase poverty for the global sample, Africa, and Latin America. However, in the case of Asia, emissions help decrease poverty. This relationship is found to be bidirectional, with increases in the household's final consumption expenditure *per capita* indicating a decrease in CO2 emissions for the full sample and all subsamples. Institutional and structural characteristics may be a reason why results differ from one subsample to another (Dhrifi *et al.*, 2020).

Dorband, Jakob, Kalkuhl, and Steckel (2019) also focus on CO2 emissions but from a different perspective: they investigate how carbon pricing for CO2 emissions may impact the populations in low- and middle-income countries, using household data for 87 countries in this group. They conclude that the majority of the countries in the sample would lose less than 2.5% of their income at current consumption levels, with Sub-Saharan African and lower-income countries in South East Asia and Latin America showing progressive results regarding the carbon pricing application, as carbon pricing is expected to be progressive for countries with an average annual per capita income under a turning point of around 15000 USD (PPP-adjusted). Carbon pricing might be easier to introduce in poorer countries, based on the previous presented results, but it would be important to complement it with other policies, since the poorest will still suffer with its negative consequences (Dorband *et al.*, 2019).

Temperature is another climatic variable that can affect poverty. Park, Bangalore, Hallegatte, and Sandhoefner (2018) study how it can influence the location of households and the wealth distribution between them in developing countries. The sample consists of 52 countries with household-level data obtained through surveys and climatic data originating from the Climatic Research Unit at the University of East Anglia. Measuring if a household is poor through the poverty exposure bias or the wealth percentile the household belongs, the authors conclude that poorer households tend to be located in hotter zones inside hotter developing countries and that poorer individuals are more likely to work in situations with a greater exposure to heat, both inside a specific country and between them. This means that climate change, through the effect of temperature increase and excess heat, can be regressive in hotter developing countries (Park *et al.*, 2018). In other hand, in colder countries this effect is not observed as living in hotter areas is associated with higher wealth percentiles, which means climate change can be beneficial for the poorer households that live in colder areas inside the country (Park *et al.*, 2018).

Letta and Tol (2019) also explore how temperature may affect poverty but in an indirect way, investigating the relationship between climate change and total factor productivity (TFP). Using data for sixty developed and developing countries in the period of 1960-2006, whose climatic data was obtained from the University of Delaware, they estimate a fixed effect panel model and conclude that TFP growth is only negatively affected by temperature shocks in poor countries, with a less significant result of the same effect obtained in hot countries. After a certain threshold of gross domestic product *per capita*, climate change has a neglectable impact in any given country's TFP growth (regardless of its temperature). This means that climate policy must, in the future, intrinsically include a poverty reduction effort, as poor countries will suffer the most with this phenomena (Letta and Tol, 2019).

Connecting both the impacts of temperature and precipitation on poverty, Azzarri and Signorelli (2020) use household level information, sub-regional monthly data on rainfall and temperature and the SPEI index of evapotranspiration for 24 Sub-Saharan African countries to understand how long-term climatic conditions and extreme weather shocks affect poverty and welfare in this region. The authors estimate both an OLS and Spatial auto-correlation model and conclude that long-term humidity is positively correlated with welfare and that long-term temperature is negatively correlated with welfare (the last one also positively correlated with poverty). At the same time, long-term precipitation has no significant impact on welfare but contributes to the reduction of poverty. Finally, while flood shocks negatively impact welfare and are associated with an increase of extreme poverty, drought and heat shocks have ambiguous effects: while a drought shock is beneficial in West Africa, heat waves contribute to improved results in Central Africa.

Similar to Letta and Tol (2019), Damania, Desbureaux, and Zaveri (2020) explore how climate change may impact economic growth, but focusing primarily on precipitation. They estimate a fixed effects panel model for a set of developed and developing countries, between 1990 and 2014. They find that a concave relationship between rainfall and GDP growth existed in this period, with one additional drop of precipitation promoting a higher marginal economic return in drier areas, that slowly decreases as the weather becomes wetter. The positive impact precipitation has on GDP growth is mainly explained by its effect on agriculture. They also find that this effect is only significant in developing economies. Altogether, by positively impacting economic growth in developing economies, precipitation may be an important factor for poverty alleviation, mainly in drier countries.

Turning now to forest area, this variable happens to be very present in the literature, even though results do not always seem to point in the same direction. In one hand, Vedeld, Angelsen, Bojö, Sjaastad, and Berg (2007) investigate if poor people living in forested areas in developing countries depend of environmental income. They run a meta-analysis for 51 case studies from 17 countries in Africa, Asia, and Latin America and, even though acknowledging that results are fragile and should be seen with caution, find that, on average, forest environmental income is important for the poor since it accounts 22% of mean total household income, the most dependent group of this type of income has half the total income of the rest of the sample, and, in the same community, poorer households depend more of forests than the wealthier ones. In other hand, Wunder (2001) reviews several literature contributions related to possible synergies between poverty alleviation and forest conservation. The author concludes that forests have little scope to promote poverty alleviation. Instead, policymakers should focus more on promoting education, health, and institutional capacity-building. Even though he acknowledges that there are same cases of success at the micro-and macro-level, forest can mainly be beneficial to poorer people in a "defensive" way, helping secure secondary sources of food and subsistence, leaving little room to actively contribute to poverty reduction, mainly due to the features surrounding them (low population density, poor geographical conditions, lack of access to credit and quality infrastructures, tropical diseases, tribal warfare, etc.).

We end with a research work that shows how regional differences can influence the way climate change impacts poverty. Winters, Murgai, Sadoulet, De Janvry, and Frisvold (1998) use three regional archetype multisectoral and multiclass computable general equilibrium models for Africa, Asia, and Latin America to analyse the various impacts of climate change across continents, sectors of economic activity and social groups. They show how the specificities of countries may influence the effect of climate change on poverty in low- and lower middle-income countries. For example, Africa would suffer the most in case of a shock caused by climate change while, in other hand, Asia could bear a situation of real income growth, with climate change possibly turning out to be beneficial to the poor.

These literature examples show that climate change may, indeed, contribute to different poverty outcomes. Depending on the type of climatic variable, specific characteristics of countries (in terms of regional and structural specificities) and their level of development, the intensity and impact climate change has on poverty may change from one case to another.

In this research, we intend to see how climate change, particularly CO2 emissions, temperature, precipitation, and forest area, affects poverty in developing countries. In the next chapters we will show the methodology and estimate the models to measure the possible existence of a causal relationship between both phenomena.

Chapter 3. Methodology

In this chapter we present the econometric model regression used to measure the impact of climate change on poverty. We also describe the data and variables used for the model estimation.

3.1 The model

We consider a sample of 76 low- and middle-income countries, following the World Bank's classification[8], in the period between 1998 and 2014, to analyse the impact of climate change on poverty in less developed countries. We only select countries that have at least three observations for the dependent variable in the period covered. Data limitations did not allow us to cover a higher number of countries and years. Additionally, we felt it was relevant to investigate if there are key differences regarding the way climate change impacts poverty across different regions, since climatic conditions and its impacts strongly link with particular regional characteristics. We create four regional subsamples that group countries by geographic region, following the United Nations Statistics Division classification[9]: Africa, Asia, Europe and Latin America and the Caribbean.

We investigate this relationship only in low- and middle-income countries because, in one hand, poor countries are the ones that suffer the most with climate change (Letta and Tol, 2019) and, in the other hand, since we use both cross-sectional and time-series data, it makes sense to include countries classified as middle-income today as they might had a lower classification in part of the time period this research covers.

As our model combines both cross-sectional and time-series information, we apply panel data estimation. The variables used in the model do not always account for complete information for the countries and period of the sample, indicating that we are working with an unbalanced dataset (Greene, 2012).

According to Greene (2012), fixed effects and random effects are useful to adjust a

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[8] World Bank defines, for the year of 2020, a low-income country as having a GNI *per capita* of $1.025 or less in 2018; a lower middle-income country as having a GNI *per capita* between $1.206 and $3.995 in 2018; an upper middle-income country as having a GNI *per capita* between $3.996 and $12.375 in 2018. GNI *per capita* is calculated using the World Bank Atlas method (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups (accessed on 10/02/2020).

[9] The United Nations Statistics Division divides each country by continent, which is further subdivided into sub-regions and intermediary regions. Following this classifications, we divided our sample countries in four regions: Africa, Asia, Europe, and Latin America and the Caribbean. Since our sample only has two observations for Oceania, we considered it together with Asia. For more information regarding each country's regional classification please see https://unstats.un.org/unsd/methodology/m49/ (accessed on 21/03/2020).

panel data model so that it can be estimated through a linear regression without providing biased and inconsistent estimators. In a fixed effects model (FEM), it is assumed that the unobserved individual effects are correlated with the explanatory variables and, in a random effects model (REM), the same effects are not correlated with the model variables (Greene, 2012).

Our econometric model can be described as follows:

$$\boldsymbol{y_{it} = \beta_1 X_{it} + \beta_2 Z_{it} + \alpha_i + \mu_{it}}$$

with *i* representing the country (*i*= 1, …, 76) and *t* the year of analysis (*t*= 1998, …, 2014). $\boldsymbol{y_{it}}$ is the dependent variable and indicates a measure of poverty for country *i* in year *t* ; $\boldsymbol{\beta_1}$ is a vector of coefficients associated with the explanatory variables; $\boldsymbol{X_{it}}$ is the vector of explanatory variables corresponding to climate change for country *i* in year *t* ; $\boldsymbol{\beta_2}$ is a vector of coefficients associated to the control variables; $\boldsymbol{Z_{it}}$ is the vector of control variables for country *i* in year *t* ; $\boldsymbol{\alpha_i}$ represents the unobserved country specific effect (constant in FEM and random in REM). $\boldsymbol{\mu_{it}}$ is the random term for country *i* in year *t*.

We use version 10 of the *EViews* software package to estimate the above presented model.

3.2 Data

As previously presented, we study the impact of climate change on poverty in developing economies using a sample of low- and middle-income countries. Our data is secondary and was collected from different sources, as detailed below. Table 2 displays the 76 countries included in our sample by level of income. It is possible to see that the majority of the countries are middle-income ones, but low-income and lower middle-income countries, summed up, account for the biggest portion of the sample, even though the upper middle-income countries are very close to them in total number.

Table 2 – Countries in the sample by income level

Threshold	GNI *per capita*	Countries in the sample
Low-income	1.025 or less	14
Low middle-income	Between 1.206 and 3995	27
Upper middle-income	Between 3.996 and 12.375	35
High-income	12.376 or more	0

Source: own elaboration with data from the World Bank.

We will now procced to a deep description of the variables used in the model. Firstly, we will present the dependent variable and its data sources, followed by the same relevant information for the explanatory and control variables.

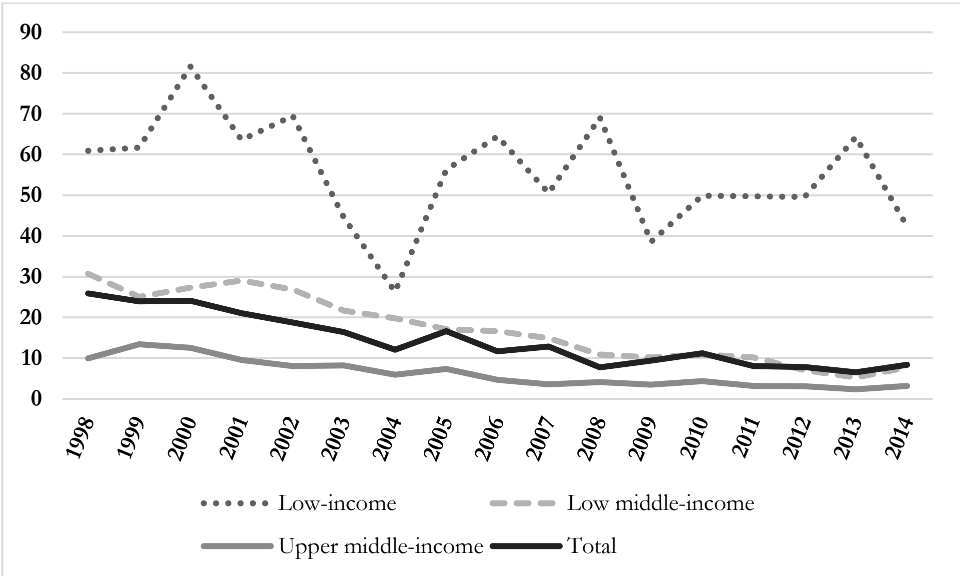
3.2.1 Dependent variable

Our dependent variable is poverty. Following the literature (*e.g.* Campagnolo and Davide (2019), Azzarri and Signorelli (2020)) we use the **Poverty Headcount Ratio (HCR)** at 1.90 dollars a day, in 2011 prices at PPP, and data is collected from the World Bank's World Development Indicators (World Bank, 2019). The HCR gives us the number of individuals with an income below $1.90 a day as a ratio to total population (see subchapter 2.1) (Todaro and Smith, 2015). We choose the Poverty Headcount Ratio (HCR) over other poverty indicators since it is the most used measure of poverty in the literature, enabling a more direct comparison with other studies, and has a very complete set of data across our panel. It also better adjusts to the research objectives since we aim to analyse the impact of different climatic variables in total poverty. We intended to complement our investigation with a multidimentional indicator of poverty (*e.g.* Multidimentional Poverty Index) but were unable to do so due to the lack of available information.

