Examining the relationship between climate change-related research output and CO2 emissions

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Abstract

Climate change has been a pressing global issue in current times, which has seen many initiative programs set out to try and limit the rise in CO2 emissions globally. The main purposes of this study are to first determine if the importance of climate change research output has increased by undergoing a bibliometric analysis using the Clarivate Analytics core collection (between 1956-2019). Findings showed that the overall number of climate change-related research output has gone up exponentially from 1956 up to 2019 and that the proportion of climate change-related papers to total papers has gone up substantially during that period. Next will be to examine the causal dynamics between CO2 emissions, Research Output and expenditure on R&D (GERD), considering the role GDP plays with those variables for the top 50 climate change-related research output producing countries. This study also looks at this relationship by isolating developed vs developing countries and doing an income-based classification between the countries. Panel data techniques were employed as proposed by Emirmahmutoglu and Kose (2011) for the period 1996-2019. From the Granger causality analysis, findings showed that causality runs from Research Output to CO2, CO2 to GERD and GDP to GERD for the entire sample. To account for any limitations in the test results, the individual WALD test statistics and p-values for every country using the LA-VAR Granger causality method is also reported.

Keywords: Research Output; GDP; R&D; Global warming; Climate Change; CO2 emissions

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1. Introduction

Climate change is defined as the long-term change in the average weather patterns that have come to define the earth's climates (NASA, 2019). The international scientific and policy community have all agreed that the global temperatures are increasing at rapid rates that will lead to negative future consequences unless action is taken now in the present day, rather than later (Hakimi & Inglesi-Lotz, 2020). Based on recent research, scientists and top officials have made it clear that something has to be done now to help slow down global warming (Hakimi & Inglesi-Lotz, 2020). Recent data support this assertion by showing a consistent rise in global CO2 emissions up to the latest available data on CO2 emissions (The World Bank, 2020a). The data is a clear motivation for researchers to increase their investigations in the field to find present-day solutions for future problems that will inevitably be caused by climate change. The seriousness of the problem as shown in the adoption of the Kyoto protocol in 1997 in which some countries came together and agreed to slow down their GHG emissions to fulfil their commitments to try and reduce average global temperatures from rising (UNFCCC, 2012). A more recent global consensus reached in signing the Paris Agreement by the United Nations (UN) framework to try and keep global temperatures rise below 2°C above pre-industrial levels mirrored by the urgency of addressing the global climate change challenge (UNFCCC, 2015).

Society is faced with the challenge of moving towards cleaner energy while still maintaining a high level of production. Only through improving current technology to help industries and countries to become more energy-efficient and move towards green energy solutions as a whole, will we achieve this. This in turn will lead to non-energy benefits such as reduced capital costs, less strain on the environment and improved productivity (Worrell et al., 2002). This is where the importance of energy and climate change research comes in to play, to help educate society to understand the importance of lowering GHG emissions and offer solutions. This will help put pressure on governments to prioritise their focus on developing technology and implement policies that will lower emissions and slow down global warming. Increasing such research will help governments with future policy implementation to lower emissions and transition towards cleaner energy solutions. This is shown by countries like South Africa and Canada imposing a carbon tax system (Duff, 2008; van Heerden et al., 2016) and most European countries following the European Union's emissions trading system (ETS) to help lower GHG emissions (Skovgaard, 2017). There are also potential problems that can arise from research in the climate change field. Rosen (2015) argues that the Kyoto Protocol is a case of institutional design failure which stems from the introduction of initiatives without adequate research. Countries know that climate change is unavoidable, but rather a case of avoiding worst-case scenarios, hence implementing the appropriate policies and climate change plans is of utmost importance (IPCC, 2014). Rosen's (2015) argues that the Kyoto Protocol's main failure comes at the cost of the global community's main commodity that cannot be replaced: time. The adoption of a flawed institution has meant that experts have missed out on promoting alternative methods that could potentially have performed better which has set back two decades worth of climate change solutions. It is indisputable that research is of great importance in all fields of study, but ultimately if not done thoroughly and if the implementation of the proposed solutions thereof is not done appropriately, can lead to costly consequences.

Most of the literature discusses the causality between research output and economic growth, all from which used different periods and country groups in their samples which has revealed some interesting results (Hakimi & Inglesi-Lotz, 2020; Inglesi-Lotz et al., 2014, 2015; Lee et al., 2011; Ntuli et al., 2015). The resulting conclusions were that in many of the countries discussed, mutual causality was found to be the result between research output and economic growth, however, there were also several countries which showed unidirectional causality or no causality at all such as the United States, Germany, Switzerland, France, etc., mainly industrialised countries. Developing countries such as Brazil, India, South Korea, Singapore, Taiwan and many other Asian countries appeared to show some form of a causal relationship between the variables (Inglesi-Lotz et al., 2014, 2015; Lee et al., 2011; Ntuli et al., 2015). For those that showed causality, research revealed that an increase in investment towards Research and Development (R&D) activities and academic institutions will promote higher economic growth to even better research performance and improved human capital and vice versa (Inglesi-Lotz et al., 2015). It is clear from research already conducted that the relationship between research output and economic growth is weaker with developed countries compared to developing ones (Inglesi-Lotz et al., 2014; Lee et al., 2011).

The purpose of this study is to examine the impact of climate change-related research output on the CO2 emissions through R&D by quantitively determining the existence and direction of the causality between climate change-related research output and CO2 emissions. It is therefore essential to understand and use the studies that already exist, that look at the relationship between academic research output and economic growth, followed by the relationship between economic growth and CO2 emissions and lastly the relationship between innovation and CO2 emissions A variety of different indicators were used in the literature for knowledge such as R&D (Fedderke & Schirmer, 2006) or scientometric indicators (De Moya-Anegón & Herrero-Solana, 1999; Inglesi-Lotz & Pouris, 2013; King, 2004; Lee et al., 2011; Vinkler, 2008). One of the most objective and simplest methods of analysing innovation and research in a country is through the use of scientometric indicators (Pouris & Pouris, 2009). According to Inglesi-Lotz, Balcilar and Gupta (2014) this may refer to "the quantity of research output (number of published academic papers), specific quantity or share (number of published academic papers per capita or share of a country's published academic papers to the world) or impact to the literature (number of citations or the average number of citations per published academic paper)" (2014, p. 204). One of the most objective and simplest methods of analysing innovation and research in a country is through the use of scientometric indicators (Pouris & Pouris, 2009)

From a policy point of view, the results can potentially be useful in terms of the funding that goes into research institutions in investigating climate change and searching for solutions.

This study will start with a bibliometric analysis of climate change-related literature to examine the patterns of this kind of research between the period 1956-2019. The study aims to use the results obtained from the analysis to see if there has been any noticeable trend in the literature over time. It will also look to see if the importance of the topic “climate change” has risen in terms of the number of academic papers published or other indicators as their share to other fields from the countries in the sample.

The second part of this study will use econometric methods to test if a causal relationship exists between scientific climate change-related research output and CO2 emissions in the top 50 countries releasing climate change-related research output from the year 1996 up until the end of 2019. More specifically, a panel data method proposed by Emirmahmutoglu and Kose (2011) will be used to test for Granger causality for the period of 1996-2019. The top 50 countries will be chosen via ranking of the information in the first part of the study with data derived from the Clarivate Analytics Core Collection which consists of the - Science Citation Index Expanded, Social Sciences Citation Index, Arts and Humanities Citation Index, Emerging Sources Citation Index, Conference Proceedings Citation Index, Book Citation Index, Current Chemical Reactions and Index Chemicus. Through a phrase-based query approach, we will be able to see who the top contributors are when it comes to publishing climate change-related papers (Pouris, 2016).

This study is structured as follows: section 2 presents an analysis of recent studies in the field. Section 3 gives details on the methodology and data description, while section 4 presents the empirical findings and the last section concludes and provides policy insights.

2. Literature Review

The study of the impact of the changes and improvements in the academic literature on climate change and its effect on overall GHG emissions has not been explored in recent literature. Research plays an important role in the process of improving productivity levels in an economy through either technological improvements or improved human capital. The idea of improved human capital in the sense of a more skilled, educated and knowledgeable workforce leading to higher economic growth is not a new one. Romer (1986) argued that a firms productivity level is higher, the higher the average knowledge stock of their labour base is. Both theoretical (Becker et al., 1990; Lucas, 1988; Romer, 1986) and applied studies on the matter (De Moya-Anegón & Herrero-Solana, 1999; Fedderke & Schirmer, 2006; Fedderke, 2005; Inglesi-Lotz et al., 2014, 2015; King, 2004; Lee et al., 2011; Ntuli et al., 2015; Shelton & Leydesdorff, 2012; Vinkler, 2008) have shown some form of evidence on the relationship, highlighting that improved human capital can be obtained through the accumulation of knowledge. From a microeconomic perspective, knowledge externalities are positive for economic productive capacity as well as from the macroeconomic side in which higher knowledge from the labour force brings about numerous advantages when it comes to economic growth, innovation and development.

Based on the two variables looked at, economic growth is one that can easily be obtained by looking at a country's level of GDP or GDP per capita (Inglesi-Lotz et al., 2014). The important questions that arise, however, is how the quality of human capital can be measured and further improved (Inglesi-Lotz et al., 2014)? Several activities could be looked at such as training, life education and higher education. Producing new and improved academic literature in the field (research output) can be a factor in improving human knowledge and expertise that is responsible for the level of human capital in a country (Inglesi-Lotz & Pouris, 2013).