The following figures (Figure 1 and Figure 2) present a simple characterization of the sample, portraying the mean HCR by level of income and region, respectively, between 1998 and 2014.

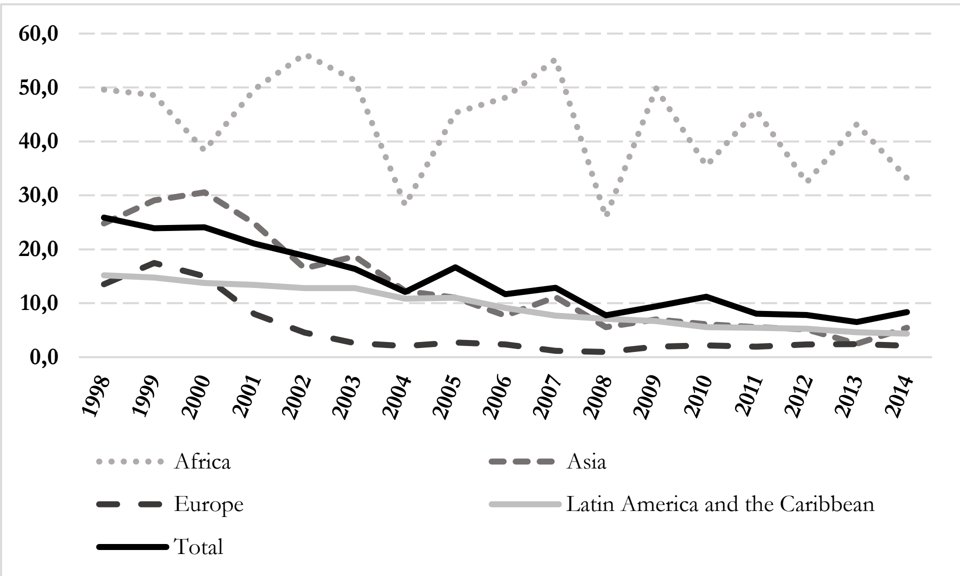
In Figure 1 we can see that the mean HCR, as expected, is much higher in low-income countries than in lower middle- and upper middle-income ones. In fact, while the later levels of income mentioned appear to converge to a mean HCR level below 10%, in low-income countries, even though its value is erratically decreasing, it was still above 40%, in 2014. Similarly, in Figure 2, the mean HCR shows a much more stable movement towards values below 10% in Asia, Latin America and the Caribbean, and Europe (in this later case the value is near 2%, in 2014) than in Africa, where the mean HCR seats between 30% and 40%, in 2014. We must note that, even though the mean HCR tendencies in Figures 1 and 2 show the expected behaviour, they are not fully accurate since our data is unbalanced.

Figure 1 – Mean HCR by income level, 1998-2014



Source: own elaboration with data from the World Development Indicators (World Bank, 2019).

Figure 2 – Mean HCR by region, 1998-2014



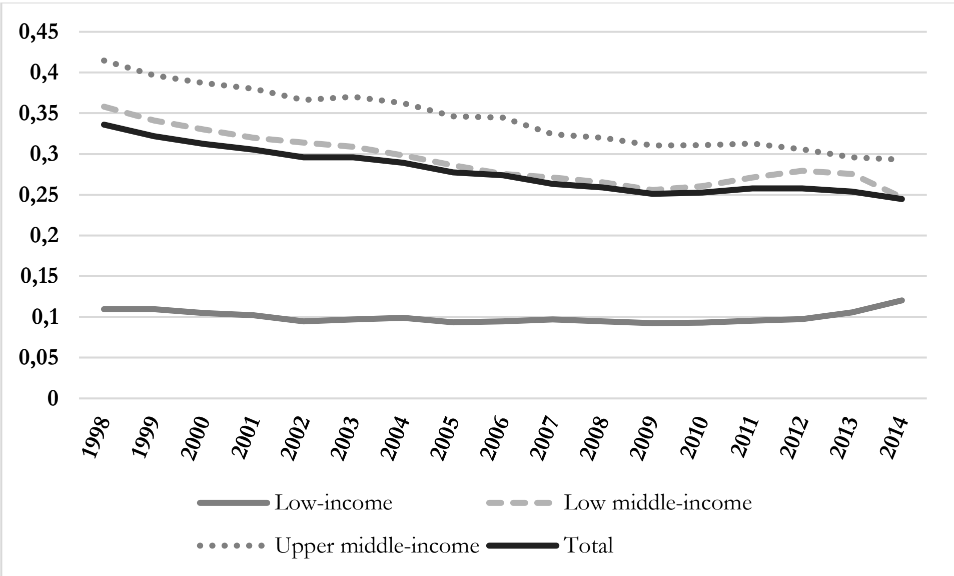
Source: own elaboration with data from the World Development Indicators (World Bank, 2019).

3.2.2 Explanatory variables

As we have explored in section 2.3, environmental degradation (*e.g.* higher temperatures, excess precipitation, natural disasters, etc.) can increase poverty, both directly and indirectly, through several channels (consumption, assets, productivity, and opportunities) (Leichenko and Silva, 2014; Hallegatte *et al.*, 2014). We showed many literature examples that postulate these impacts, including, also, situations in which climate change lead to a positive outcome in poverty.

Figure 3 and Figure 4 show, respectively, the mean CO2 emissions (kg per 2011 PPP dollars of GDP) by level of income and by region, between 1998 and 2014. Figure 5 displays the mean forest area (% of land area) by region, between 1998 and 2014.

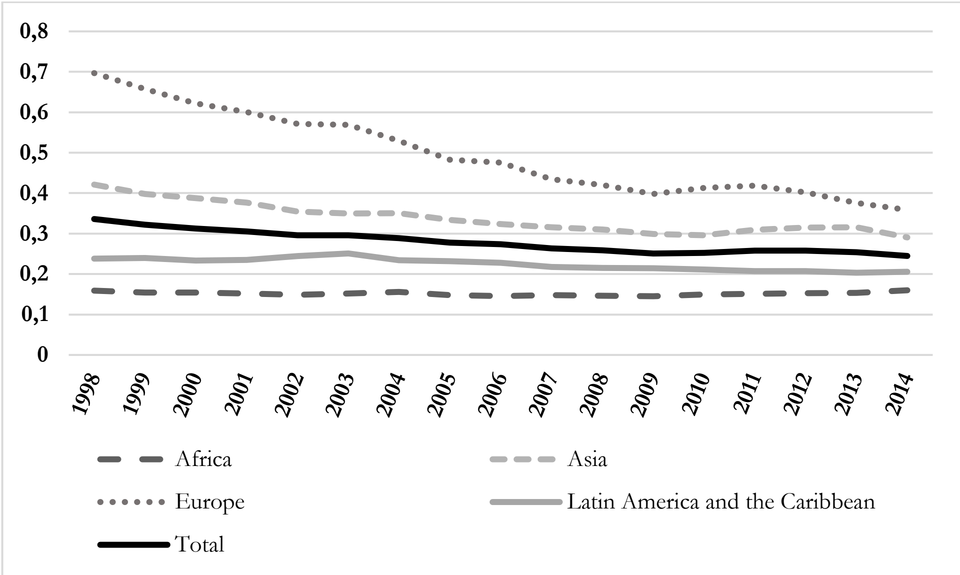
Figure 3 – Mean CO2 emissions (kg per 2011 PPP dollars of GDP) by level of income, 1998-2014



Source: own elaboration with data from the World Development Indicators (World Bank, 2019).

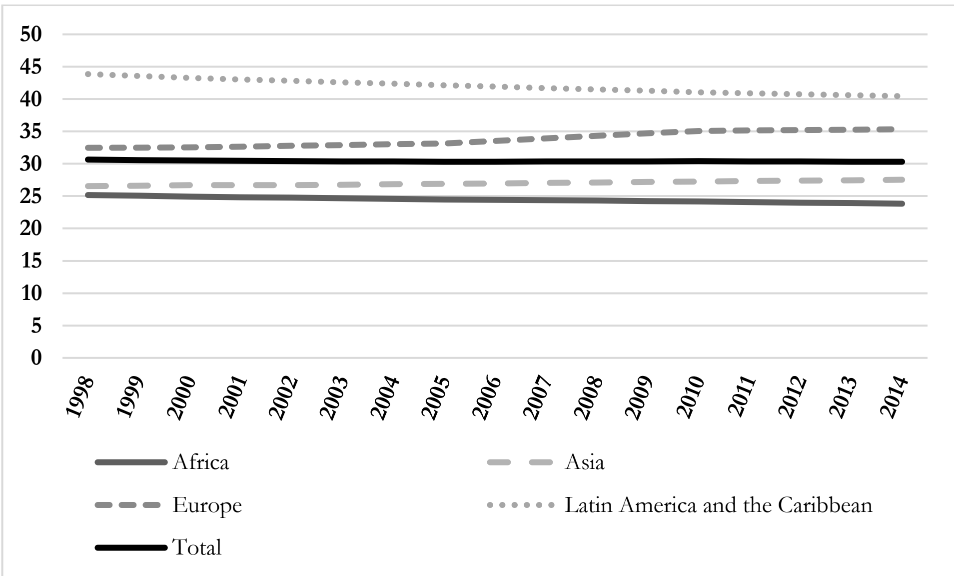
As we can see in Figure 3, the tendency of the sample shows a decreasing trajectory of the mean CO2 emissions (kg per 2011 PPP dollars of GDP), between 1998 and 2014. This first observation stays true for upper and low middle-income countries, while low-income ones appear to have a more or less stable behaviour of this variable for most of the time covered, with it starting to present a growing trajectory in 2012. It is also interesting to note that, as expected, upper middle-income countries present the highest values of CO2 emissions (kg per 2011 PPP dollars of GDP) in all the covered period, followed closely by low middle-income countries (both range between 0.45 and 0.24). Low-income countries are clearly in a lower tier compared with the other two groups, with a level of CO2 emissions near 0.1 kg per 2011 PPP dollars of GDP between 1998 and 2014.

Figure 4 – Mean CO2 emissions (kg per 2011 PPP dollars of GDP) by region, 1998-2014



Source: own elaboration with data from the World Development Indicators (World Bank, 2019).

Figure 5 – Mean forest area (% of land area) by region, 1998-2014



Source: own elaboration with data from the World Development Indicators (World Bank, 2019).

Focusing now on Figure 4 and Figure 5, we can see that Europe and Asia both clearly show a decreasing tendency of mean CO2 emissions (kg per 2011 PPP dollars of GDP) in the covered period (Europe with the highest levels but also with the most drastic decrease, up to the point of having a level of emissions near the one observed in Asia, in 2014). At the same time, both regions increase their forest area (in terms of all land area) between 1998 and 2014, with Europe showing the most notorious increase. In a parallel analysis we see that Africa and Latin America and the Caribbean have a more or less stable tendency of mean CO2 emissions (kg per 2011 PPP dollars of GDP) in the period covered (this last region slightly decreases the level of emissions), while both regions present a decreasing tendency of forest area (in terms of all land area) between 1998 and 2014. Finally, just note that the total sample has a constant evolution of forest area, with the different forces balancing themselves as a whole.

We now procced to the presentation of the climatic explanatory variables used to measure the impact of climate change on poverty. They go as follows:

- CO2 emissions, measured by **CO2 emissions in kg per GDP in dollars, in 2011 prices at PPP (CO2GDP)**[10]. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). The negative correlation of economic growth with poverty is largely described in the literature (*e.g.* Dollar and Kraay, 2002), and there are several studies that analyse the impact of climate change on economic growth (*e.g.* Letta and Tol, 2019), with CO2 emissions also seen as responsible for climate change (*e.g.* Stern, 2007). In one hand, climate change can reduce economic growth, which would indirectly harm poverty. In other hand, an important tool to reduce poverty comes from the shift of work from low-productivity agriculture to manufacturing (Hallegatte *et al.*, 2014), meaning emissions are, in this case, important to reduce poverty. From this indirect perspective, CO2 emissions can both have a positive or negative impact on poverty. Finally, Dhrifi *et al.* (2020), testing the effect of climate change on poverty, show that CO2 emissions are positively and strongly correlated with poverty meaning that, from this direct perspective, we can expect CO2 emissions to increase poverty.
- Temperature, measured by the **average annual temperature in degrees Celsius**

[10] We also tested another variable for CO2 emissions (CO2 metric tons per capita) but results were not as satisfying and it was correlated with the variable GDP *per capita*, which made us decide in favor of CO2 emissions in kg per GDP in dollars, in 2011 prices at PPP.

(TEMP), is collected from the Climatic Research Unit of the University of East Anglia (2020). The majority of the literature we gathered and presented in subchapter 2.3 (*e.g.* Park *et al.* (2018), Letta and Tol (2019), Azzarri and Signorelli (2020)) include temperature when investigating the impact of climate change on poverty. The evidence points to temperature being associated with higher poverty in developing countries, with poorer households being located in hotter zones (Park *et al.*, 2018), total factor productivity (TFP) being negatively affected by temperature shocks in poor countries (Letta and Tol, 2019), while long term temperature increases poverty in Sub-Saharan Africa (Azzarri and Signorelli, 2020). At the same time, temperature increase and temperature shocks show positive effects on poverty in colder developing countries (Park *et al.*, 2018) and, after a certain level of development is achieved, temperature has no significant impact on TFP (Letta and Tol, 2019). Also, heat shocks are seen as positive for welfare and poverty in Central Africa (Azzarri and Signorelli, 2020). Based on the characteristics of our sample (low- and middle-income countries mainly located in hot areas, as can be seen by the mean average temperature of the sample, in Table 3) we expect temperature to be positively correlated with poverty.

- Precipitation, measured by the **average annual precipitation frequency in millimetres (PRE)**, is collected from the Climatic Research Unit of the University of East Anglia (2020). This variable is also associated to climate change and is included in part of the literature we gathered (*e.g.* Park *et al.* (2018), Letta and Tol (2019), Azzarri and Signorelli (2020)). In the first two papers mentioned it was used as a control variable, but Azzarri and Signorelli (2020) include this variable in the form of long-term precipitation, flood shocks, and drought shocks to measure its impact on welfare and poverty in Sub-Saharan Africa. They find that long term precipitation decreases poverty and also that, while flood shocks negatively impact welfare and positively impact poverty, drought shocks are mainly positive in West Africa. Also, Damania *et al.* (2020) find that precipitation has a concave relationship with economic growth, promoting a marginal economic gain in drier developing countries, particularly. Since economic growth is important for poverty reduction (Dollar and Kraay, 2002) poverty is expected to decrease if rainfall increases. We expect precipitation to negatively impact poverty, following the results of Azzarri and Signorelli (2020) regarding long term precipitation and the relationship found by Damania *et al.* (2020)

for rainfall and economic growth, but regional differences might bring an opposite result, as seen by the impact of drought shocks in only part of the sample (Azzarri and Signorelli, 2020).

- Forest area, measured by the **percentage of forest area in terms of total land area (FOREST)**, collected form the World Bank's World Development Indicators (World Bank, 2019). Vedeld *et al.* (2007) shows that poor households depend more of forest related activities for their income, but, in other hand, Wunder (2001) states that it is very hard to alleviate poverty through forest related investments and that they are better suited for "defensive strategies" (not to reduce but to prevent poverty of increasing). Also, forest areas typically aggregate a number of features that relate to higher poverty (*e.g.* lack of access to credit and quality infrastructures, low population density) (Wunder, 2001). Based on the literature we expected higher levels of forest area to increase poverty.

3.2.3 Control variables

We use several variables to control the impact of climate change on poverty in less developed countries. They compound a set of macroeconomic and structural change variables that are described in the literature as being associated with poverty or helping to alleviate it. They go as follows:

- Macroeconomic variables:

- **Logarithm Gross Domestic Product *per capita*, in 2011 constant international dollars at PPP (LOGGDP)**, is used to control the level of economic development in a country. The data is collected from the World Bank's World Development Indicators (World Bank, 2019) and the indicator was computed afterwards. Following the results of Campagnolo and Davide (2019), income *per capita* is negatively correlated with poverty headcount ratio (HCR) at 1.90 dollars a day, in 2011 prices at PPP, meaning that higher levels of economic development, in this sense, are associated with lower levels of poverty. The literature also suggests that economic growth is important for the reduction of poverty (*e.g.* Dollar and Kraay, 2002). We expect GDP *per capita* growth to negatively impact poverty.
- **GINI index (GINI),** which measures the inequality on a country's income distribu-

tion, and ranges from 0 (perfect equality in income distribution) to 100 (perfect inequality). The data is collected from the World Bank's World Development Indicators (World Bank, 2019). Ravallion (1997) argues that high income inequality contracts growth, which may limit the progress of poverty reduction or even worsen it in developing countries. Campagnolo and Davide (2019) test the impact of another inequality measure (Palma ratio) on the poverty headcount ratio (HCR) at 1.90 dollars a day, in 2011 prices at PPP, and conclude that they are positively correlated, which indicates that higher income inequality is associated with more people living below the poverty line. Income inequality is expected to positively impact poverty.

- **Public expenditure in health and education (EDUCH)**, which measures the sum of the domestic general government health expenditure with the government expenditure in education, in terms of total GDP, is used to control the quality of the human capital in a country. The data on education and health expenditure is collected from the World Bank's World Development Indicators (World Bank, 2019) and the indicator was later computed. Higher human capital (associated with health and education) is one of the ways to escape poverty and for parents to promote better opportunities to their children, reducing the intergenerational transmission of poverty (Hallegatte *et al.*, 2014). We expect it to negatively impact poverty.
- **Inflation (INF)**, measured by the consumer price index is used to control the price changes in a country. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). Dollar and Kraay (2002) find evidence to support that low levels of inflation have a positive impact on the income of the poor. Inflation is expected to be positively correlated with poverty.
- **Unemployment (UNEMP)**, measured by the percentage of labour force without work in terms of total labour force is used to control the level of unemployment in a country. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). According to Zizzamia (2020), employment creation is essential to reduce poverty, especially in high-unemployment developing countries. However, the author advices that the impact of employment on individual wellbeing depends of outside work opportunities and if the benefits outweigh the costs of low-skilled employment. We expect unemployment to be positively correlated with poverty.

- Structural change variables:

- **Gross capital formation (GCF)**, measured as percentage of GDP is used to control for the level of investment in a country. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). Akobeng (2017) studies the impact gross fixed capital formation has on poverty in Sub-Saharan African countries and concludes that they are negatively correlated (gross fixed capital formation helps to reduce poverty). We expect investment rate to negatively impact poverty.
- **Population growth (POPGROWTH)** is used to control the growth in a country's population. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). Moav (2005) argues that poor countries, due to high levels of fertility, are not able to attain sufficient progress in education, limiting their development potential and converging, therefore, to a low-income *per capita* steady state. An example of this argument can be seen in Azzarri and Signorelli (2020), as they find that the variable number of children with less than six years old per household is positively correlated with poverty (more children with less than six years olds indicates more poverty). We expect population growth to be positively correlated with poverty.
- **Urban population (URBAN)**, measured by the number of people living in urban areas as a ratio of total population, is used to control for a country's level of urbanization. The data is collected from the World Bank's World Development Indicators (World Bank, 2019). According to Ravallion (2002), the incidence of poverty in developing countries is higher in the rural areas composing them. However, the author finds that the poor urbanize faster than the nonpoor, estimating that, by 2035, urban poor will represent 50% of total poor population, increasing with the rate of urbanization. In spite of this evidence, Ravallion (2007) states that urbanization generally helps alleviate poverty due to the positive interconnection it has with economic growth. Yet, this effect seems more important for rural poverty reduction and poverty reduction as a whole, as the pace of urban poverty reduction is slowing down (Ravallion, 2007). We expect urbanization to be negatively correlated with poverty, even though the evidence around urban poverty might bring different results.
- **Extractive goods exports (EXTRACTIVE)**, measured by its percentage in terms of all merchandise exports is used to control a country's dependency on the export

of its natural resources. The raw data is collected from the World Bank's World Development Indicators (World Bank, 2019) and then we compute the indicator used (sum of agricultural raw material exports, fuel exports, and ore and metal exports, as a ratio of all merchandise exports). Literature shows that a huge dependence of natural resources can be detrimental for a country's development. Gylfason (2001) notes that economic growth tends to be slower in countries rich in natural resources and specifies four channels through which this negative impact can be felt: the Dutch disease (overvaluation of the national currency), rent seeking behaviours from producers, overconfidence (lower incentive to promote good development policies), and neglect of education. An excessive dependency of natural resources can, thus, be negative for poverty. We expect extractive goods exports to be positively correlated with poverty.

Table 3 displays the summary of statistics of the variables previously presented as well as data sources.

Finally, Table 4 presents the correlation matrix between each pair of variables. We can see that FOREST is the only explanatory variable that does not significantly impact poverty (HCR). All the other explanatory variables are significantly correlated with the dependent variable: CO2GDP negatively impacts HCR (for a level of significance of 0.01); TEMP positively impacts HCR (for a level of significance of 0.01); PRE positively impacts HCR (for a level of significance of 0.05). At first sight, this suggests that more CO2 emissions reduce poverty and, at the same time, higher temperatures and excess rain increase poverty.

Analysing the correlation coefficients we can see that most of them are lower than 0.6. The only exceptions are the correlation coefficients between some of the climatic variables (not included simultaneously in the same models), between LOGGDP and HCR, and between URBAN and LOGGDP. Even though these correlation coefficients are high, since they are lower than 0.7 (-0.6918 and 0.6963, respectively), the estimation will not be compromised by the joint inclusion of the referred variables.

In the next chapter we will present and discuss our model estimation results.

Table 3 – Summary of statistics

	Variable		Mean	Median	Max	Min	Standard deviation	Source
Dependent Variable	**HCR**	Poverty Headcount Ratio (% of population)	13.613	6.700	86.000	0.000	17.819	World Bank
Climate Change Variables	**CO2GDP**	CO2 Emissions (kg per 2011 PPP $ of GDP)	0.279	0.221	1.666	0.019	0.234	World Bank
	TEMP	Annual Mean Temperature (degrees Celsius)	19.527	23.000	29.300	-5.100	8.004	University of East Anglia
	PRE	Average Annual Precipitation Frequency (millimetres)	1183.010	1017.400	4394.600	26.700	842.954	University of East Anglia
	FOREST	Forest Area (% of land area)	30.402	31.021	80.469	0.056	20.661	World Bank
Macroeconomic Variables	**LOGGDP**	Logarithm GDP *per capita*, PPP (constant 2011 international $)	8.555	8.692	10.148	6.380	0.862	World Bank
	GINI	Gini Index	41.463	40.300	64.800	24.000	8.961	World Bank
	EDUCH	Public Expenditure in Health and Education (% of GDP)	5.010	4.535	15.343	0.000	2.764	World Bank
	INF	Inflation, consumer prices (annual %)	8.664	5.925	293.679	-18.109	14.417	World Bank
	UNEMP	Unemployment (% of total labour force)	8.721	7.053	37.250	0.200	6.803	World Bank
Structural Change Variables	**GCF**	Gross Capital Formation (% of GDP)	24.246	22.980	67.911	0.000	8.981	World Bank
	POP-GROWTH	Population Growth (annual %)	1.458	1.435	8.118	-9.081	1.257	World Bank
	URBAN	Urban Population (% of total population)	48.730	49.715	91.377	7.830	19.304	World Bank
	EXTRAC-TIVE	Extractive Goods Exports (% merchandise exports)	32.300	23.223	98.810	0.129	27.170	World Bank

Source: own elaboration.

Table 4 – Correlation Matrix

	HCR	CO2GDP	TEMP	PRE	FOREST	LOGGDP	GINI	EDUCH	INF	UNEMP	GCF	POP-GROWTH	URBAN	EXTRAC-TIVE
HCR	1.0000 (-----)													
CO2GDP	-0.2495 (0.000) ***	1.0000 (-----)												
TEMP	0.2758 (0.000) ***	-0.6514 (0.000) ***	1.0000 (-----)											
PRE	0.1158 (0.027) **	-0.4798 (0.000) ***	0.6698 (0.000) ***	1.0000 (-----)										
FOREST	-0.0093 (0.859)	-0.2807 (0.000) ***	0.2985 (0.000) ***	0.6400 (0.000) ***	1.0000 (-----)									
LOGGDP	-0.6918 (0.000) ***	0.1736 (0.001) ***	-0.1858 (0.000) ***	0.0025 (0.961)	0.2987 (0.000) ***	1.0000 (-----)								
GINI	0.1862 (0.000) ***	-0.4042 (0.000) ***	0.5441 (0.000) ***	0.4969 (0.000) ***	0.5066 (0.000) ***	0.0807 (0.123)	1.0000 (-----)							
EDUCH	-0.3061 (0.000) ***	0.1902 (0.000) ***	-0.1890 (0.000) ***	-0.0742 (0.156)	-0.0577 (0.270)	0.0843 (0.107)	-0.1000 (0.056) *	1.0000 (-----)						
INF	0.0048 (0.927)	0.1845 (0.000) ***	-0.1453 (0.005) ***	-0.0804 (0.124)	0.0496 (0.343)	0.0123 (0.815)	-0.1003 (0.055) *	0.0150 (0.775)	1.0000 (-----)					
UNEMP	-0.0520 (0.320)	0.1409 (0.007) ***	-0.1631 (0.002) ***	-0.1770 (0.007) ***	-0.1190 (0.023) **	0.1324 (0.011) **	0.0765 (0.144)	0.0348 (0.507)	-0.1012 (0.053) *	1.0000 (-----)				
GCF	-0.1056 (0.043) **	0.2048 (0.000) ***	-0.2640 (0.000) ***	-0.2009 (0.000) ***	-0.0979 (0.061) *	0.056027 (0.284)	-0.3115 (0.000) ***	-0.0908 (0.082) *	0.0176 (0.737)	-0.1275 (0.015) **	1.0000 (-----)			
POP-GROWTH	0.4733 (0.000) ***	-0.4368 (0.000) ***	0.5484 (0.000) ***	0.2558 (0.000) ***	0.0286 (0.586)	-0.3680 (0.000) ***	0.3862 (0.000) ***	-0.3264 (0.000) ***	-0.1120 (0.032) **	-0.1413 (0.007) ***	-0.1397 (0.007) ***	1.0000 (-----)		
URBAN	-0.4922 (0.000) ***	0.1269 (0.015) **	-0.1109 (0.034) **	0.0416 (0.427)	0.3453 (0.000) ***	0.6963 (0.000) ***	0.2985 (0.000) ***	0.2233 (0.000) ***	0.0926 (0.077) *	0.1789 (0.001) ***	-0.1765 (0.001) ***	-0.2182 (0.000) ***	1.0000 (-----)	
EXTRAC-TIVE	0.0393 (0.453)	0.1355 (0.009) ***	-0.2341 (0.000) ***	-0.0895 (0.087) *	0.2227 (0.000) ***	0.1417 (0.007) ***	-0.0162 (0.757)	-0.0150 (0.775)	-8.78E-05 (0.999)	0.0235 (0.654)	0.0371 (0.478)	0.0843 (0.107)	0.1755 (0.001) ***	1.0000 (-----)

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Chapter 4. Does climate change impact poverty in developing countries?