Vinkler (2008) and Lee et al.(2011) argue that the direction of the causality comes from a countries stage in economic development. It was shown that Brazil and most Asian countries, which are all developing nations from the test groups showed mutual causality between economic growth and research output. This was in contrast to the other test groups which were developed countries, which either showed one-way causality or no relationship at all (Lee et al., 2011). This could be due to the industrial development showed by the developing nations which have been guided by their technology and science policies they have implemented to improve their productivity (Lee et al., 2011). In contrast, causal relationships between research and economic growth are weak for more wealthy and developed nations due to grants for research being targeted primarily to enhancing future potential growth rather than on immediate industrial requirements (Vinkler, 2008). Most studies assume that changes in a countries level of development as well as policies implemented for research at higher levels can alter the direction of the causality. All of the studies agree that the direction of causality will remain the same in the long-run unless the country's overall level of development changes. Ultimately, research has shown that the relationship between research output and economic growth is weaker in developed countries compared to developing, and also show that developed countries show a stronger relationship when they going through economic slumps such as a recession (Inglesi-Lotz et al., 2014; Lee et al., 2011). Granger causality tests were used to determine if there is causality between the two variables in either a single country (Inglesi-Lotz & Pouris, 2013) or multicountry analysis (Lee et al., 2011; Vinkler, 2008) but were then improved by using a bootstrap Granger non-causality test with fixed size rolling subsamples to analyse the time-varying causal links between the two series (Inglesi-Lotz et al., 2014). This was done because the initial tests ignored structural shifts and instability in the economy, which would influence results where the bootstrap method would not.

Looking at the relationship between CO2 emissions and economic growth, some studies (Anwar et al., 2020; Aye & Edoja, 2017; Chen et al., 2019; Farhani & Rejeb, 2012; Kais & Ben Mbarek, 2017; Kasman & Duman, 2015; Mohmmed et al., 2019; Omri, 2013; Ozturk & Acaravci, 2010; Sharif et al., 2019; Song et al., 2019; Uddin et al., 2017; York, 2012; Zakarya et al., 2015; Zhou et al., 2018) showed that an increase in GDP per capita would lead to an increase in emissions (Anwar et al., 2020; Chen et al., 2019; Mohmmed et al., 2019; Omri, 2013; Sharif et al., 2019; Song et al., 2019; York, 2012; Zakarya et al., 2015; Zhou et al., 2018) while others found no link at all either in the long-run or the short-run (Farhani & Rejeb, 2012; Ozturk & Acaravci, 2010). Rejeb and Farhani (2012) tested the link between economic growth, energy consumption and CO2 emissions in MENA countries and found that there was no causal relationship between GDP and energy consumption; and between CO2 emissions and energy consumption in the short run. However, they found that there was unidirectional causality from GDP and CO2 emissions to consumption in the long-run. York (2012, p.

762) found that the variables used were inelastic and obtained diminishing returns as an increase in GDP per capita in affluent nations lead to an increase in CO_2 emissions which were less than those in low-income countries. Similar studies found that an increase in energy consumption was the major cause of the increase in emissions and that economic growth was the main determinant in the increase in energy consumption (Omri, 2013; Zhou et al., 2018). Researchers also looked if those countries supported the Environmental Kuznets Curve (EKC) hypothesis, which in turn would support the relationship between an increase in CO_2 emissions through economic growth up to a certain point (Chen et al., 2019; Kasman & Duman, 2015; Omri, 2013; Sharif et al., 2019; Song et al., 2019; Zhou et al., 2018). (Ozturk & Acaravci, 2010). Kasman and Duman (2015) tested the causal relationship between energy CO_2 emissions, energy consumption, trade openness, urbanization and economic growth for a panel of new EU member and candidate countries from the year 1992 to 2010. The EKC hypothesis was supported by their study (Kasman & Duman, 2015).

All the literature used panel data models to obtain their results, where they tested the relationship using cointegration techniques (Anwar et al., 2020; Aye & Edoja, 2017; Farhani & Rejeb, 2012; Kais & Ben Mbarek, 2017; Kasman & Duman, 2015; Ozturk & Acaravci, 2010; Sharif et al., 2019; Uddin et al., 2017; Zakarya et al., 2015), others created a logarithmic mean divisia index (LMDI) (Mohmmed et al., 2019) and some used simultaneous equations models to obtain their results (Omri, 2013).

Turkey showed different results to most of the studies conducted, as there was no causal relationship found between real GDP per capita and CO_2 emissions as well as energy consumption and CO_2 emissions (Ozturk & Acaravci, 2010). , while a study by Aye and Edoja (2017) used a dynamic panel threshold model to test the effect of economic growth on CO_2 emissions. They found that from a Panel of 31 developing countries, that economic growth had a negative effect on CO_2 emissions in low growth regimes and a positive one on CO_2 emissions in high growth regimes (Aye & Edoja, 2017). The same test was done on three North-African countries namely Algeria, Tunisia and Egypt where results showed unidirectional causality running from economic growth to CO_2 and also from energy consumption to CO_2 emissions using Panel cointegration techniques (Kais & Ben Mbarek, 2017). Another study (Anwar et al., 2020) looked at the impact of urbanization and economic growth on CO_2 emissions using a panel data-fixed effect model that accounts for time-invariant country-specific characteristics in far east Asian countries. Results showed that economic growth, trade openness and urbanization had significant effects on overall CO_2 emissions in the Asian countries tested. Uddina (2017) did a similar test on the 27 highest emitting countries using Pedroni co-integration tests, followed by using the DOLS (dynamic ordinary least squares) and FMOLS (fully modified ordinary least squares) tests. The findings showed that a long-run relationship does indeed exist between all the variables and that EF and real income share a positive and significant long-run relationship. Results also showed that trade openness had a negative impact on EF and that financial development reduces EF. Finally, a study by Hatemi-J. et al. (2016) looked at the relationship between economic growth and CO_2 emissions in G7 countries because they contributed 73.46% of global research output. More recently, Inglesi-Lotz and Ndlovu (2020) which tested the causal relationship between economic growth and RE and Non-RE energy through R&D for the BRICS countries for the period 1996-2015. There was one-way causality from Non-RE to GDP in South-Africa and Brazil; from Non-RE to R&D for Brazil, China and Russia and from GDP to R&D in South-Africa, Russia and India (Ndlovu & Inglesi-Lotz, 2020).

Lastly, focusing at the relationship between innovation and CO_2 emissions, Hashmi and Alam (2019) examined the effects of environmental regulation and innovation on carbon emission reduction of OECD countries during the period 1999 to 2014 using a STIRPAT ("stochastic impacts by regression on population, affluence, regulation, and technology) model. Another study by Lee and Min (2015) examines the impact of development investment and green research for eco-innovation on financial and environmental performance. The study was done on a sample of Japanese manufacturing firms from 2001 to 2010. Findings showed that there is a negative relationship between green R&D and CO_2 emissions, whilst green R&D is positively related to financial performance at the firm level (Lee & Min, 2015).

The literature that studies the nature and direction among the variables discussed here has not reached consensus as this kind of relationships change often. A positive relationship between GDP per capita and energy consumption does not constitute a necessary condition for the increase of CO2 emissions, as the type of energy used (renewable or non-renewable) also plays a role (Chen et al., 2019). Developed countries with higher economic growth can provide better opportunities to improve their knowledge and produce better human capital due to their wealth compared to developing countries (The World Bank, 2020). Developing countries, on the other side, are benefitted by improved human capital through R&D. This could be due to the industrial development showed by these nations which have been guided by their technological improvements and science policies which have been implemented to improve their overall productivity levels (Lee et al., 2011).

Taking into consideration the positive impact of economic growth to CO2 emissions and the role of innovation and R&D in this relationship, this paper explores the question of how the climate-change research output might influence or get influenced by CO2 emissions. This paper is close to the study by Hakimi and Inglesi-Lotz (Hakimi & Inglesi-Lotz, 2020) that confirmed a positive impact of emissions to innovation.

3. Methodology and Data analysis

This study will consist of a mixed methodological approach of qualitative and quantitative data analysis as it would best represent the relationship between climate change-related research output and CO2 emissions to help prove the hypothesis in question. The research will focus on a quantitative study, which will consist of doing a bibliometric analysis on climate change-related research output between the period 1956-2019. This will be followed by using a Granger causality test proposed by Emirmahmutoglu and Kose (2011) to determine if a relationship does indeed exist between climate change-related research output and CO2 emissions between the years 1996-2019.

3.1 Theoretical framework

The hypothesis of this paper stems from a question yet to be answered in previous papers, which is "examining the relationship between climate change-related research output and CO2 emissions". Based on similar studies, we looked at papers that examined the relationship between CO2 emissions and economic growth, economic growth and research output and lastly between innovation and CO2 emissions. With global warming and climate change becoming ever-growing global issues, it becomes more important to examine studies that can potentially help contribute to future policymaking when it comes to decisions that can help lower overall CO2 emissions. Following the review of related studies (Anwar et al., 2020; Aye & Edoja, 2017; Becker et al., 1990; Chen et al., 2019; De Moya-Anegón & Herrero-Solana, 1999; Emirmahmutoglu & Kose, 2011; Farhani & Ozturk, 2015; Farhani & Rejeb, 2012; Fedderke, 2005; Fedderke & Schirmer, 2006; Hakimi & Inglesi-Lotz, 2020; Hatemi-J et al., 2016; Inglesi-Lotz et al., 2014, 2015; Inglesi-Lotz & Pouris, 2013; Kais & Ben Mbarek, 2017; Kasman & Duman, 2015; King, 2004; Lee & Min, 2015; Lee et al., 2011; Lucas, 1988; Mohmmed et al., 2019; Ndlovu & Inglesi-Lotz, 2019, 2020; Ntuli et al., 2015; Omri, 2013; Pouris & Pouris, 2009; Romer, 1986; Sharif et al., 2019; Shelton & Leydesdorff, 2012; Song et al., 2019; Uddin et al., 2017; Vinkler, 2008; York, 2012; Zakarya et al., 2015; Zhou et al., 2018) examining these points, there was one main link that remained to be tested which is looking if there is any link between climate change-related research output and CO2 emissions. This will determine if climate change research has made any difference when it comes to curbing CO2 emissions and will help with future policymaking when it comes to funding into climate change research as well as the actual implementation of it.