In this chapter we present and discuss the main results of the model that analyses the impact of climate change on poverty in developing countries. We start by considering the full sample and then allow for the regional subsamples that classify the countries per continent, following the United Nations Statistics Division classification.

4.1 Climate change and poverty in developing countries: Full sample

As previously explained, we analyse the impact of climate change on poverty considering a sample with 76 low- and middle-income countries according to the World Bank's classification. Our dataset comprises countries with at least three observations for the dependent variable in the period 1998-2014.

We estimate eight models (I-VIII) with different combinations of explanatory and control variables. Both country and year effects are included in order to highlight endogenous differences between countries and, also, exogenous shocks that influenced poverty levels in all countries in the period covering the sample[11].

According to Greene (2012), the Fixed Effects Model has the shortcoming of costing degrees of freedom due to the dummy variable approach, but, in other hand, has the advantage of treating the individual effects as being correlated with the remaining regressors, something that the Random Effects Model does not do, which may bring inconsistency to this type of estimation. Fixed effects are always consistent but, if random effects do not suffer from inconsistency, they have the advantage of not costing degrees of freedom.

We apply the Hausman Test as it allows to test for the consistency of random effects in the model. Under the null hypothesis of no correlation, OLS, LSDV, and FGLS estimators are consistent (but OLS estimators are inefficient) while, under the alternative, LSDV estimators are consistent but FGLS ones are not (Greene, 2012). So, if the null hypothesis is rejected, fixed effects should be used and, if it is not rejected, random effects are appropriate. We also run the Redundant Fixed Effects Test to see if, in case of deciding in favour of fixed effects, they increase the quality of the model (null hypothesis is rejected) or are redundant (null hypothesis is not rejected).

Table 5 compounds the results of these tests. The Hausman Test rejects the null

[11] The *EViews* package does not allow to estimate automatically two-way random effects models while using an unbalanced dataset. Because of this, in addition to automatic country effects, time effects were manually added using dummy variables per year.

hypothesis for all models (V, VI, VII, and VIII for all significance levels; I and II for a significance level of 0.05; III and IV for a significance level of 0.1), which means that fixed effects are more appropriate to estimate them. The Redundant Fixed Effects Test also rejects the null hypothesis of fixed effects being redundant in all models (for all significance levels). Based on these results, all eight models are estimated using cross-sectional fixed effects (with year dummies manually added).

Table 5 – Specification and significance group effects tests

		Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Hausman Test (cross-section)		33.735484	31.343115	26.202893	27.658489	112.463836	88.690750	89.819296	92.306644
		(0.0136)**	(0.0263)**	(0.0952)*	(0.0674)*	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Redundant Fixed Effects Test	Cross-section F	27.780996	25.196428	26.162855	24.863991	25.393662	21.188387	20.989637	20.442780
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
	Cross-section Chi-square	973.481826	927.959535	945.662929	921.745349	631.268801	577.640327	574.901001	567.256506
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***

Note(1): p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Note(2): since only cross-sectional fixed effects were automatically generated, *EViews* only allows to run the Hausman and Redundant Fixed Effects tests on the cross-sectional part of the sample. All models subjected to the tests include year dummies.

We now present the estimation results of the eight models, all corrected from heteroskedasticity, displayed in Table 6. Models I to IV are the baseline models and include only the dependent variable (HCR), the control logarithm GDP *per capita* (LOGGDP), and each one of the explanatory variables (one per model). Models V to VIII follow the same order as the first four but include all the controls.

Table 6 – Climate change impact on poverty - full sample (1998-2014)

Dependent Variable: Poverty Headcount Ratio (HCR								
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Constant	177.3410 (0.0000)***	101.9245 (0.0000)***	129.5265 (0.0000)***	130.8041 (0.0000)***	180.6276 (0.0000)***	80.92801 (0.0522)*	103.2495 (0.0138)**	105.3728 (0.0132)**
CO2GDP	-24.36267 (0.0000)***				-36.42075 (0.0000)***			
TEMP		1.377825 (0.0215)**				1.166336 (0.0567)*		
PRE			-0.000685 (0.5754)				0.001527 (0.2239)	
FOREST				0.310430 (0.0436)**				0.029943 (0.9056)
LOGGDP	-17.07744 (0.0000)***	-12.13979 (0.0000)***	-12.39212 (0.0000)***	-13.82538 (0.0000)***	-21.47535 (0.0000)***	-12.87023 (0.0060)***	-13.30619 (0.0048)***	-13.40032 (0.0059)***
GINI					0.092365 (0.5432)	0.062111 (0.6921)	0.086318 (0.5808)	0.080047 (0.6102)
EDUCH					-0.778675 (0.0000)***	-0.811195 (0.0000)***	-0.830169 (0.0000)***	-0.826489 (0.0000)***
INF					0.011839 (0.3259)	-0.012758 (0.3412)	-0.010441 (0.4119)	-0.010326 (0.4198)
UNEMP					0.103060 (0.5477)	0.026588 (0.8828)	-0.012470 (0.9439)	0.008045 (0.9639)
GCF					-0.014072 (0.8617)	-0.157771 (0.0779)*	-0.162097 (0.0691)*	-0.161532 (0.0655)*
POP-GROWTH					-0.055501 (0.9409)	1.360452 (0.0511)*	1.469706 (0.0420)**	1.430176 (0.0526)*
URBAN					0.613730 (0.0014)***	0.523708 (0.0067)***	0.519091 (0.0074)***	0.517624 (0.0107)**
EXTRAC-TIVE					0.118589 (0.0191)**	0.120046 (0.0322)**	0.123588 (0.0301)**	0.121661 (0.0307)**
Model Summary								
R-Squared	0.925741	0.922551	0.921862	0.922622	0.934791	0.924469	0.923903	0.923666
Adjusted R-Squared	0.911845	0.908088	0.907270	0.908171	0.917130	0.904013	0.903294	0.902992
F-statistic	66.62125	63.78526	63.17539	63.84839	52.93013	45.19242	44.82894	44.67790
Prob (F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	591	592	592	592	367	367	367	367
Number of countries	76	76	76	76	53	53	53	53

Note (i): p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).
Note (ii): year dummies are part of the models' outputs but their coefficients and significance levels are not reported in the table.

The baseline models (I to IV) have both R-squared and adjusted R-squared higher than 0.9, indicating that the regressors explain more than 90% of the poverty headcount ratio (HCR) variation. In addition, the F-statistic indicates that the null hypothesis of all regression coefficients being equal to zero is rejected, meaning that the four models are globally significant.

The estimation results of models I to IV show that three of the four climatic variables have a significant impact on HCR (CO2GDP, TEMP, and FOREST). CO2 emissions (CO2GDP) (Model I) have a negative impact on HCR (for all significance levels). This result can be explained by the importance of CO2 emissions for economic growth that, ultimately, is important for poverty reduction (Dollar and Kraay, 2002). In other hand, this result contradicts the one observed by Dhrifi *et al.* (2020), that finds that CO2 emissions increase poverty in developing countries as a whole. Our results differ probably because the majority of our panel includes middle income economies (approximately 82% of the sample), whose higher economic growth in the period 1998-2014 can expectably be associated with a continuous transition to a more productive manufacture sector, described by Hallegatte *et al.* (2014) as important to reduce poverty.

Temperature (TEMP) (Model II) shows a positive impact on HCR (for a level of significance of 0.05). In Table 3 we can see that the mean average temperature of the full panel is, approximately, 19.5 degrees Celsius, pointing to a sample compounding a relatively strong number of countries with medium to high overall temperatures. Since we are working with developing countries, this result seems to be in accordance with the literature, following the results of Park *et al.* (2018), Letta and Tol (2019) and Azzarri and Signorelli (2020) that show that in developing countries (mainly hot), poorer households are located in hotter zones, total factor productivity (TFP) is negatively impacted by temperature shocks, and one additional degree Celsius increases poverty in 2.8 percentage points, respectively.

Forest area (FOREST) (Model IV) has a positive impact on HCR (for a level of significance of 0.05). This indicates that, in developing countries, an increase in forest area in terms of total area increases poverty. The literature shows examples in both directions but, even though Vedeld *et al.* (2007) demonstrates that poorer households depend more heavily of forest environmental income, Wunder (2001) states that populations living near forest areas have features that are characteristic of higher poverty (*e.g.* lack of access to credit and quality infrastructures, low population density). And so, even if forest activities contribute to the subsistence of poor people, it makes sense that higher share of forest area negatively impacts poverty, as it serves more as a security than as a tool to escape poverty.

Precipitation (PRE) (Model III) is the only explanatory variable that does not have significant impact on HCR. This result does not confirm the one observed by Azzarri and Signorelli (2020), that find that long term precipitation negatively impacts poverty and of Damania *et al.* (2020), that find thar rainfall positively impacts economic growth in developing countries. Even though precipitation might affect poverty in developing countries, we did not find it significant in this sample.

Finally, logarithm GDP *per capita* (LOGGDP) is used as a control variable and, as expected, results are in accordance with the literature (*e.g.* Campagnolo and Davide (2019), Dollar and Kraay (2002)), negatively and significantly impacting HCR.

With the introduction of the controls the quality of the models remains unchanged, with both the R-squared and the adjusted R-squared ranging between 0.9 and 0.94, and the F-statistic still rejecting the null hypothesis of all regression coefficients being equal to zero, confirming that the models V to VIII all have global significance.

CO2 emissions (CO2GDP) (Model V) and temperature (TEMP) (Model VI) confirm their significance when explaining the poverty headcount variation (at 0.01 and 0.1, respectively) meaning that, of the three climatic variables that were significant in the baseline models, only forest area (FOREST) (Model VIII) lost that status. This is a confirmation that, to some extent, environmental degradation (represented here by CO2 emissions) might be necessary for developing countries to achieve a certain threshold of economic development in order to efficiently fight back poverty, as a 1% increase in emissions is estimated to decrease poverty in 36%. At the same time, climate change in the form of temperature increase is a cause of concern, as one additional degree Celsius is estimated to increase HCR in, approximately, 1.17 percentage points.

The last explanatory variable to mention is precipitation (PRE) (Model VII). With the introduction of the controls this variable still has a non-significant impact on HCR. This was expected, following the result seen in the baseline model, which points to other reasons being more relevant to explain the poverty headcount variation in this sample of developing economies.

In terms of the behaviour of the controls, six of these nine variables have a significant impact on poverty. In one hand, GDP *per capita* growth (LOGGDP), education and health (EDUCH), and investment (GCF) all have a negative and significant impact on HCR.

These results find confirmation in the literature, that shows the importance of economic growth, (Dollar and Kraay, 2002), education and health (Hallegatte *et al.*, 2014), and investment (Akobeng, 2017) for poverty alleviation.

In other hand, urbanization rate (URBAN), extractive goods exports (EXTRACTIVE), and population growth (POPGROWTH) all positively and significantly impact HCR. These results are confirmed by the literature, particularly in the case of a higher dependency of raw material extraction, noted by Gylfason (2001) as a cause of slower growth due to, for example, the Dutch disease and the neglect of education, and population growth, where high levels of fertility in low-income countries limit the progress in education and, therefore, their development (Moav, 2005), which contributes to higher poverty, as seen in as seen in Azzarri and Signorelli (2020). Finally, the literature on urbanization in developing countries states that it is important to alleviate poverty, mainly in rural areas, due to its link with economic growth (Ravallion, 2007). Yet, evidence also shows that urbanization increases the share of urban poor as they urbanize faster than the nonpoor (Ravallion, 2002), which might be effect captured by the estimation results.

The other control variables (income inequality (GINI), inflation (INF), and unemployment (UNEMP)) are not statistically significant to explain the poverty headcount variation, even though the literature frequently claims that they contribute to higher poverty.

4.2 Regional subsamples

In order to detail our analysis, we also estimate the model considering regional subsamples in accordance with the countries' geographical characteristics and classification by the United Nations Statistics Division. Table 7 presents each subsample and its composition.

Table 7 – Subsamples' characteristics and country distribution

Subsample	Countries per subsample
Africa	22
Asia[12]	27
Europe	11
Latin America and the Caribbean	16

Source: own elaboration with data from the United Nations Statistics Division.

[12] Since we only have two countries from Oceania, we decided to include them together with Asia, as they probably share some regional similarities.

The impact of certain climatic events as well as their frequency and intensity commonly change depending on the different regions they occur, as shown by Winters *et al.* (1998) and Azzarri and Signorelli (2020). With these four subsamples we intend to capture this heterogeneity and see how it may affect poverty.

Due to the small number of observations per each subsample, it is not possible to estimate two-way random effects models, even with the manual inclusion of time effects (year dummies)[13].

As can be observed in Appendix 2, the Redundant Fixed Effects Test always rejects the null hypothesis of cross-section fixed effects being redundant. Conversely, the same test does not reject the null hypothesis of period effects being redundant in several models across the subsamples (particularly in Africa and Latin America and the Caribbean). Therefore, we choose to only include country fixed effects.

In addition, the Hausman Test, particularly for Africa and Latin America and the Caribbean subsamples (models IV to VIII in the first; models V to VIII in the second), does not reject the null hypothesis of cross-section random effects being the most appropriate for the models' estimation, and so they are estimated using cross-section random effects. The remaining models are estimated with cross-section fixed effects. The results of the tests are available in Appendix 2.

Following the process adopted for the full sample, we estimate eight models (I-VIII) for each subsample, all corrected from heteroskedasticity. The first four models (I to IV), in each subsample, are the baseline models and include only the dependent variable (HCR), logarithm GDP *per capita* (LOGGDP), and each one of the explanatory variables (one per model). Models V to VIII follow the same order as the first four but include all the controls. The results are available in Appendix 3 and displayed by subsample.

Depending on the subsample considered and whether the model is estimated with fixed or random effects, the R-squared and Adjusted R-squared explains 48% to 93% of the poverty (HCR) variation. In addition, in all subsamples and for all the models the F-statistic indicates that the null hypothesis of all regression coefficients being equal to zero is rejected, meaning that all the models are globally significant.

The estimation results show that the only explanatory variable that does not have a

[13] When trying to estimate the model using automatically generated cross-section dummies and manually added year dummies, *EViews* stops the estimation process claiming that, in order to estimate the random effects innovation variance, number of cross-sections must be higher than coefficients for between estimator.

significant impact on poverty (HCR) is precipitation (PRE). Contrary to Azzarri and Signorelli (2020), that find that, in different regions of Sub-Saharan Africa, flood shocks always have a positive impact on poverty and that drought shocks negatively impact poverty only in Central Africa, these type of regional similarities/differences were not observed in any of the four subsamples concerning the possible outcomes of precipitation on poverty.

CO2 emissions (CO2GDP) have a significant negative impact on two of the four subsamples (Asia and Europe). Interestingly enough, it is only significant with the introduction of the controls (Model V) for a level of significance of 0.01 in both subsamples. A 1% increase in emissions (as percentage of GDP) is estimated to decrease poverty in 42% in Asia and 20% in Europe. These results are in accordance with the one observed for the full sample, confirming the importance of CO2 emissions for economic growth, that promotes poverty alleviation (Dollar and Kraay, 2002). Curiously, Dhrifi *et al.* (2020) finds that CO2 emissions are important for poverty alleviation (increase households final consumption expenditure *per capita*) in Asia, confirming our results for this subregion. The fact that Europe also shares this result with Asia is not surprising as many countries in both regions, particularly in our sample, are close in terms of distance and probably share similar characteristics.

Temperature (TEMP) negatively and significantly impacts HCR in Asia and Latin America and the Caribbean (Model VI). We estimate that one additional degree Celsius decreases poverty in 1.61 and 1.04 percentage points in Asia and Latin America and the Caribbean, respectively. Park *et al.* (2018) shows that, even though poor people are commonly located in hotter areas inside hot developing countries and work in occupations more exposed to heat, the opposite is observed in colder countries, were poorer people may benefit with an increase in temperature. Yet, our sample is mainly composed by hot developing countries (average mean temperature of the sample is 19.5 degrees Celsius, as seen in Table 3) although with a high heterogeneity, mainly in Asia, which does not allow to fully associate our result with the one observed by Park *et al.* (2018). Since this result diverges from the one observed in the full sample that is the most validated by the literature (Park *et al.* (2018), Letta and Tol (2019), Azzarri and Signorelli (2020)) and the method of estimation for the regional subsamples is less robust than the one used for the full sample, this particular result must be seen with some precaution.

The last explanatory variable to mention is forest area (FOREST) and results show that it both significantly impacts poverty in Europe and Latin America and the Caribbean.

However, in the case of Europe, forest area negatively impacts HCR only with the introduction of the controls (Model VIII, at 0.05, with an 1% increase in forest area estimated to decrease poverty in 3.95%) while, in the case of Latin America and the Caribbean, it positively impacts HCR both in the baseline model (Model IV, at 0.01) and with the introduction of the controls (Model VIII, at 0.05, with an 1% increase in forest area estimated to increase poverty in 0.26%). As it can be seen in Figure 5, between 1998 and 2014, forest area as percentage of total land area increased in Europe but decreased in Latin America and the Caribbean. Bhattarai and Hammig (2001) find evidence for an EKC between income and deforestation in Latin America and the Caribbean, indicating that countries in this region might still be in the ascending part of the curve. At the same time, political institutions and governance quality help reduce deforestation and the lack of its foundation may also translate into poverty. Zambrano-Monserrate, Carvajal-Lara, Urgilés-Sanchez, and Ruano (2018) find evidence of an EKC for European countries (four in five) and also accept the importance of reinforcing environmental policies and institutions, as Bhattarai and Hammig (2001). In Europe the fact that forest area negatively impacts poverty can be associated with European countries being in the descending part of the EKC, having a level of income associated with forest recovery in the EKC, to which the indirect action by the European Union (mainly through agricultural policy and its modernization) is seen as essential (Zambrano-Monserrate *et al.*, 2018).

The majority of the controls have the expected coefficient signs but there are a few exceptions. It is important to remind that some subsamples do not have all the controls. Both logarithm GDP *per capita* (LOGGDP) and education and health public expenditure (EDUCH) are present in all models and, as expected, negatively and significantly impact HCR (in all models and subsamples). This is in accordance with the results of the full sample and with the literature, that states that GDP *per capita* growth is important for poverty reduction (Dollar and Kraay, 2002) and that investment in education and health are essential tools for poverty alleviation and to prevent the formation of poverty traps (Hallegatte *et al.*, 2014).

Inflation (INF) is another control that is present in all models and subsamples and that positively and significantly impacts poverty in Europe (Model V, at 0.01) and in Latin America and the Caribbean. This result is supported in the literature, as high levels of inflation decrease the income of the poor (Dollar and Kraay, 2002). In the full sample inflation is not significant, but interestingly, Latin America and the Caribbean is the only region were this variable seems to strongly influence the poverty levels and this is probably due to the region's historical difficulty in controlling inflation. Income inequality (GINI) is significant in all subsamples but shows two different results: while it positively impacts poverty in Africa, Europe, and Latin America and the Caribbean (in accordance with Ravallion, 1997, that shows how high income inequality can limit or even worsen poverty alleviation), in the case of Asia it negatively affects HCR. This result goes against the idea of "growth with equity" (Fritzen, 2002) but there are specific cases of Asian countries that observed periods of economic growth, poverty reduction, and inequality increase. Most notably, Vietnam had, in the 90s, one of the fastest poverty reduction paces ever recorded, combined with strong economic growth (average of 7.6% in this period) but, in spite of these two results, income inequality increased (Fritzen, 2002). China is another example of this situation, with economic growth promoting a strong poverty reduction between 1981 and 1995 but, at the same time, leading to an increase in income inequality (Fritzen, 2002). Finally, in India, this phenomena was also observed in the 90s (Kijima, 2006).

Urbanization (URBAN) and population growth (POPGROWTH) are excluded in Africa subsample and both positively and significantly impact HCR in the other subsamples. Both results are supported in the literature. While in the case of urbanization literature points to its importance to reduce poverty, mainly in rural areas (Ravallion, 2007), it also states that it increases the share of urban poor (Ravallion, 2002), which supports the result observed. Population growth, due to the higher levels of fertility in low-income countries, can limit their ability to develop by restraining education (Moav, 2005), translating into higher poverty.

Extractive goods exports (EXTRACTIVE) is not present in Europe subsample but it significantly impacts HCR in Asia and Latin America and the Caribbean, but in different directions. While, in the case of Asia, its impact is positive (in accordance with Gylfason, 2001, as well as with the full sample), in Latin America and the Caribbean it helps to reduce poverty. Bozigar, Gray, and Bilsborrow (2016) find that oil extraction activities in the Ecuadorian Amazon, contrarily to what the Dutch Disease points, can bring benefits to indigenous populations living in this area by, for example, increasing household's access to wage employment and consumer goods. This means that, through these effects, absolute poverty may decrease with natural resource exploration activities in Latin America and the Caribbean.

Finally, unemployment (UNEMP) and investment (GCF) do not have a significant impact in any of the regions represented, indicating that there are other factors more important to explain absolute poverty in these regions.

A final note regarding the differences in the sample as a whole and each of the subsamples: even though it is normal to find differences when comparing the full sample and each of the subsamples, it is important to take into account that, in our case, while the models estimated for the full sample had both country and year fixed effects, the models estimated for each subregion only included country effects (fixed or random) and results could be different if year effects were also included. Therefore, it is more prudent to only compare the results of the subsamples between them.

4.3 Discussion of results

There are two scopes that can be followed when assessing the impact of climate change on poverty in developing economies: focusing on the full sample of countries and seeing if the different climatic variables affect poverty in these countries as a whole, or classifying the countries in different subregions and trying to understand whether their specific institutional and geographical characteristics change the way climate change may affect poverty. Our results indicate that climate change affects poverty (seen in absolute terms as the number of people living with less than 1.90 dollars a day, in 2011 prices at PPP) in developing economies in both these scopes, at least through part of the selected climatic variables. Since the estimation method assumed for the full sample is different than the one used for the subsamples, results are discussed separately.

Considering the sample as a whole we found that there are three climatic variables that significantly impact poverty: CO2 emissions (negatively), temperature (positively), and forest area (positively). While the first two climatic variables are relevant to explain the HCR variation even with the introduction of the controls, forest area loses significance with the controls' inclusion, indicating that there are other factors that explain poverty in the sample as a whole (population growth, urbanization, and natural resources dependency). While CO2 emissions are important for economic growth that, thereafter, helps reduce poverty (Dollar and Kraay, 2002), this result contradicts the one observed by Dhrifi *et al.* (2020), that find that CO2 emissions are a factor of higher poverty. This difference can probably be justified by our sample being composed mainly by middle income countries. Nevertheless, CO2 emissions might be necessary for developing economies to develop and, in the process, fight back poverty.

Temperature increase is described as having a negative impact on economic growth (Letta and Tol, 2019) and a positive impact on poverty (Park *et al.* (2018), Azzarri and

Signorelli (2020)), mainly in hot developing countries (highest portion of our sample). This is an alert for developing countries, as one additional degree Celsius is estimated to increase poverty in 1.17 percentage points. Policymakers should be attentive to temperature increase and develop policies that mitigate its impact on poverty and help the most affected populations to better adapt to it since, even if countries around the world seriously commit to fight back climate change, temperature is still expected to increase (Stern, 2007).

Forest area positively and significantly impacts poverty in the baseline model. This is in accordance with Wunder (2001), that describes forest dependent populations as having, mainly, characteristics typically associated with higher poverty. The introduction of the controls shows that, globally, there are other causes of poverty and tools that policymakers must prioritize to alleviate it (*e.g.* invest in education and health, control the population growth) but, nevertheless, they should be alert to forest populations as they depend of them to subsist (Vedeld *et al.*, 2007) and try to allocate their efforts to develop the country and fight back poverty in these areas.

The final climatic variable is precipitation. As previously described, there are several ways precipitation can affect poverty but, in our case, we found no significance in this relationship. This seems to point for precipitation, at the macro level, not having a strong influence on poverty compared to the other climatic variables. Yet, Damania *et al.* (2020) shows that the macro-econometric literature fails to find a significant impact of rainfall on several measures of aggregate economic output because the "aggregation to large spatial scales masks the heterogeneity of impacts of rainfall on aggregated economic growth" (Damania *et al.*, 2020 p. 7-8). This opens the possibility of a similar situation on poverty investigation, which implies that future investigation in this topic should take into consideration this imprecision so that the possible impact of rainfall on poverty is not underestimated.

Regarding the controls results point to the importance of GDP *per capita* growth, education and health, and investment for poverty alleviation. At the same time population growth, urbanization, and extractive goods exports all positively and significantly impact poverty. This opens two paths for policymakers that should both be addressed: in one hand, the promotion of growth, better education and health, and investment all are critical to achieve lower levels of poverty and are well described in the literature (Dollar and Kraay (2002), Hallegatte *et al.* (2014), and Akobeng (2017), respectively); in the other hand, the promotion of a more aware growth of population and urbanization, as well as diversifying activities in order to reduce the excessive dependency of natural resources should all be addressed to prevent the possible positive impacts they may have on poverty if not controlled, as seen in the literature (Moav (2005), Ravallion (2002, 2007), and Gylfason (2001), respectively). Finally, income inequality, inflation, and unemployment, even though being de-scribed in the literature as contributing to higher poverty, do not seem relevant to explain the HCR variation in this sample.

Focussing now on the subsamples that divided the full sample in four different regions (Africa, Asia, Europe, Latin America and the Caribbean) we see that there are several variables whose impact on poverty seems to be affected by their regional differences and specificities.

Africa is the only region where none of the explanatory variables affect the HCR variation. Instead, GDP *per capita* growth and education and health are two controls that negatively and significantly affect poverty, while income inequality significantly contributes to higher poverty. As already seen, these results are in accordance with the literature and point to the urgency of promoting structural change and development policies in these countries. Due to the lower level of development of African countries compared to the rest of the sample (of the fourteen low income countries, twelve are from Africa) it is not surprising that institutional and structural reasons seem to be the major causes of attention to alleviate poverty compared to climatic reasons. Still, policymakers must be aware of the negative impacts climate change may have on African populations, especially at the micro level, even if recognizing that much must be done in terms of development in other areas to alleviate poverty.