The theoretical framework that will be used in this study will come from the combined experience of others, mainly by Emirmahmutoglu and Kose (2011). This paper proposes a Granger causality test using an LA-VAR approach by Toda and Yamamoto (1995) in heterogenous mixed panels using a Meta-analysis (2011). Monte Carlo experiments are used to examine the finite sample properties of the causality test based on the Meta-analysis on mixed panels characterized by both cross-section dependency and cross-section independency. Each Monte Carlo experiment considers four different data generating processes (DGP's) in mixed panels involving I(0), I(1), cointegrated and non-cointegrated series (2011). The simulation results for the LA-VAR approach under both cross-section dependency and cross-section independency indicate that it is still very strong, even if it is in the presence of a small N and T. That being said, the LA-VAR approach seems to have a good empirical size for a large T in mixed panels under cross-section independence (2011). The empirical size is converging at a 5% nominal size when N is fixed and $T \rightarrow \infty$, however, when N becomes large, size distortions occur for small values for T (2011). Using the bootstrap approach, the Monte Carlo experiment results show that for a finite sample under the cross-section dependency assumption, the LA-VAR approach undergoes serious size distortions for small values of T as $N \rightarrow \infty$. However, the empirical size corrects itself as $T \rightarrow \infty$ and it converges back to the 5% nominal size (Emirmahmutoglu & Kose, 2011).

This framework is then applied to determine the linkage between Research Output and CO2 emissions, and GERD and CO2 emissions and what role GDP plays on both of these variables by using the LA-VAR approach for a balanced panel of the top 50 climate change-related research output producing countries for the period of 1996-2019. To deal with the cross-correlations within the panels in our sample, the bootstrap method is used to generate the empirical distributions of the Fisher test (2011).

3.2 Empirical methodology

If the variables are found to be stationary or first-differenced, therefore I (1) and not cointegrated, then the traditional pairwise Granger causality tests are valid. If the variables are found to be a mix of I (1) and I (0), then the methodology set by Emirmahmutoglu and Kose for mixed panels will be used (2011). For us to test for the presence of unit roots and determine the order of cointegration of a panel, it will require to undergo stationarity and cointegration tests. Unit root and cointegration tests have been used in the recent literature for studies examining the interlinkages of research output (Hakimi and Inglesi-Lotz, 2020; Hatemi-J. et al. 2016; Inglesi-Lotz and Pouris, 2013)

To determine whether GDP, CO2 emissions, Research Output and expenditure on R&D (GERD) are stationary, two-unit root tests will be carried out, namely: the Pesaran and Shin (2003) and the Fisher unit root tests(1932) as it does not require a balanced data set. The Fisher test will consist of both the Phillips Perron (1988) and the Augmented Dickey-Fuller method (Levin et al., 2002). In statistics, the Dickey–Fuller test tests the null hypothesis that a unit root is present in an autoregressive model (where A statistical model is autoregressive if it predicts future values based on past values. For example, an autoregressive model might seek to predict a stock's future prices based on its past performance. The alternative hypothesis is different depending on which version of the test is used, but is usually stationarity or trend-stationarity.

The Kao (1999) and Pedroni (2004) tests will be used to determine if cointegration exists, as they are used with panel data. The Johansen test (1988) will also be used to determine if there is cointegration for each panel, which will also be used to estimate the two combined likelihood ratios that capture the individual tests. The two likelihood ratios are based on the two that are suggested by Johansen (1988). The first test statistic is the trace statistic and the second is the maximum or maximum eigenvalue statistic (Ndlovu & Inglesi-Lotz, 2020). Both these test statistics uses an almost identical methodology to derive their hypotheses, however they are different. The trace statistic is used to test for H_0 of r cointegrating relationships against H_1 of n cointegrating relationships. In contrast, the maximum eigenvalue statistic is used to test H_0 of r cointegrating relationships versus the H_1 of $r + 1$ cointegrating relationships.

Pedroni's test is used because it can control for country size and heterogeneity, allowing for multiple regressors. Pedroni (2000) provides seven cointegration test statistics for seven tests (Uddin et al., 2017). Four (panel-v, panel-p, panel-pp and panel-ADF) conduct within dimension tests, while the other three (group-p, group-pp and group-ADF) conduct between dimension or group statistic tests. The following expressions are used with the relevant cointegration tests, which are (Pedroni, 1999):

Panel v-statistic:

$$Z_v = \left(\sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{2} \right)^{-1} \tag{1}$$

Panel p-statistic:

$$Z_p = \left(\sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{2} \left(\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i \right) \tag{2}$$

Panel pp-statistic:

$$Z_t = \left(\hat{\sigma}^2 \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{2} \left(\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i \right) \tag{3}$$

Panel ADF-statistic:

$$Z_p^{*} = \left(\hat{s}^{*2} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}_{11}^{-2} \hat{e}_{it-1}^{*2} \left(\hat{e}^{*}{}_{it-1} \Delta \hat{e}_{it} \right) \tag{4}$$

Group p-statistic:

$$\tilde{Z}_p = \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \hat{e}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{T} (\hat{e}_{it-1}^{2} \left(\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i \right) \tag{5}$$

Group pp-statistic:

$$\tilde{Z}_t = \sum_{i=1}^{N} \left(\hat{\sigma}^2 \sum_{i=1}^{T} \hat{e}_{it-1}^{2} \right)^{-1/2} \sum_{i=1}^{T} (\hat{e}_{it-1}^{2} \left(\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i \right) \tag{6}$$

Group ADF-statistic:

$$\tilde{Z}_t^{*} = \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \hat{s}^{2} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{i=1}^{T} (\hat{e}_{it-1}^{*} \left(\hat{e}_{it-1} \Delta \hat{e}_{it} \right) \tag{7}$$

The null hypothesis of no cointegration is the same for all the test statistics, $H_0: \gamma_i = 1 \; for \; all \; i = 1, \ldots .. N$, whereas the alternative hypothesis for between and within dimension based cointegration tests differ. For between-dimension based $H_1: \gamma_i < 1 \; for \; all \; i = 1, \ldots .. N$ and for within-dimension based $H_1: \gamma = \gamma_i < 1 \; for \; all \; i = 1, \ldots .. N$ (Pedroni, 1999).

Kao's (1999) test for cointegration undergoes a similar process to that of Pedroni, however, Kao's test will differentiate between cross sections by specifying that the intercepts are heterogenous while the coefficients are homogenous as will be seen by equation (8) below:

$$y_{it} = \alpha_i + \delta_i t + \sum_{m=1}^{M} \beta_{mi} x_{mit} + e_{it} \tag{8}$$

Where:

$t = 1, \ldots, T$ and T is the number of time periods

$i = 1, \ldots, N$ and N is the number of cross-sections

$m = 1, \ldots, M$ and M is the number of regressors.

When we apply the results from the panel multivariate regression in equation (8), the seven tests in Pedroni (1999) can be calculated. These seven tests are divided into four tests which relate to pooling along within the dimension and three tests that relate to pooling along between the dimension. The within dimension tests $H_0: \gamma_i = 1 \; \forall i$ versus $H_1: \gamma_i = \gamma < 1 \; \forall i$, while the between dimension tests $H_0: \gamma_i = 1 \; \forall i$ versus $H_1: \gamma_i < 1 \; \forall i$. The within dimension statistics forces homogeneity across cross-sections while the between dimension statistics allows for heterogeneity across the cross-sections (Pedroni, 1999).

Moving on now with the Emirmahmutoglu and Kose (2011) method to test for pairwise Granger non-causality, will involve combining an LA-VAR approach of Toda and Yamamoto (1995) with a Granger causality test procedure for heterogenous mixed panels. Under cross-section dependence, the LA-VAR approach has good empirical size for a large T in mixed panels. To test the Granger non-causality hypothesis in heterogeneous panels the Fisher test statistic proposed by Fisher (1932) is used. The Fisher test statistic (λ) is defined as follows:

$$\lambda = -2\sum_{i=1}^{N} \ln(p_i) \tag{9}$$

where $i = 1, \dots, N$ in this case p_i is the p-value corresponding to the Wald statistic for the i-th individual cross-section. This specific test statistic has a Chi-square distribution of 2 N degrees of freedom; however, the limit distribution of the Fisher test statistic will no longer be valid due to the presence of cross-correlations among cross-sectional units. To deal with the cross-correlations within panels, the bootstrap methodology to test for cross-sectional dependent panels is used. This will mean running the following linear panel regression for each of the cross-sections:

$$y_{i,t} = \alpha_i + \sum_{j=1}^{k_i+d\,max_i} \theta_i^j x_{i,t-j} + \sum_{j=1}^{k_i+d\,max_i} \beta_i^j y_{i,t-j} + \varepsilon_{i,t} \tag{10}$$

Equation (10) above is estimated without imposing parameter restrictions on it, after which the individual Wald statistics are calculated to test for non-causality H_0 separately for each cross-section. These individual Wald statistics has an asymptotic Chi-square distribution with k_i degrees of freedom and are used to compute the individual p-values from which the optimal lag orders for each cross-section is identified. Thereafter, we obtain the Fisher test statistic from equation (9). H_0 and H_1 can then be defined as follows:

H_0: $\beta_i = 0\ for\ i = 1, \dots, N$

$$H_1: \beta_i = 0 \; for \; i = 1, \dots, N_1, \beta_i \neq 0 \; for \; i = N_1 + 1, \dots, N$$

Rejection of H_0 with $N_1 = 0$ will imply that all x Granger causes y for all i, whereas the rejection of H_0 with $N_1 > 0$ will imply that there are variations of the regressions model and causality across individuals. This is done to control for mixed panels involving I (0), I (1), cointegrated and non-cointegrated in the series of variables.

3.3 Data

For the bibliometric analysis, a phrase-based query approach will be used to determine the overall amount of research papers that have been published around the field of “climate change” and “global warming”. The scientometric analysis proxies the countries’ performance in climate-change related research by published papers within the Clarivate Database and not by researcher as we follow the literature suggesting every study contributes to the knowledge stock of the field.

The following list of words will be used for this approach: "Climate change", "global warming", "CO2", "emissions", "carbon dioxide", "carbon tax", "ETS", "emissions trading system", "greenhouse gasses", "GHG", "fossil fuels", "global average temperature", "sea-level rise", "renewable energy", "COP", "UNFCCC", "INDC", "IPCC", "PPM", "Methane" and "pre-industrial levels of carbon dioxide". The selection of the words/phrases used for the approach was based on the recurring nature they have in the papers in the field. The starting date of 1956 for the scientometric part of the analysis was chosen because it is the starting date for the Clarivate Analytics database. This period will allow for a sufficient time to observe any trends that may have occurred and observe any spikes or troughs in the scientific output after the introduction of the Kyoto Protocol and Paris agreement. The Core collection is a collection of over 21000 peer-reviewed, high-quality scholarly journals published worldwide in over 250 social science, humanities and science disciplines (Matthews, 2020). The selection process to make this collection must have the basic principles of selectivity, objectivity and collection dynamics. There is a single set of 28 criteria which focuses on quality and impact when evaluating every journal, hence making the use of the core collection for this analysis is an appropriate one (Clarivate, 2020). This selection was made due to the availability of publication data necessary and because it provides great variability in terms of the types of economies that will be tested in this study.

Results showed that 28 out of the top 50 countries producing climate change-related research output were developed countries and the remaining 22, developing countries as per the classification of the World Bank (2020). This will allow us not to only test this hypothesis on the respective 50 countries but in terms of developed vs developing countries. Due to the unavailability of data of Taiwan and USSR, they were omitted from the list, hence the introduction of the next two countries from the bibliometric analysis are added to make up the updated top 50 list.

Moving on to the dataset to be used in the econometric modelling, the period of 1996-2019 is chosen as it would be a sufficient period to see if there is any causal relationship between climate change-related research output and CO_2 emissions, and due to data availability for each country and all the variables used in the model. As mentioned earlier, the selection of countries will allow for us to test this hypothesis not only between the top 50 climate change-related research output producing countries but also on developing vs developed nations, followed by grouping these countries in categories of lower-middle, upper-middle- and high-income countries.

The data that will be used for the empirical analysis in this study will consist of economic growth measured GDP in constant 2005 US $; total CO_2 emissions measured in kt; Climate change-related research output obtained from our bibliometric analysis which is based on the Clarivate Analytics Core Collection; and expenditure on R&D (GERD) which will act as a proxy for climate change-related research output. Annual time-series data will be gathered for GDP, CO_2 emissions and GERD data from the World Bank database. The CO_2 data, however, was only available up until 2016 on the World Bank database, hence the remaining 3 years was obtained from BP's statistical review of world energy report issued in June 2020 and was rounded to the nearest hundred (BP statistics, 2020).

Classification of country groups between developed and developing countries and low, middle and high-income countries will be through the World Bank's ranking of these countries (The World Bank, 2020).

Due to gaps in the data set with GERD, linear interpolation was done to get the necessary unit and cointegration tests to work. This form of interpolation is useful when trying to estimate the value of a variable such as GERD for a point at which there is no data (Kenton, 2020). It is done by geometrically rendering a straight line between two adjacent points on a graph or plane, where all the values besides the original two are the interpolated values (Technopedia, 2020).

Table 1: Variables descriptive statistics

Variables	Observations	Mean	Standard deviation	Min	Max
$lnGDP_{(contant2005US\$)}$	1198	26.93924	1.313083	23.56067	31.25185
$lnCO2emissions_{(kt)}$	1175	12.15622	1.308309	9.43208	16.14687
$lnResearchOutput_{(records)}$	1200	5.913078	1.578011	0	10.24906
$lnGERD_{(contant2005US\$)}$	1181	15.59663	1.534405	12.04032	19.98212

4. Empirical results

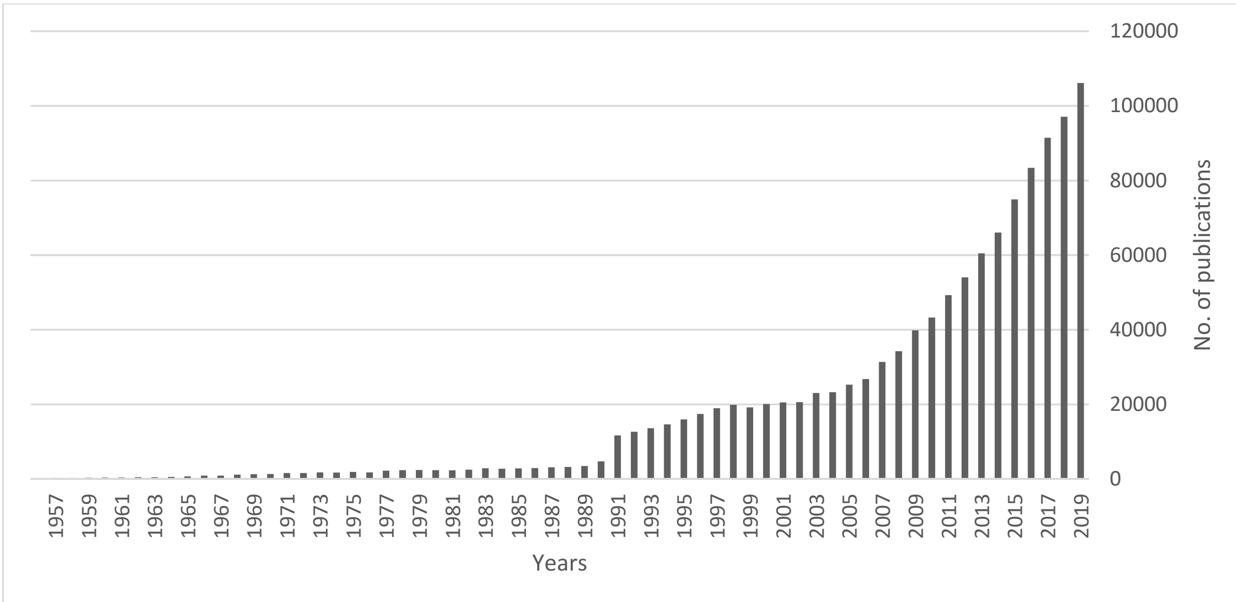
4.1. Bibliometric analysis

Figures 1-4 are a summary of the results obtained for the bibliometric analysis from the Clarivate analytics core collection from the period of 1956 to 2019. As illustrated by Figure 1, it is clear that the overall number of climate change-related research papers published has exponentially grown over the years showing its first big spike in the 1990s, which is during the period of the adoption of the Kyoto protocol (Clarivate Analytics, 2020). Several reasons will contribute to the rise of these published papers such as an increase in the population and hence more researchers. There are also more Journals and platforms available to publish academic/scientific work, as well as the difficulty and time needed to submit and publish a paper, has changed. Lastly, the importance of the field/topic has gone up over the years shown by the introduction of the Kyoto Protocol and Paris agreement. All three reasons will contribute to the rise, however, with climate change becoming an ever-growing problem, a lot more research on finding solutions to the problem is expected.

Figure 2 represents the countries that make up the top 50 climate change-related output producing countries. What is interesting from the top 50 list is that they are not all high income and developed countries, but represent a diverse mix of countries (Clarivate Analytics, 2020). That showcases that the issue of climate change is taken seriously by all countries and not only the larger economies that are more responsible for the rise in GHG emissions.