In Asia both CO2 emissions and temperature negatively impact poverty, even though the result regarding temperature is questioned. While the reasons behind this behaviour were already exposed, it is interesting to mention that Dhrifi *et al.* (2020), even though supporting the opposite result for the sample as a whole, find the same result regarding CO2 emissions when considering Asia alone. This indicates that, in terms of the possibility of climate change increasing poverty, policymakers do not seem to need to be especially attentive to this possibility. In terms of the controls, GDP *per capita* growth, better education and health, and income inequality all are important for poverty reduction. In other hand, urbanization (only in one model) and extractive goods exports positively and significantly impact poverty. All these results are supported by the literature, even though the result for income inequality is not the normally expected one (still, many Asian countries saw situations of economic growth, poverty alleviation and income inequality increase in some periods of time, as shown by Fritzen (2002) and Kijima (2006)). Policymakers, in order to successfully end poverty in Asia must continue to promote economic growth, invest in education and health, promote a good and stable urbanization, and diversify activities to reduce exposure to the negative impacts of an excessive dependency of natural resources. Regarding income inequality, even though it seemingly appears that in helps reduce poverty, policymakers should promote policies that strengthen income equality and economic growth, as a continuous increase in income inequality can jeopardize economic performance and slowdown the efficiency of poverty reduction (Fritzen, 2002).

In Europe both CO2 emissions and forest area negatively and significantly impact poverty. Again, the fact that CO2 emissions are important for poverty reduction makes sense due to its connection to economic growth. At the same time, it is curious that the result is shared with Asia and may be due to the proximity between both regions (none of the other two regions shares this result). The fact that a higher share of forest area is associated with less poverty is probably due to the fact that total share of forest area is increasing in this region, as seen in Figure 5. The existence of an EKC between income and deforestation in Europe is confirmed by Zambrano-Monserrate *et al.* (2018), indicating that European countries are in the descending part of the curve, with an increase in income being associated with forest recovery and probably indicating a decrease in poverty. All controls that are significant have the expected behaviour: GDP *per capita* growth, and better education and health help to alleviate poverty, while urbanization, population growth, income inequality, and inflation (only in one of the models) positively and significantly impact poverty. This indicates that policymakers must continue to pursue economic growth and invest in education and health to end poverty, with the relationship with forest area indicating that its preservation must continue. In the other hand, an effort must be done to promote a good urbanization, control the growth of population, and develop policies that enforce income equality.

Last but not least, in Latin America and the Caribbean both temperature and forest area significantly impact poverty, but in opposite ways: temperature negatively and forest area positively. The first result was already mentioned and we question its validity since it does not find support in the literature and is opposite to the one found in the full sample, where a more robust estimation method was applied. The relationship of forest area and poverty may come from the same reason seen in Europe, but in a symmetric way: as Figure 5 shows, Latin America and the Caribbean have been reducing its forest area and, since an EKC is confirmed in the region (Bhattarai and Hammig, 2001), it may be the case that the countries are in the ascending part of the curve. This can be seen as a sign for policymakers to strengthen political institutions and governance quality, seen as important for forest recovery (Bhattarai and Hammig, 2001). The controls, with one exception, all have the expected coefficients signs: GDP *per capita* growth and better education and health negatively impact poverty while income inequality, inflation, and urbanization positively impact poverty. All is confirmed in the literature with the exception of dependency of natural resources as it, in this region, negatively impacts HCR. Since Bozigar *et al.* (2016) find that oil extraction activities in Ecuadorian Amazon can be beneficial to indigenous people in this area, translating to a possible reduction of absolute poverty, it may be that cases like this translate in extraction goods exports, negatively impacting poverty. Based on this it seems crucial that policymakers in Latin America and the Caribbean start to invest in forest conservation activities and at the same time, continue to promote economic growth and investments in education and health. In the other way, inflation is particularly severe in this region and must be addressed, while efforts to reduce income inequality and promotion of a good urbanization are needed. The result surrounding the extraction goods exports may indicate the need for policymakers to act directly in more remote areas were poverty is higher and development is lower, promoting the positive effects seen in Bozigar *et al.* (2016) and caused by oil extraction activities.

Chapter 5. Conclusions

This dissertation intended to understand how climate change impacts poverty in developing economies. We employed several climatic variables (CO_2 emissions, temperature, precipitation, forest area) and an absolute measure of poverty (poverty headcount ratio, assessed by the number of individuals with an income below $1.90 a day, in 2011 prices at PPP, in terms of the total population) to estimate a two-way fixed effects OLS panel econometric model for a set of 76 low- and middle-income countries for the period 1998-2014. In order to understand if regional and institutional characteristics, as well as different developmental stages, affect the way climate change may impact poverty, we also create four subsamples (Africa, Asia, Europe, Latin America and the Caribbean) and estimate cross-sectional fixed/random effects OLS models, for the period 1998-2014.

Our results show that climate change, measured by this four variables, impacts poverty in developing economies and that those impacts can change based on the intrinsic differences between regions. We find that, for the full sample, temperature positively impact poverty and CO_2 emissions negatively impact poverty. Additionally, forest area positively impact poverty but only in the baseline model. Precipitation is the only climatic variable that does not have a significant impact on poverty. In terms of the controls, both GDP *per capita* growth, investment, and health and education are important for poverty reduction, while population growth, urbanization rate, and extractive goods exports are all found to increase poverty.

Regarding the subsamples, results highlight the differences that regional, institutional, and developmental characteristics can have on the way climate change translates into poverty: in Asia and Europe an increase in CO_2 emissions is estimated to significantly decrease poverty, while forest area has mixed results over poverty: an increase in forest area in terms of total land area negatively impacts poverty in Europe and is associated with an increase in poverty in Latin America and the Caribbean. As for precipitation, it is never found to be significant. The controls also show different behaviours depending on the considered subsample: GDP *per capita* growth and education and health negatively impact poverty in all subsamples; income inequality negatively impacts poverty in Asia but in the other three subsamples it is associated with an increase in poverty; the urbanization rate is also found to positively impact poverty in all subsamples (except Africa, as it was not included); inflation and population growth contribute to higher poverty in Europe and Latin America and the

Caribbean; extractive goods exports increase poverty in Asia but decreases it in Latin America and the Caribbean.

Policymakers must take climate change seriously and act accordingly with their impact on poverty, especially if they desire to eradicate extreme poverty until 2030. Yet, results are not conclusive in terms of a single way to proceed. The increase of temperature and its impact on poverty is a cause of concern when considering the full sample. Alternatively, CO2 emissions are found to decrease poverty both in the full sample and two of the four subsamples, indicating that we may need to accept further climate degradation in developing countries through the increase in CO2 emissions, as these countries may need them to achieve a certain threshold of development in order to fully eradicate absolute poverty, with the burden of the decrease of emissions being assumed mainly by developed economies. Forest area is only significant for the baseline model (full sample) and show opposite results in Europe and Latin America and the Caribbean, indicating that forest area is important for poverty reduction in the first, but contributes to its increase in the second, which shows that policymakers must address this issue differently depending on the region considered. Finally, there are clear indicators that GDP *per capita* growth, health and education promotion, and investment all are important for the reduction of poverty and policy efforts must be made in these areas. Alternatively, a more aware promotion of urbanization and population growth is essential, while income equality and a lower dependency of extractive goods exports should be targeted by policymakers (even in the countries where it was seen that they were associated with poverty reduction, for the reasons already presented). It is important to control inflation and it must by a priority for policymakers in Latin America and the Caribbean.

Even though this dissertation addresses a very prominent area of research, its results must be seen with caution, as they compound several limitations: firstly, our analysis is limited by the fact that two different types of estimations were used for the full sample and subsamples, incurring in a homogeneity loss in our results. Secondly, it would be important to include a more multidimentional variable of poverty to better access the impact of climate change on the poor, since our results are limited to the absolute poor but many other people suffering from other levels of poverty are also affected by climate change and it is important to access its impact on them. Thirdly, even though our results provide an interesting scope on how regional differences affect the way climate change impacts poverty in developing countries, our subsamples are wider than desired (a continent includes countries with very different characteristics), which limits the comprehension we can have of the regional impact of climate change. Finally, it is important to note that, with all the advantages this type of macro level research has, it is still necessary to investigate the impact of climate change on poverty in more local and specific areas inside countries, as poor people living in specific areas can severely suffer with this phenomena.

All in all, we hope that this dissertation opens the opportunity for other researchers to further explore the impact climate change has on poverty, taking into account our results but, more importantly, its limitations, so that further steps may be done towards a more inclusive and sustainable development. Particularly, future research should incorporate a more multidimentional indicator of poverty in order to access the impact of climate change in a wider scope of poor people. Additionally, microdata (*e.g.* household level surveys) should be the primordial source of data as it would allow for a better understanding of the impact of climate change near the poor affected by it, as well as aggregating the regions in more homogeneous groups.

Much must be done in terms of research in this topic, particularly assuming an aggregated group of countries and, as stated by Stern (2007), climate change can have drastic consequences in our livelihoods and the poorest and most vulnerable will always suffer the most with it.

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Appendices

Appendix 1- Climate change and poverty: literature details

Author(s)	Main goals	Research Method	Sample	Explained variable	Explanatory variable(s)	Estimated effect	Conclusions
Winters *et al.* (1998)	Measure and compare the impact of global climate change on developing countries.	Computable General Equilibrium Model	41 developing countries from Asia, Africa, and Latin America. Induced effects predicted for the period between 1985-2050	Climate change (induced agricultural shocks for cereals and export crops)	---	---	The research focused on a General Equilibrium analysis of the future impacts of climate change, using Africa, Asia and Latin America as proxies, giving an idea of its possible consequences for global income losses. Global warming and climate change can promote negative and positive effects in developing countries, depending on their economic and social structure.
Kelly and Adger (2000)	To understand what vulnerability is and how it impacts the adaptation to climate stress situations.	Case Study	Northern Vietnam. Focused on the vulnerability to tropical storms impacts in coastal Vietnam (Red River Delta and adjacent regions)	---	---	---	Vulnerability can be defined as the capacity to respond to external stress situations. By studying the case of costal Vietnam, the authors concluded that the situation of the most vulnerable could be improved by implementing policies to reduce poverty, promote risk-spreading through income diversification, preserve property right with common interest and promote collective security.
Wunder (2001)	To review the possible synergies be-	Literature review	---	---	---	---	There is little space for forests to help alleviate poverty. The stronger focus should always be

	tween poverty alleviation and forest conservation, if they can be achieved together.						investing in education, health, institutional capacity-building, and agriculture (could promote deforestation). Forests may help poor people secure food and subsist, but its activities are not suited to alleviate poverty in a dynamic sense (few cases of success).
Heller and Mani (2002)	To present the threats developing countries face with climate change and what they can do to improve their ability to adapt to climate change.	Descriptive statistics	---	---	---	---	Climate change can impact negatively developing countries in many ways, including higher incidence of diseases, etc. It is, therefore, essential to adapt to climate change: countries must acknowledge their vulnerability so they can balance investments in mitigation/adaptation and in strengthening the economy; stimulate real growth before economic losses start to mount. The assistance of the international community is essential.
Vedeld *et al.* (2007)	Analyse if poor people in forested areas in developing countries depend on income from forest environmental resources.	Meta-analysis	51 case studies from 17 developing countries from Africa, Asia, and Latin America	---	---	---	Forest environmental income is important for the poor. The authors found that, based on the sample, forest environmental income constituted an average of about 22% of mean total household income. Also, the most dependent group on this type of income had only, on average, half the total income of the rest of the sample and, in the same community, poor households depended more on forests than the wealthier

							households.
Hertel and Rosch (2010)	Investigate the impact of climate change on poverty through its effects on agriculture.	Literature review	---	---	---	---	Climate Change can negatively influence agriculture, increasing poverty. It is important to consider that many factors influence this relationship and intervention is needed. The majority of policies used for economic development are also positive to lessen the burden of climate change on the poor.
Hallegatte *et al.* (2014)	To present the main channels through which climate change and climate policies may affect poverty.	Appreciative literature review Theoretical model	---	---	---	---	Based on four channels (prices, assets, productivity, and opportunities) that determine household consumption the authors conclude that climate change is likely to represent a major obstacle to a sustained eradication of poverty; climate policies are compatible with poverty reduction if some conditions are respected; climate change does not modify how poverty policies should be designed, but creates urgency to act.
Leichenko and Silva (2014)	To present a review of literature concerning poverty, vulnerability, and climate change, namely by exploring the channels through which poverty is impacted by climate change.	Literature review	---	---	---	---	the connections between climate change and poverty are complex, multifaceted, and context-specific. Researchers have articulated many channels though which climate change can contribute to impoverishment, directly (biophysical impact) and indirectly (associated to social, cultural, and institutional factors).