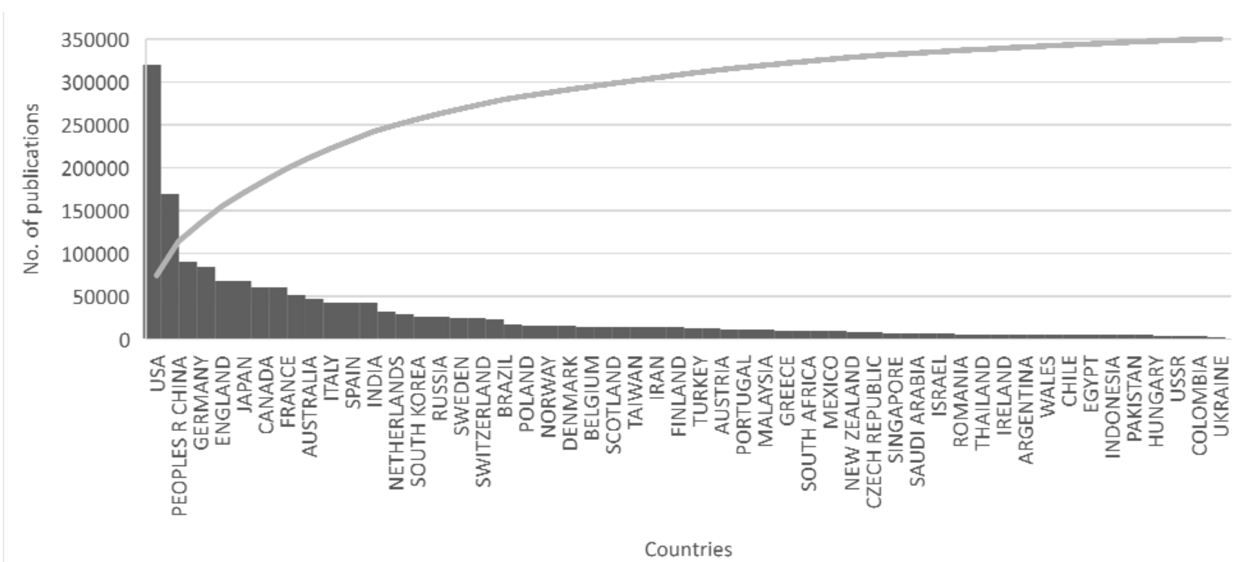
Figures 3 and 4 indicates the top 50 Clarivate Analytics categories and research areas that make up the climate change-related research output. In other words, it will show us which groups are most interested in researching the field of climate change and global warming based on our phrase-based approach in our analysis. Looking at both Figures 3 and 4, it is clear to see that the research areas people and institutions are most interested in researching are engineering, environmental sciences, chemistry, energy fuels, meteorology atmospheric sciences, material sciences and geology (Clarivate Analytics, 2020). These represent mostly scientific research areas which would typically represent the groups that would try and find solutions to help slow down global warming. Major fossil fuel companies have also begun to spend a lot more money on energy R&D in the hopes of finding more efficient energy solutions to limit their CO2 emissions, hence seeing energy fuels on the list is expected (IEA, 2020).

Figure 1: Published climate change-related research output between 1956-2019



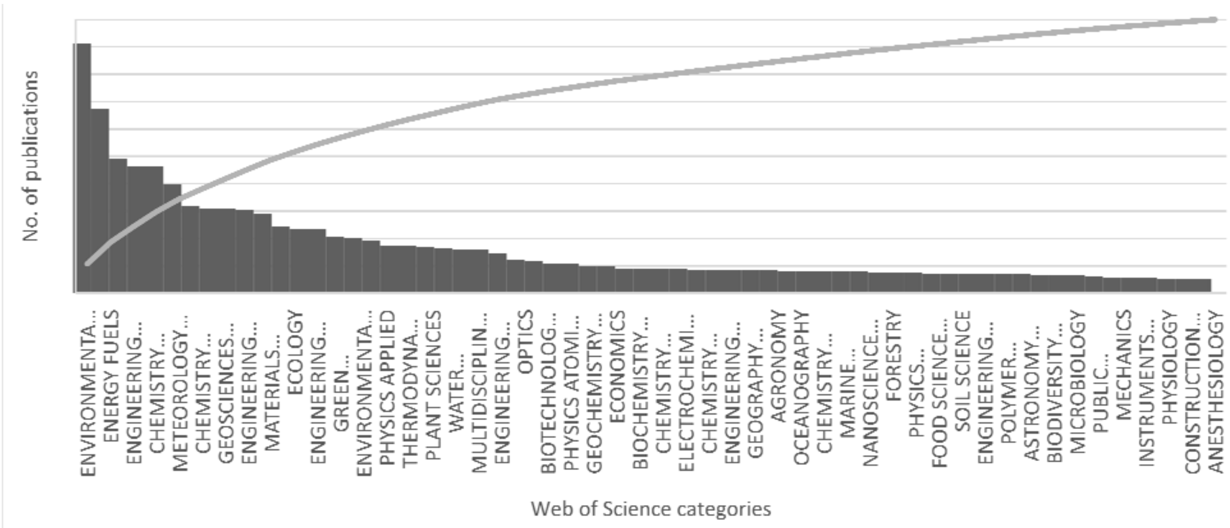
Source: Authors calculation from Clarivate Analytics

Figure 2: Distribution of the top 50 countries in terms of their respective climate change-related research output



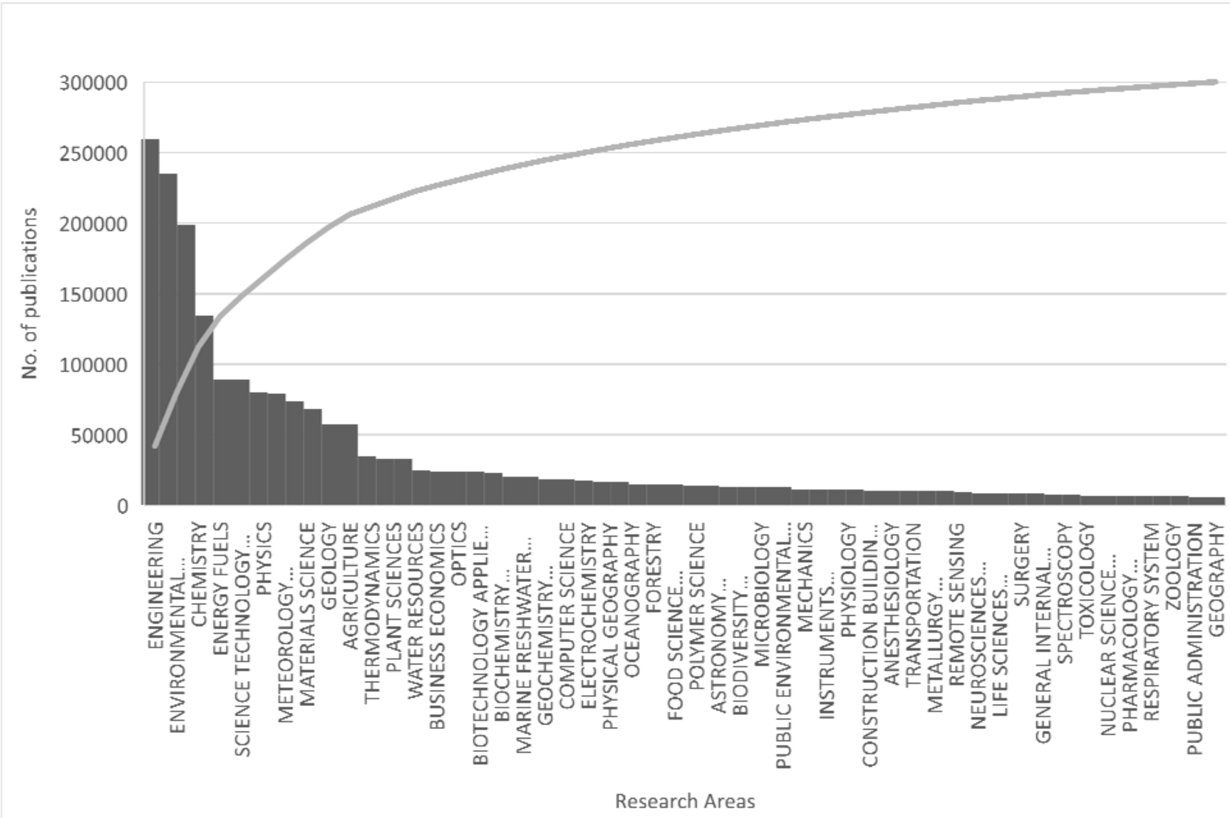
Source: Authors calculation from Clarivate Analytics

Figure 3: Top 50 Clarivate analytics categories from the climate change-related research output analysis



Source: Authors calculation from Clarivate Analytics

Figure 4: Distribution of top 50 research areas in terms of total climate change-related research output published



Source: Authors calculation from Clarivate Analytics

The ranking of the main research areas associated with climate change has changed over the years. The top 20, 10-year citation rates and aggregate counts of the most highly cited papers of different research fields can allow the researchers to evaluate how many of our top 50 list of research areas associated with climate change (Figure 4) will make the overall top 20 list of the highest-ranked research fields aggregated from the last 10 years in all fields.

Table 2: Top 20 Baselines-field rankings

RESEARCH FIELDS	NUMBER OF PAPERS	NUMBER OF CITATIONS	CITATIONS PER PAPER	HIGHLY CITED PAPERS
AGRICULTURAL SCIENCES	461003	4683342	10.16	4633
BIOLOGY & BIOCHEMISTRY	773798	13633446	17.62	7762
CHEMISTRY	1826753	29215059	15.99	18261
CLINICAL MEDICINE	2942586	39526641	13.43	29321
COMPUTER SCIENCE	408859	3483516	8.52	4060
ECONOMICS & BUSINESS	301091	2921929	9.7	2984
ENGINEERING	1491145	14079684	9.44	14838
ENVIRONMENT/ECOLOGY	583684	7971101	13.66	5785
GEOSCIENCES	502457	6863716	13.66	4982
IMMUNOLOGY	272454	5255343	19.29	2726
MATERIALS SCIENCE	985562	15895770	16.13	9787
MATHEMATICS	458756	2195893	4.79	4634
MICROBIOLOGY	221551	3581914	16.17	2211
MOLECULAR BIOLOGY & GENETICS	501397	12110980	24.15	5047
MULTIDISCIPLINARY	23406	423822	18.11	235
NEUROSCIENCE & BEHAVIOR	539298	10037137	18.61	5368
PHARMACOLOGY & TOXICOLOGY	435488	5771696	13.25	4306
PHYSICS	1114358	13258475	11.9	11017
PLANT & ANIMAL SCIENCE	778100	7795841	10.02	7667

The highlighted rows represent the fields that are associated with climate change research.