Winkler *et al.* (2015)	To reconsider how development should be made by reflecting on climate change.	Appreciative	---	---	---	---	Climate policy must explore different paths of development. The current economic order obsession with economic growth must be replaced by a discussion about the quality in development (mainly what constitutes well-being). To do so, the population's mindset must be changed in order to support a social contract that allows to lift the poor out of poverty without compromising the emissions.
Barbier and Hochard (2018)	Understand the impact of climate change on specific disadvantaged areas in less developed countries (less-favoured agricultural areas and areas along the coast with less than 10 meters of elevation).	Descriptive statistics: new global dataset created to estimate infant mortality using other datasets	Less developed countries from East and Pacific Asia, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, South Asia and Sub-Saharan Africa. Results estimated for 2000 and 2010	Poverty, using infant mortality as proxy	---	---	People living in in less favoured agricultural areas and in low elevation coastal zones have a higher risk of poverty-environment traps, further increasing their vulnerability to climate change. To fight back these situations a combination of policies is needed, and it should include the promotion of economic growth, encouragement of out-migration and improvement of the livelihoods in the stated regions.
Park *et al.* (2018)	Measure the cross-sectional relationship between household wealth and extreme heat exposure/occupation exposure to heat stress within	OLS	Household data from 52 less developed countries (survey years range between 1994 and 2013). Average	Poverty exposure bias for country *i* (share of poorest quintile exposed/share of all quintiles expose-1)	Temperature (annual average temperature from 1961–99) GDP per capita (PPP)	(+) n.s.	Poorer households tend to be located in hotter locations within hot countries, and poorer individuals are more likely to work in occupations with greater exposure to heat, not only across but also within

	countries.		monthly temperature and precipitation data collected from the CRU at the University of East Anglia (1960-2013) For GDP, agriculture share and urbanization values obtained from WB World Development Indicators		Share of agriculture (share of employment in agriculture)	n.s.	countries. This suggests that the impacts arising from climate change may be regressive within countries. However, in cold countries poor people tend to live in marginal colder areas and may benefit from moderate warming.
					Share of population living in urban areas (urbanization rate)	n.s.	
					Regional dummy	(+) in Africa	
				Wealth percentile of household *i* in country *j*	Average temperature for the hottest month of household *i* between 1960-survey year	(+), (-), n.s. depending of the country	
					<u>*Control variables*</u> Rural/urban status Household size (nº of individuals) Average annual precipitation Elevation		
Campagnolo and Davide (2019)	Understand if there is a trade-off between the Paris Agreement NDCs each country-member commits and the eradication of poverty.	Panel OLS (complemented by an inter-temporal Computable Equilibrium System Model)	Panel of 130 developed and less developed countries between 1990 and 2014	Poverty prevalence (poverty headcount ratio) Inequality (Palma ratio)	<u>*Poverty explanatory variables*</u> Average per capita income (GDPPPP2011 per capita)	(-)	A full implementation of the NDCs is projected to increase the population below the poverty line worldwide by 4.2% in 2030. If financial support for mitigation action in developing countries is provided through an international climate fund, the prevalence of poverty will be slightly reduced at the aggregate level (the country-specific effect depends of the relative
					Palma ratio (unequal income distribution indicator)	(+)	

							size of the funds and the country's economic structure).
Dorband *et al.* (2019)	Understand how carbon pricing for CO2 emissions will impact the population of low- and middle-income countries.	Microsimulation Model	Household expenditure data from 2010 and carbon intensity data from a MRIO model from 2011 collected for 87 low- and middle-income countries	Total annual additional expenditures arising from the carbon price of income	Carbon intensities of consumption items from each sector and country Total expenditures taxation	---	Neglecting medium- to long-term adjustment processes, the disposable income of the poorest group is reduced by 0.2–5.5%. In countries with an average annual per capita income below a turning point of around USD 15.000 (PPP-adjusted), carbon pricing is likely to be progressive. Even though the impact of carbon pricing in poorer countries is not very significant, it needs to be complemented by other policies and consider country effects.
Letta and Tol (2019)	Understand if weather variability and climate change influence Total Factor Productivity growth.	Fixed effect panel estimation	60 developed and developing countries covering the period between 1960 and 2006. Climatic data collected from the University of Delaware *Terrestrial Air Temperature and Precipitation: 1900-2006 Monthly Time Series*	TFP (annual growth rate of TFP)	Temperature (annual temperature change), interacted with dummy for countries that are "poor" or "hot" *Control variables*: Precipitation (annual change in precipitation levels)	(-), very significant when interacted with dummy for poor countries, hot or not; less significant when interacted with dummy for hot country	TFP is negatively affected by temperature shocks in poor countries; smaller evidence for same effect in hot countries. After a certain threshold of development is obtained by a country, climate change has near zero influence in TFP growth. This means that poverty reduction is an essential feature of future climate policy. As this research has some limitations, results must be seen with caution.
Azzarri and Signorelli (2020)	Understand what is the impact of long-term climatic condi-	OLS Spatial Autocorrelation Model	Household survey information ranging from 2002 to 2014 for	Welfare (household per capita total expenditure	*Poverty explanatory variables* *Panel A: Using*		Living in more humid areas is positively associated with welfare, while the opposite occurs living in hotter areas. Flood

tions as well as extreme weather shocks on poverty and welfare in Sub-Saharan Africa.	24 Sub-Saharan African countries. Spatial data capturing climatic conditions for several datasets used to construct annual and long-term averages for the spatial variables from 1950/1990 to the year of the household survey	and food expenditure) Poverty (poverty headcount ratio)	*SPEI shocks*		shocks are associated with a decrease in welfare and increase in extreme poverty. Extreme shortages of rain and heat shocks show an uncertain effect. Given the heterogeneous effects of climatic events across Sub-Saharan Africa macro-regions, local-specific adaptation and mitigation strategies are suggested to help households stride through a sustainable path.
			SPEI, long term average	(-)	
			SPEI flood shock dummy (1 sd)	(+)	
			SPEI drought shock dummy (1 sd)	n.s.	
			Panel B: Using temperature and rain shocks		
			Rainfall long term average (dm)	(-)	
			Temperature long term average (C)	(+)	
			Rainfall flood shock dummy (1 sd)	(+)	
			Rainfall drought shock dummy (1 sd)	(-)	
			Temperature heat shock dummy (2 sd)	n.s.	
			<u>*Control variables*</u>		
			Household is rural	(+)	
			Household head is female	n.s.	
			Age of household head	(+)	
			Mean level of education of adults (>15) in the household	(-)	
			Share of working	(-)	

					age in the household		
					Number of children (<6) in the household	(+)	
					Population density (nightlight)	(-)	
					Growing period (days, mean)	n.s.	
					Elevation (meter, mean)	n.s.	
					Per capita crop land area in the district (Ha)	(-)	
					Per capita total livestock units in the district (Ha)	(+)	
					Time to 20 k market (hrs, median	(-)	
Damania *et al.* (2020)	To understand how temperature and precipitation impact economic growth.	Fixed effects panel estimation	Panel combining set of developed and developing countries, between 1990 and 2014	GDP per capita adjusted for inflation	Rainfall Squared rainfall Temperature Squared temperature	(+) (-) (+) (-)	The authors find that precipitation has a concave relationship with GDP growth, in the period 1990-2014. The marginal economic return of an additional drop of rainfall is highest in arid areas and slowly decreases as the weather becomes wetter, until it becomes neglectable. The rainfall impact on GDP growth is only significant in developing countries. It is also found that the effects of rainfall on agriculture explain the majority of the variation on GDP growth.

					Poverty model:	Global	Africa	Asia	LA	
Dhrifi *et al.* (2020)	To test the causal linkages between foreign direct investment, poverty, and environmental quality in developing countries.	Simultaneous equation models, estimated by 3SLS	Panel of 98 developing countries from Africa, Asia and Latin America, between 1995 and 2017	Poverty index (households final consumption expenditure *per capita*)	CO2 emissions (metric tons *per capita*)	(-)	(-)	(+)	(-)	Focusing on the relationship between poverty and CO2 emissions, the authors found that results differ between the full sample and each of the regional subsamples. CO2 emissions are a factor of higher poverty when considering the sample as a whole, Africa and Latin America. In the case of Asia, emissions help reduce poverty. Also, the authors found evidence of bidirectional causality between poverty and CO2 emissions. Results vary due to institutional and structural characteristics of the countries.
					Foreign direct inflows ($ USD)	(+)	(-)	(+)	(+)	
					GDP growth *per capita* ($ USD)	(+)	(+)	(+)	(+)	
					Urbanization (urban population share of total population)	n.s	(+)	n.s	n.s	
					Financial development (total credit to the private sector as a ratio of GDP)	(+)	(+)	(+)	(+)	
					Population growth	n.s	n.s	(-)	n.s	
					Inflation rate (GDP deflator, %)	(-)	(-)	(-)	(-)	
					Education (secondary school enrolment)	(+)	(+)	(+)	(+)	

Note: the table includes the main empirical research presented in subchapter 2.3 as well as other contributions that explore the relationship between climate change and poverty.

Appendix 2- Specification and significance group effects tests for the four subsamples

Africa		Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Redundant Fixed Effects Test	Cross-section F	7.82375 (0.000)***	7.18211 (0.000)***	7.41029 (0.000)***	6.91489 (0.000)***	10.00635 (0.000)***	10.00718 (0.000)***	9.76256 (0.000)***	10.57432 (0.000)***
	Cross-section Chi-square	130.48239 (0.000)***	124.98366 (0.000)***	126.98212 (0.000)***	122.57874 (0.000)***	154.04839 (0.000)***	154.05316 (0.000)***	152.63072 (0.000)***	157.23242 (0.000)***
	Period F	0.72954 (0.749)	0.72628 (0.752)	0.74913 (0.729)	0.66944 (0.806)	0.75776 (0.710)	0.87192 (0.605)	0.79382 (0.677)	0.71053 (0.753)
	Period Chi-square	20.29253 (0.207)	20.2123 (0.211)	20.77309 (0.187)	18.80015 (0.279)	31.09319 (0.013)**	34.68623 (0.004)***	32.25048 (0.009)***	29.54476 (0.021)**
	Cross-section/Period F	5.18145 (0.000)***	4.70211 (0.000)***	4.78089 (0.000)***	4.46937 (0.000)***	6.84766 (0.000)***	6.79926 (0.000)***	6.63541 (0.000)***	7.10838 (0.000)***
	Cross-section/Period Chi-square	140.6352 (0.000)***	134.2140 (0.000)***	135.30490 (0.000)***	130.90264 (0.000)***	166.14580 (0.000)***	165.73107 (0.000)***	164.30622 (0.000)***	168.33441 (0.000)***
Hausman Test (Cross-section)		7.50811 (0.023)**	2.16663 (0.339)	6.48467 (0.039)**	2.97043 (0.227)	7.99851 (0.333)	6.49609 (0.483)	6.08824 (0.530)	8.98840 (0.254)

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Asia		Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Redundant Fixed Effects Test	Cross-section F	12.71076 (0.000)***	12.09760 (0.000)***	12.32963 (0.000)***	11.68448 (0.000)***	15.09013 (0.000)***	13.51891 (0.000)***	8.21188 (0.000)***	11.07081 (0.000)***
	Cross-section Chi-square	228.07846 (0.000)***	221.66468 (0.000)***	224.21799 (0.000)***	217.03633 (0.000)***	170.11790 (0.000)***	160.29969 (0.000)***	75.80638 (0.000)***	143.17863 (0.000)***
	Period F	1.53230 (0.095)*	1.59164 (0.077)*	1.59214 (0.077)*	1.43160 (0.134)	2.70251 (0.002)***	3.03122 (0.001)***	2.400203 (0.010)**	3.28656 (0.000)***
	Period Chi-square	29.398279 (0.021)**	30.42380 (0.016)**	30.43250 (0.016)**	27.56551 (0.036)**	53.59826 (0.000)***	58.73472 (0.000)***	44.81683 (0.000)***	62.57691 (0.000)***
	Cross-section/Period F	9.98736 (0.000)***	9.95220 (0.000)***	10.22300 (0.000)***	9.80172 (0.000)***	14.17904 (0.000)***	12.94865 (0.000)***	6.80351 (0.000)***	11.60424 (0.000)***
	Cross-section/Period Chi-square	261.63549 (0.000)***	261.48952 (0.000)***	265.42040 (0.000)***	259.27119 (0.000)***	231.05431 (0.000)***	221.86360 (0.000)***	122.68336 (0.000)***	210.93650 (0.000)***
Hausman Test (Cross-section)		21.93911 (0.000)***	9.81207 (0.007)***	10.69756 (0.005)***	11.21017 (0.004)***	56.75937 (0.000)***	44.65603 (0.000)***	57.16276 (0.000)***	99.03303 (0.000)***

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Europe		Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Redundant Fixed Effects Test	Cross-section F	4.81424 (0.000)***	5.37108 (0.000)***	5.35392 (0.000)***	4.88475 (0.000)***	15.10541 (0.000)***	5.06665 (0.000)***	8.21188 (0.000)***	11.19425 (0.000)***
	Cross-section Chi-square	51.35163 (0.000)***	55.98815 (0.000)***	55.84814 (0.000)***	51.94972 (0.000)***	110.77576 (0.000)***	53.73980 (0.000)***	75.80638 (0.000)***	92.64080 (0.000)***
	Period F	2.60690 (0.003)***	2.01252 (0.022)**	1.86296 (0.037)**	1.86181 (0.037)	4.42949 (0.000)***	2.35415 (0.011)**	2.400203 (0.010)**	3.53324 (0.000)***
	Period Chi-square	45.73828 (0.000)***	36.87024 (0.002)***	34.52037 (0.005)***	34.50205 (0.005)	70.49744 (0.000)***	44.13863 (0.000)***	44.81683 (0.000)***	60.05585 (0.000)***
	Cross-section/Period F	4.66399 (0.000)***	4.26463 (0.000)***	3.86952 (0.000)***	3.99776 (0.000)***	10.52868 (0.000)***	4.93842 (0.066)*	6.80351 (0.000)***	8.57460 (0.000)***
	Cross-section/Period Chi-square	100.56228 (0.000)***	94.78863 (0.000)***	88.75861 (0.000)***	90.75263 (0.000)***	153.23614 (0.000)***	102.25853 (0.000)***	122.68336 (0.000)***	138.51815 (0.000)***
Hausman Test (Cross-section)		23.31772 (0.000)***	15.13731 (0.001)***	15.26546 (0.001)***	15.24393 (0.001)***	107.35326 (0.000)***	64.49511 (0.000)***	97.90529 (0.000)***	99.03303 (0.000)***