Source: **(Clarivate analytics, 2020**

Table 2 above shows that only 7 of the top 20 list does not match up with the top 50 research areas associated with climate change-related research output, namely: clinical medicine, immunology, mathematics, microbiology, molecular biology and genetics and multi-disciplinary (Clarivate analytics, 2020). That means that although we can't statistically show that the rank of the topic under observation (climate change) has significantly gone up for the period studied in the bibliometric analysis (1956-2019), we can strongly prove that based on our analysis done and results observed, that the most important and cited papers in the last 10 years in terms of research fields published are associated with the top climate change-related research areas. Furthermore, 7 of the top 10 research areas associated with climate change-related research output, make the top 20 list, further strengthening the argument that research in the field of climate change and global warming is one of the major areas focused on, at least in the last 10 years (Clarivate analytics, 2020).

Lastly, to observe if the overall importance of climate change-related research output has gone up over the years, we look if the proportion of climate change-related research output to total output based on the Clarivate Analytics Core Collection database has increased from 1960 to 2019. Table 3 below shows the proportion of climate change-related research output to total output which is spaced approximately 20 years apart to see if there is a clear difference between the periods before and after the introduction of the Kyoto Protocol and Paris agreement. Results showed an increase from 1960 up to 2019 in climate change research output. It is particularly interesting to point out that the increase from 1960 to 1980 was only 0.046% which was before the introduction of the Kyoto protocol. However, from 1980 to 2000 which transitions to just after the introduction of the Kyoto Protocol we see an increase of 1.169% which is quite a substantial rise from the previous 0.046%. From 2000-2019, we move into a period where there is much greater awareness of climate change and also falls in the era of the introduction of the Paris agreement. Results support the argument of increased awareness by showing a further increase of 1.715%. It is clear based on the results obtained that after the introduction of these initiatives that research into climate change has become a more important topic of interest.

Table 3: Results on the proportion of climate change-related research output to total output based on the Clarivate Analytics Core Collection for the years 1960, 1980, 2000 and 2019

	1960	**1980**	**2000**	**2019**
No. of climate change-related papers	419	2411	20111	107031
Total No. of papers	151862	749494	1348908	3338865
Proportion of climate change-related papers to total amount of papers (%)	0,276%	0,322%	1,491%	3,206%

(Clarivate Analytics, 2020)

4.2. Econometric analysis

Table 4 shows that all variables in the study are of first order of integration (I(1)) based on the unit root tests used. Table 5 shows the Pedroni test results, which confirms cointegration in the whole sample with both the ADF and Phillips-Perron p-values. The Kao test for cointegration presented in Table 6, rejects the presence of a cointegrating relationship using the Augmented Dickey-Fuller p-value. Consequently, the results between the Pedroni and Kao test are inconsistent and could be since the Kao's (1999) test for cointegration will differentiate between cross sections by specifying that the intercepts are heterogenous while the coefficients are homogenous where the Pedroni test does not. This further stipulates that the cross-sections from the panels in the sample are heterogeneous and mixed and indicates that the countries in the panel differ in characteristics. This will support the decision to therefore choosing the methodology used by Emirmahmutoglu and Kose (2011) when running the Granger causality test.[2]

Table 4: Panel unit root tests

Variables	IPS test statistic	IPS p-value	Fisher PP test statistic (Inverse chi-squared)	Fisher PP p-value	Fisher ADF test statistic (Inverse chi-squared)	Fisher ADF p-value	Inference
$lnGDP_{(contant2005US\$)}$	4.3645	1.0000	42.4595	1.0000	35.5767	1.0000	Unit root
$lnCO2emissions_{(kt)}$	6.6260	1.0000	44.9927	1.0000	44.4491	1.0000	Unit root
$lnResearchOutput_{(records)}$	2.4290	0.9924	142.8255	0.0032[c]	77.2625	0.9555	Unit root
$lnGERD_{(contant2005US\$)}$	2.5826	0.9951	90.7486	0.7350	154.9513	0.0004c	Unit root
$\Delta lnGDP_{(contant2005US\$)}$	-13.5661	0.0000[c]	438.6580	0.0000[c]	489.4541	0.0000[c]	No unit root
$\Delta lnCO2emissions_{(kt)}$	-26.1049	0.0000[c]	604.0712	0.0000[c]	1127.1606	0.0000[c]	No unit root
$\Delta lnResearchOutput_{(records)}$	-28.7474	0.0000	2028.5780	0.0000[c]	885.6339	0.0000[c]	No unit root
$\Delta lnGERD_{(contant2005US\$)}$	-15.0150	0.0000[c]	347.1415	0.0000[c]	641.5552	0.0000[c]	No unit root

[2] Table A1 (in Appendix) illustrates separate cointegrating tests done for each cross-section including lnCO2 to determine if a long-run relationship exists with lnResearchOutput, lnGDP and lnGERD. Results confirmed cointegration for the whole sample.

Table 5: Pedroni's test for cointegration

	Test statistic	**p-value**
Phillips-Perron t	-3.3251	0.0004***
Augmented Dickey-Fuller t	-4.1198	0.0000***

* (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC.

Table 6: Kao's test for cointegration

	Test statistic	**p-value**
Dickey-Fuller t	-1.4722	0.0705*
Augmented Dickey-Fuller t	0.2683	0.3942

* (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC.

Table 7 presents the results of the bivariate pairwise Granger causality test between lnResearchOutput, lnGDP, lnCO2 and lnGERD for the entire top 50 countries list of climate change-related output producing countries.[3] This test will determine if there is a causal relationship running from one variable to the other in this model in a pairwise manner for the panel of countries; the LA-VAR Granger causality simulation determines the optimum lag for each cross-sectional unit (Emirmahmutoglu & Kose, 2011; Ndlovu & Inglesi-Lotz, 2020). Starting with the entire top 50 countries list of climate change-related output producing countries, results show that causality only runs from lnResearchOutput to lnCO2, lnCO2 to lnGERD and from lnGDP to lnGERD; while all the other hypotheses could not be rejected for the top 50 climate change-related output producing countries panel.

[3] , whereas Table A2-A6 (in Appendix) show the results for developed, developing, high income, upper middle income and lower-middle-income countries from the top 50 list.

Table 7: Panel Causality for the top 50 climate change-related research output producing countries

Hypothesis	Fisher Statistic	Conclusion
$lnResearchOutput \rightarrow lnCO2$	183.049*	One-way causality from Research output to CO2
$lnCO2 \rightarrow lnResearchOutput$	167.130	No Causality
$lnGDP \rightarrow lnResearchOutput$	138.608	No Causality
$lnResearchOutput \rightarrow lnGDP$	181.040	No Causality
$lnResearchOutput \rightarrow lnGERD$	182.929	No Causality
$lnGERD \rightarrow lnResearchOutput$	148.832	No Causality
$lnGERD \rightarrow lnCO2$	123.368	No Causality
$lnCO2 \rightarrow lnGERD$	173.948*	One-way causality from CO2 to GERD
$lnGDP \rightarrow lnCO2$	156.297	No Causality
$lnCO2 \rightarrow lnGDP$	130.234	No Causality
$lnGDP \rightarrow lnGERD$	227.729**	One-way Causality from GDP to GERD
$lnGERD \rightarrow lnGDP$	144.985	No Causality

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Looking at the results from Table 7 of the entire sample, causality that runs from Research Output to CO2 emissions represents the progress countries like India, China, Norway, the UK and many countries that fall under the EU have made at lowering emissions to try and meet the Paris Agreement targets (Mulvaney, 2019). These countries have plans in place to transition large portions of their power generation to renewable energy, combined with the efforts of policies such as the ETS set by the EU to try and lower emissions (Mulvaney, 2019). Causality running from CO2 emissions to GERD makes intuitive sense because a country's investment into climate change-related R&D will be very much related to their specific performance in trying to lower emissions. Same goes with causality running from GDP to GERD, investment into R&D will be very much linked to the country's overall economic performance. In other words, if a country performed well, they are more likely to increase R&D investment or keep it at the same level compared to if they had not.

Similar results were obtained for developed countries (see Appendix), which would make sense since the majority of the countries that make up the top 50 list are developed countries which can potentially drive the overall results of the group. However, there was no causality found from lnResearchOutput to lnCO2 indicating that industrialized countries might currently be less focused on using climate change-related research output or stick to already known methods when trying to lower emissions compared to developing countries as per results show. Causality found for this group has the same reasonings as for the entire group explained above.

Developing countries (see Appendix) showed that there is two-way causality found between lnResearchOutput and lnCO2, and lnGERD and lnGDP. This makes intuitive sense because developing countries are more likely to invest in GERD if their GDP is strong and vice versa, seeing that these countries are still in the process of trying to catch up with too many of the more industrialised countries. They will focus more heavily on R&D to find more efficient ways to grow their economies. This means that these countries are very reliant on R&D when it comes to implementing policies and new technology in trying to combat climate change and lower emissions as supported by the results. There was also a one-way causality that ran from lnResearchOutput to lnGERD. This makes intuitive sense because if a country consistently produces high-quality climate change-related research output, it will influence the government's decision-making process to invest more heavily into GERD compared to if they were not producing consistent top-quality research and vice-versa.

To account for any limitations in the test results, because of the panel Fisher test statistics which are created for large numbers of cross-sections N and the possibility that some countries, due to their size, will affect the overall group results, we report the individual WALD test statistics and p-values for the LA-VAR Granger causality method in the Appendix, summarised in Table 8. This was done to see if there are any causal relationships for the 50 countries between all three variables.