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Latin America and the Caribbean		Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
Redundant Fixed Effects Test	Cross-section F	17.14520 (0.000)***	18.86290 (0.000)***	19.28827 (0.000)***	18.18416 (0.000)***	10.12483 (0.000)***	6.67846 (0.000)***	11.10162 (0.000)***	12.64034 (0.000)***
	Cross-section Chi-square	187.56589 (0.000)***	199.45037 (0.000)***	202.28849 (0.000)***	194.83747 (0.000)***	117.10851 (0.000)***	87.82631 (0.000)***	124.32751 (0.000)***	134.93847 (0.000)***
	Period F	1.99221 (0.016)**	1.95383 (0.019)**	2.01665 (0.015)**	1.07294 (0.385)	1.00193 (0.462)	1.20143 (0.605)	0.95221 (0.515)	1.06815 (0.397)
	Period Chi-square	35.09351 (0.004)***	34.47184 (0.005)***	35.48818 (0.003)***	19.65341 (0.236)	21.36470 (0.165)	25.22676 (0.283)	20.38396 (0.203)	22.65956 (0.123)
	Cross-section/Period F	13.59493 (0.000)***	15.70448 (0.000)***	16.01078 (0.000)***	16.09024 (0.000)***	6.37660 (0.000)***	3.86753 (0.066)*	7.18968 (0.000)***	7.70592 (0.000)***
	Cross-section/Period Chi-square	253.55318 (0.000)***	274.80591 (0.000)***	277.71390 (0.000)***	278.46152 (0.000)***	145.02237 (0.000)***	105.19381 (0.000)***	155.67469 (0.000)***	162.00817 (0.000)***
Hausman Test (Cross-section)		78.81926 (0.000)***	57.81931 (0.000)***	61.80018 (0.000)***	83.43059 (0.000)***	6.80813 (0.743)	4.84046 (0.902)	6.78089 (0.746)	10.85175 (0.369)

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Appendix 3- Climate change impact on poverty per subsample- Africa, Asia, Europe, Latin America and the Caribbean (1998-2014)

Dependent Variable: Poverty Headcount Ratio (HCR)- Africa								
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Constant	343.8663 (0.0000)***	289.0026 (0.0000)***	316.8413 (0.0000)***	247.4194 (0.0000)***	209.7551 (0.0000)***	234.3200 (0.0000)***	207.5713 (0.0000)***	209.8238 (0.0000)***
CO2GDP	-86.38543 (0.1151)				-6.621120 (0.8540)			
TEMP		-0.965844 (0.2194)				-0.634979 (0.4876)		
PRE			-0.020215 (0.2459)				0.003309 (0.5488)	
FOREST				0.229854 (0.1895)				0.250731 (0.2314)
LOGGDP	-37.05886 (0.0000)***	-28.88762 (0.0000)***	-33.27640 (0.0001)***	-27.27101 (0.0000)***	-24.68298 (0.0000)***	-25.97280 (0.0000)***	-24.83488 (0.0000)***	-25.01409 (0.0000)***
GINI					0.824521 (0.0057)***	0.803845 (0.0048)***	0.815483 (0.0026)***	0.728946 (0.0058)***
EDUCH					-0.875301 (0.0319)**	-0.919391 (0.0348)**	-0.918370 (0.0235)**	-0.856440 (0.0281)**
INF					-0.050706 (0.8217)	-0.039059 (0.8610)	-0.052319 (0.8132)	-0.039949 (0.8598)
GCF					-0.187578 (0.2792)	-0.173134 (0.2968)	-0.180698 (0.2911)	-0.186627 (0.2520)
EXTRAC-TIVE					-0.060000 (0.4024)	-0.044404 (0.5312)	-0.059516 (0.4282)	-0.071226 (0.3540)
Model Summary								
R-Squared	0.923244	0.487997	0.920433	0.498169	0.619195	0.624365	0.621768	0.632257
Adjusted R-Squared	0.892272	0.474869	0.888327	0.485301	0.570729	0.576556	0.573629	0.585453
F-statistic	29.80927	37.17145	28.66855	38.71538	12.77584	13.05979	12.91620	13.50871
Prob (F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observa-tions	81	81	81	81	63	63	63	63
Number of countries	22	22	22	22	21	21	21	21

Note (1): p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).
Note (2): UNEMP is highly correlated with CO2GDP (0.92), TEMP (-0.73), LOGGDP (0.79), and GINI (0.67). POPGROWTH is highly correlated with HCR (0.75), CO2GDP (-0.63), TEMP (0.85), and LOGGDP (-0.88). URBAN is highly correlated with HCR (-0.72), CO2GDP (0.66), TEMP (-0.76), and LOGGDP (0.89). Because of this the three variables were excluded from the Africa subsample.

Dependent Variable: Poverty Headcount Ratio (HCR)- Asia								
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Constant	249.1561 (0.0000)***	216.7542 (0.0000)***	219.8926 (0.0000)***	214.9364 (0.0000)***	349.9403 (0.0000)***	330.4273 (0.0000)***	303.6743 (0.0000)***	303.6236 (0.0000)***
CO2GDP	-24.10294 (0.1359)				-41.54839 (0.0001)***			
TEMP		0.444161 (0.5868)				-1.612536 (0.0696)*		
PRE			0.003579 (0.2867)				-0.000176 (0.9428)	
FOREST				0.555025 (0.4433)				-0.011268 (0.9835)
LOGGDP	-25.97638 (0.0000)***	-24.07291 (0.0000)***	-24.12965 (0.0000)***	-24.63114 (0.0000)***	-35.64069 (0.0000)***	-32.18507 (0.0000)***	-31.76246 (0.0000)***	-31.74058 (0.0000)***
GINI					-0.771033 (0.0000)***	-0.716493 (0.0001)***	-0.746603 (0.0000)***	-0.747517 (0.0001)***
EDUCH					-1.566731 (0.0000)***	-1.813610 (0.0000)***	-1.752822 (0.0000)***	-1.754867 (0.0000)***
INF					-0.088315 (0.1735)	-0.093299 (0.1641)	-0.089759 (0.2008)	-0.089514 (0.2040)
UNEMP					-0.055361 (0.8486)	-0.054782 (0.8522)	-0.069375 (0.8230)	-0.069032 (0.8288)
GCF					0.073583 (0.4834)	-0.037867 (0.7210)	-0.022291 (0.8381)	-0.022201 (0.8400)
POP-GROWTH					-0.119345 (0.8957)	0.270220 (0.8160)	0.001694 (0.9988)	0.001755 (0.9987)
URBAN					0.359961 (0.0924)*	0.402508 (0.1115)	0.346074 (0.1651)	0.345249 (0.1560)
EXTRAC-TIVE					0.347409 (0.0002)***	0.378070 (0.0001)***	0.369681 (0.0003)***	0.368684 (0.0004)***
Model Summary								
R-Squared	0.807325	0.805263	0.805907	0.807302	0.914355	0.904980	0.901774	0.901771
Adjusted R-Squared	0.775590	0.773376	0.774125	0.775749	0.890151	0.878127	0.874014	0.874010
F-statistic	25.43973	25.25378	25.35782	25.58568	37.77683	33.70084	32.48511	32.48400
Prob (F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	199	200	200	200	119	119	119	119
Number of countries	27	27	27	27	17	17	17	17

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).

Dependent Variable: Poverty Headcount Ratio (HCR)- Europe								
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Constant	197.3826 (0.0021)***	146.3350 (0.0000)***	145.9011 (0.0000)***	146.6584 (0.0000)***	100.2383 (0.0299)**	41.09888 (0.2785)	42.51796 (0.2856)	123.4170 (0.0342)**
CO2GDP	-12.16863 (0.2344)				-19.58481 (0.0034)***			
TEMP		1.252569 (0.2604)				0.600926 (0.5032)		
PRE			-0.000357 (0.8860)				0.000256 (0.9445)	
FOREST				-0.087948 (0.5892)				-3.949944 (0.0340)**
LOGGDP	-20.28754 (0.0016)***	-16.45259 (0.0000)***	-15.32754 (0.0000)***	-15.11320 (0.0000)***	-25.76741 (0.0000)***	-20.65589 (0.0001)***	-20.42247 (0.0001)***	-12.43708 (0.0019)***
GINI					0.888203 (0.0000)***	0.860325 (0.0000)***	0.866989 (0.0000)***	0.647427 (0.0034)***
EDUCH					-0.452691 (0.0024)***	-0.432458 (0.0056)***	-0.444416 (0.0047)***	-0.420812 (0.0043)***
INF					0.021292 (0.0087)***	0.011323 (0.2465)	0.013344 (0.1661)	0.008558 (0.3571)
UNEMP					-0.009491 (0.9685)	-0.055014 (0.8393)	-0.113443 (0.6699)	0.134357 (0.5968)
GCF					0.082495 (0.4975)	0.038167 (0.7572)	0.038897 (0.7521)	0.029560 (0.7906)
POP-GROWTH					1.923765 (0.1607)	4.079515 (0.0168)**	4.095690 (0.0224)**	4.806848 (0.0033)***
URBAN					1.996685 (0.0002)***	2.015731 (0.0017)***	2.035907 (0.0016)***	1.598990 (0.0049)***
Model Summary								
R-Squared	0.560760	0.556557	0.549052	0.549489	0.844248	0.823046	0.821652	0.836267
Adjusted R-Squared	0.505855	0.501127	0.492684	0.493175	0.804197	0.777544	0.775791	0.794164
F-statistic	10.21327	10.04065	9.740421	9.757605	21.07953	18.08799	17.91612	19.86245
Prob (F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	109	109	109	109	89	89	89	89
Number of countries	11	11	11	11	10	10	10	10

Note (1): p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).
Note (2): EXTRACTIVE is highly correlated with TEMP (-0.85), FOREST (0.78), LOGGDP (0.68), and URBAN (0.63). Because of this EXTRACTIVE was excluded from the Europe subsample.

Dependent Variable: Poverty Headcount Ratio (HCR)- Latin America and the Caribbean								
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Constant	272.3438 (0.0000)***	274.7774 (0.0000)***	261.4319 (0.0000)***	208.6520 (0.0000)***	29.11694 (0.2743)	53.70499 (0.0311)**	30.52839 (0.1776)	34.76716 (0.1753)
CO2GDP	-17.19236 (0.1309)				-5.971187 (0.5543)			
TEMP		-0.738905 (0.3875)				-1.042949 (0.0416)**		
PRE			-0.000474 (0.6182)				-0.000721 (0.1793)	
FOREST				0.571453 (0.0000)***				0.257447 (0.0123)**
LOGGDP	-28.53914 (0.0000)***	-27.33420 (0.0000)***	-27.64993 (0.0000)***	-24.63025 (0.0000)***	-7.954381 (0.0180)**	-7.879508 (0.0035)***	-8.406505 (0.0056)***	-7.789126 (0.0137)**
GINI					0.810280 (0.0000)***	0.797826 (0.0000)***	0.805214 (0.0000)***	0.720720 (0.0000)***
EDUCH					-0.240619 (0.0295)**	-0.228091 (0.0329)**	-0.236207 (0.0316)**	-0.221639 (0.0540)*
INF					0.077760 (0.0346)**	0.077471 (0.0297)**	0.081455 (0.0287)**	0.082723 (0.0171)**
UNEMP					0.114411 (0.3925)	0.128896 (0.2749)	0.122546 (0.2978)	0.065158 (0.5961)
GCF					0.026552 (0.7978)	0.029043 (0.7679)	0.036984 (0.7275)	-0.008803 (0.9298)
POP-GROWTH					2.852635 (0.0289)**	2.279195 (0.0620)*	3.002432 (0.0084)***	0.288156 (0.8463)
URBAN					0.131026 (0.2322)	0.128551 (0.1268)	0.168167 (0.0734)*	-0.022608 (0.8159)
EXTRAC-TIVE					-0.068777 (0.0020)***	-0.076543 (0.0002)***	-0.066981 (0.0014)***	-0.084083 (0.0000)***
Model Summary								
R-Squared	0.826915	0.824422	0.823883	0.856722	0.865939	0.868699	0.864500	0.874643
Adjusted R-Squared	0.810924	0.808200	0.807612	0.843485	0.854578	0.857572	0.853017	0.864019
F-statistic	51.70957	50.82168	50.63311	64.71887	76.21967	78.06986	75.28465	82.33097
Prob (F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observa-tions	202	202	202	202	129	129	129	129
Number of countries	16	16	16	16	14	14	14	14

Note: p-value in parenthesis. Significance level at 0.01 (***), 0.05 (**) and 0.1 (*).