Table 8: Summary of results showing all countries having causality run from one variable to another

lnResearchOutput→ lnC02	**lnCO2 → lnResearchOutput**	**lnGDP → lnResearchOutput**	**lnResearchOutput → lnGDP**	**lnGERD → lnResearchOutput**	**lnResearchOutput → lnGERD**
Colombia Egypt Russia South-Africa South-Korea Thailand	Germany India Italy South-Africa South-Korea Thailand UAE Ukraine	Australia Colombia Egypt Hungary Indonesia Pakistan Slovenia South-Korea Thailand	Australia Brazil China Colombia Egypt Germany Israel Romania Serbia	China Ireland Malaysia Romania Serbia Slovakia South-Korea Spain Switzerland Turkey UAE	Belgium Canada Chile Germany India Indonesia Iran Israel Pakistan Serbia Slovenia Spain Sweden Turkey
lnGERD → lnC02	**lnCO2 → lnGERD**	**lnGDP → lnCO2**	**lnCO2 → lnGDP**	**lnGDP → lnGERD**	**lnGERD → lnGDP**
Australia Austria China Israel Pakistan Portugal South-Korea USA	Argentina Colombia Ireland Malaysia Netherlands Poland Russia Slovakia Spain USA	China Czech Republic Finland Ireland Malaysia Mexico New Zealand Pakistan Slovenia South-Africa Thailand	Argentina Brazil China Ireland Poland Portugal Slovenia South-Korea	Argentina Chile China Colombia Denmark Germany Ireland Malaysia Netherlands New Zealand Poland South-Africa South-Korea Spain Sweden Switzerland Thailand USA	Brazil China India Malaysia Russia Saudi-Arabia Slovenia Thailand Turkey UAE

The null hypothesis of Granger no causality were all rejected at 10%,5% and 1% level of significance for these countries, suggesting that lnResearchOutput and lnCO2, lnGDP and lnResearchOutput, lnGERD and lnResearchOutput, lnGERD and lnCO2, lnGDP and lnCO2 and finally lnGERD and lnGDP had a significant impact on each other for these respective countries. From the results, we can see that there is a two-way Granger causality found in South-Korea, South-Africa and Thailand between lnResearchOutput and lnCO2, in Australia, Egypt and Colombia between lnGDP and lnResearchOutput, in Spain, Turkey and Serbia between lnGERD and lnResearchOutput, in the USA between lnGERD and lnCO2, in Ireland and Slovenia between lnGDP and lnCO2 and lastly in Malaysia and Thailand between lnGERD and lnGDP. We can confirm that lnResearchOutput has a significant impact on lnCO2 based on the Granger causality result which was rejected at a 10% level of significance for the total sample. We can also confirm that lnCO2 and lnGDP has a significant impact on lnGERD based on the Granger causality result which was rejected at a 5% level of significance for the total sample.

5. Conclusion

The main research objectives of this study are to first determine if the importance of climate change research output has increased by looking at the overall number of publications using the Clarivate Analytics Core Collection (between 1956-2019) (Clarivate Analytics, 2020). This will be followed by looking at the ranking of the fields representing climate change research in terms of the average citation rates over the last 10 years through a bibliometric analysis. Results showed that there was an exponential rise in the number of climate change-related research output for all top 50 countries between 1956-2019 as well as showing that 7 of the top 10 research areas associated with climate change-related research output, make the top 20 list for most cited papers, further strengthening the argument that research in the field of climate change and global warming has grown in importance. Lastly, when looking at the proportion of climate change-related papers to the total amount of papers published based on the Clarivate Analytics Core Collection from 1960 to 2019, a clear rise in the percentage of papers published can be observed, especially after the introduction of the Kyoto Protocol and Paris agreement which has increased awareness of the issue.

Next was to study the existence and direction of the causal dynamics between CO2 emissions, climate change-related research output and expenditure on R&D considering the role GDP plays in each of the other variables. Through the use of the Pedroni (2004), Kao (1999) and Johansen Cointegration (1988) tests, we determined whether a long-run relationship exists between the variables, after determining the stationarity of the variables at first difference through the IPS and Fisher unit root tests. To estimate the causality, the Granger causality methodology used by

Emirmahmutoglu and Kose (2011) within a panel data framework, consisting of the top 50 climate change-related output producing countries between the period of 1996 and 2019 was used. The large selection of countries brought about heterogeneity issues, which was portrayed by the results, hence the inclusion of country specific studies.

Results showed that causality runs from lnResearchOutput to lnCO2, lnCO2 to lnGERD and from lnGDP to lnGERD for the total sample. Causality running from Research Output to CO2 emissions from the results answers the main objective of the study and confirms the a priori expectations. This supports the argument that climate change research output's results and findings can suggest technological improvements, policy changes and knowledge accumulation can be linked with the lowering of CO2 emissions.

Developed and high-income countries represent the more affluent nations from the sample and base their GERD expenditure on their economic performance. This, therefore, means investment in R&D is dependent on the economy doing well. A strong determinant on how much these respective countries will invest in R&D will be based on the country's performance in lowering emissions. Results also showed some variability when looking at developing and upper-middle-income countries. All upper-middle-income countries are developing countries from the list, hence these two groups showed similar results. These countries are more focused on their growth compared to putting a lot of their focus in mitigating their overall CO2 emissions, as compared to developed countries that have already reached the peak of their individual Environmental Kuznets Curve, allowing them to spend more money on R&D to find ways to mitigate and transition to clean energy solutions. This explains why results showed causality to run from lnCO2 to lnGDP for upper-middle-income countries, which represent mainly your fast-growing economies from the top 50 list such as your BRICS nations. There is also two-way causality found between lnResearchOutput and lnCO2, and lnGERD and lnGDP for these two groups. This indicates that Research Output that is implemented correctly is linked to lowering CO2 emissions, R&D expenditure is very much dependent on GDP performance and vice-versa. There was no Granger causality found for the lower-middle-income countries. This could be because only 5 of the top 50 countries made the top 50 list, and because they all differ in size, one country could potentially drive the overall results of the entire group. These results of research output affecting emissions for developed countries but not for developing and low-income countries might be able to be linked with a Kuznets-type curve, which should be explored in the future.

Due to the lack of accountability by many of the world's top emitters not being able to meet their emission reduction requirements set out by the Paris Agreement (UNFCCC, 2015) set in place in 2005, the following recommendations are made (Mulvaney, 2019):

- As a primary policy change, there needs to be a central authority put in place that ensures accountability with the countries who are part of the agreement. This central figure needs to ensure these countries are kept accountable for meeting their specific benchmark CO2 emission requirements and the exceeding of this limit must be at the cost of some sort of penalty paid out to this central authority. This must act as a form of incentive for countries to avoid breaching their CO22 emission limits.
- More emphasis needs to be put in place by countries to use R&D in CO2 mitigating policies and technology, due to the lack of a causal relationship shown from GERD to CO2 and because it is supported by the results which show countries that implement their research appropriately see results when it comes to lowering CO2 emissions.
- Given that the economy of a country is determined by its GDP, the influence it has on GERD needs to be addressed, seeing that based on the results of the study that their mutual relationship cannot be avoided.

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Table A1: Johansen test for cointegration for each panel			
		Johansen test for cointegration	
Panel	**Hypothesized number of cointegrating equations**	**Fisher Trace Test statistic**	**Fisher Max-Eigenvalue trace statistic**
United States of America	None	70.3786	33.4103
	At most 1	36.9683	27.9292
	At most 2	9.0391*	7.5001
	At most 3	1.5389	1.5389
China	None	59.7549	28.3655
	At most 1	31.3894	20.5566
	At most 2	10.8327*	8.9856
	At most 3	1.8472	1.8472
Germany	None	44.1175*	26.1028
	At most 1	18.0147	11.9826
	At most 2	6.0321	5.4522
	At most 3	0.5799	0.5799
UK	None	45.6586*	24.2582
	At most 1	21.4005	12.6555
	At most 2	8.7449	8.7004
	At most 3	0.0445	0.0445
Japan	None	51.8142	30.2853
	At most 1	21.5289*	13.3821
	At most 2	8.1469	7.9753
	At most 3	0.1716	0.1716
Canada	None	49.0664	27.4226
	At most 1	21.6439*	11.2639
	At most 2	10.3799	8.3174
	At most 3	2.0625	2.0625
France	None	41.3685*	20.7446
	At most 1	20.6239	11.3754
	At most 2	9.2485	8.7017
	At most 3	0.5468	0.5468
Australia	None	68.1044	41.9869
	At most 1	26.1175*	15.9962
	At most 2	10.1214	9.1001
	At most 3	1.0213	1.0213
Italy	None	52.1444	24.9359
	At most 1	27.2085*	18.7726
	At most 2	8.4359	8.2303
	At most 3	0.2056	0.2056
Spain	None	67.3329	33.0201
	At most 1	34.3128	22.8386
	At most 2	11.4742*	11.2602
	At most 3	0.2140	0.2140
India	None	40.1083*	25.3204
	At most 1	14.7879	10.3605
	At most 2	4.4274	4.4259
	At most 3	0.0015	0.0015
Netherlands	None	47.5889	28.0610

	At most 1	19.5279*	15.7610
	At most 2	3.7669	3.7206
	At most 3	0.0463	0.0463
South-Korea	None	70.7922	34.5917
	At most 1	36.2005	22.3683
	At most 2	13.8322*	9.3969
	At most 3	4.4353	4.4353
Russia	None	30.7487*	15.2011
	At most 1	15.5476	10.5501
	At most 2	4.9975	4.8834
	At most 3	0.1141	0.1141
Sweden	None	37.4456*	18.8122
	At most 1	18.6334	12.8849
	At most 2	5.7485	5.7482
	At most 3	0.0003	0.0003
Switzerland	None	62.3912	30.6926
	At most 1	31.6985	21.0759
	At most 2	10.6226*	9.4125
	At most 3	1.2101	1.2101
Brazil	None	42.9110*	25.4923
	At most 1	17.4187	10.0393
	At most 2	7.3794	7.3076
	At most 3	0.0718	0.0718
Poland	None	66.5953	32.1671
	At most 1	34.4282	19.8447
	At most 2	14.5835*	14.4997
	At most 3	0.0838	0.0838
Norway	None	41.5992*	28.5041
	At most 1	13.0951	9.0835
	At most 2	4.0116	3.4430
	At most 3	0.5686	0.5686
Denmark	None	56.2149	33.3708
	At most 1	22.8441*	16.8666
	At most 2	5.9775	5.5389
	At most 3	0.4387	0.4387
Belgium	None	36.2861*	19.9396
	At most 1	16.3465	11.2770
	At most 2	5.0695	3.9296
	At most 3	1.1399	1.1399
Iran	None	27.8227*	16.1392
	At most 1	11.6835	6.2673
	At most 2	5.4162	4.9666
	At most 3	0.4495	0.4495
Finland	None	52.3879	35.2368
	At most 1	17.1511*	12.3689
	At most 2	4.7823	4.6674
	At most 3	0.1148	0.1148
Turkey	None	35.3647*	20.7255
	At most 1	14.6392	9.6843
	At most 2	4.9549	4.8516
	At most 3	0.1033	0.1033
Austria	None	38.9968*	21.1703
	At most 1	17.8264	13.0215
	At most 2	4.8049	4.0903

	At most 3	0.7147	0.7147
Portugal	None	56.1321	27.9074
	At most 1	28.2247*	21.0767
	At most 2	7.1480	5.4470
	At most 3	1.7009	1.7009
Malaysia	None	51.6622	38.1072
	At most 1	13.5550*	7.5815
	At most 2	5.9736	4.9929
	At most 3	0.9807	0.9807
Greece	None	50.8263	20.8308
	At most 1	29.9955	16.0059
	At most 2	13.9896*	13.7674
	At most 3	0.2222	0.2222
South-Africa	None	52.2053	26.6196
	At most 1	25.5857*	16.2552
	At most 2	9.3305	8.0525
	At most 3	1.2780	1.2780
Mexico	None	49.6386	25.7263
	At most 1	23.9123*	15.8619
	At most 2	8.0504	7.9997
	At most 3	0.0507	0.0507
New Zealand	None	42.7553*	29.4393
	At most 1	13.3160	9.8729
	At most 2	3.4432	3.1769
	At most 3	0.2663	0.2663
Czech Republic	None	36.1237*	22.8560
	At most 1	13.2677	10.0445
	At most 2	3.2232	3.2229
	At most 3	0.0003	0.0003
Singapore	None	53.2754	38.2511
	At most 1	15.0243*	9.8122
	At most 2	5.2121	4.3127
	At most 3	0.8994	0.8994
Saudi Arabia	None	36.2754*	18.5257
	At most 1	17.7497	13.2640
	At most 2	4.4857	3.3243
	At most 3	1.1613	1.1613
Israel	None	39.2065*	21.7971
	At most 1	17.4094	10.8411
	At most 2	6.5683	6.4918
	At most 3	0.0765	0.0765
Romania	None	45.8890*	19.5564
	At most 1	26.3327	15.9954
	At most 2	10.3373	9.5320
	At most 3	0.8053	0.8053
Thailand	None	48.4151	33.4824
	At most 1	14.9328*	13.4333
	At most 2	1.4995	1.4882
	At most 3	0.0113	0.0113
Ireland	None	60.6224	31.5664
	At most 1	29.0560*	17.4565
	At most 2	11.5995	10.3492
	At most 3	1.2503	1.2503
Argentina	None	32.8187*	14.5070

	At most 1	18.3117	10.8047
	At most 2	7.5070	5.2587
	At most 3	2.2483	2.2483
Chile	None	93.3672	76.1435
	At most 1	17.2238*	11.6809
	At most 2	5.5429	4.3234
	At most 3	1.2195	1.2195
Egypt	None	57.3389	34.6257
	At most 1	22.7132*	11.7722
	At most 2	10.9410	10.6132
	At most 3	0.3278	0.3278
Indonesia	None	62.0395	30.6213
	At most 1	31.4182	19.2794
	At most 2	12.1388*	12.0544
	At most 3	0.0843	0.0843
Pakistan	None	37.6441*	28.6281
	At most 1	9.0159	7.0497
	At most 2	1.9663	1.9555
	At most 3	0.0107	0.0107
Hungary	None	22.3885*	10.0972
	At most 1	12.2913	9.1859
	At most 2	3.1054	2.8242
	At most 3	0.2812	0.2812
Colombia	None	55.2274	26.0135
	At most 1	29.2138*	18.2449
	At most 2	10.9689	10.4759
	At most 3	0.4931	0.4931
Ukraine	None	38.5983*	23.8973
	At most 1	14.7010	12.6490
	At most 2	2.0520	1.9994
	At most 3	0.0526	0.0526
Slovakia	None	47.1089*	26.9025
	At most 1	20.2065	14.4888
	At most 2	5.7177	4.2997
	At most 3	1.4180	1.4180
Slovenia	None	45.2683*	23.0977
	At most 1	22.1706	13.5634
	At most 2	8.6073	6.6918
	At most 3	1.9155	1.9155
Serbia	None	74.7499	31.7602
	At most 1	42.9897	29.6796
	At most 2	13.3101*	9.3552
	At most 3	3.9549	3.9549
United Arab Emirates	None	77.6808	40.1180
	At most 1	37.5628	27.0658
	At most 2	10.4970*	6.4688
	At most 3	4.0282	4.0282

Table A2: Panel Causality for developed countries from the top 50 list

Hypothesis	Fisher Statistic	Conclusion
$lnResearchOutput \rightarrow lnCO2$	72.912	No Causality
$lnCO2 \rightarrow lnResearchOutput$	68.382	No Causality
$lnGDP \rightarrow lnResearchOutput$	69.388	No Causality
$lnResearchOutput \rightarrow lnGDP$	85.652	No Causality
$lnResearchOutput \rightarrow lnGERD$	76.753	No Causality
$lnGERD \rightarrow lnResearchOutput$	83.675	No Causality
$lnGERD \rightarrow lnCO2$	83.230	No Causality
$lnCO2 \rightarrow lnGERD$	111.364**	One-way causality from CO2 to GERD
$lnGDP \rightarrow lnCO2$	72.356	No Causality
$lnCO2 \rightarrow lnGDP$	53.243	No Causality
$lnGDP \rightarrow lnGERD$	129.009**	One-way Causality from GDP to GERD
$lnGERD \rightarrow lnGDP$	46.312	No Causality

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Table A3: Panel Causality for developing countries from the top 50 list

Hypothesis	Fisher Statistic	Conclusion
$lnResearchOutput \rightarrow lnCO2$	110.137***	Two-way Causality from Research Output to CO2
$lnCO2 \rightarrow lnResearchOutput$	98.748*	Two-way Causality from CO2 to Research Output
$lnGDP \rightarrow lnResearchOutput$	69.220	No Causality
$lnResearchOutput \rightarrow lnGDP$	95.388	No Causality
$lnResearchOutput \rightarrow lnGERD$	106.176*	One-way Causality from Research Output to GERD
$lnGERD \rightarrow lnResearchOutput$	65.157	No Causality
$lnGERD \rightarrow lnCO2$	60.433	No Causality
$lnCO2 \rightarrow lnGERD$	62.584	No Causality
$lnGDP \rightarrow lnCO2$	83.941	No Causality
$lnCO2 \rightarrow lnGDP$	76.992	No Causality
$lnGDP \rightarrow lnGERD$	98.719**	Two-way Causality from GDP to GERD
$lnGERD \rightarrow lnGDP$	98.672**	Two-way Causality from GERD to GDP

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Table A4: Panel Causality for High-income countries from the top 50 list

Hypothesis	Fisher Statistic	Conclusion
lnResearchOutput → lnCO2	75.845	No Causality
lnCO2 → lnResearchOutput	82.813	No Causality
lnGDP → lnResearchOutput	81.007	No Causality
lnResearchOutput → lnGDP	93.902	No Causality
lnResearchOutput → lnGERD	94.915	No Causality
lnGERD → lnResearchOutput	90.077	No Causality
lnGERD → lnCO2	90.622	No Causality
lnCO2 → lnGERD	124.830**	One-way Causality from CO2 to GERD
lnGDP → lnCO2	77.509	No Causality
lnCO2 → lnGDP	83.897	No Causality
lnGDP → lnGERD	148.862**	One-way Causality from GDP to GERD
lnGERD → lnGDP	59.744	No Causality

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Table A5: Panel Causality for Upper middle-income countries from the top 50 list

Hypothesis	**Fisher Statistic**	**Conclusion**
$lnResearchOutput \rightarrow lnCO2$	82.343***	Two-way Causality from Research Output to CO2
$lnCO2 \rightarrow lnResearchOutput$	68.274*	Two-way Causality from CO2 to Research Output
$lnGDP \rightarrow lnResearchOutput$	40.873	No Causality
$lnResearchOutput \rightarrow lnGDP$	73.279*	One-way Causality from Research Output to GDP
$lnResearchOutput \rightarrow lnGERD$	60.548	No Causality
$lnGERD \rightarrow lnResearchOutput$	52.160	No Causality
$lnGERD \rightarrow lnCO2$	43.669	No Causality
$lnCO2 \rightarrow lnGERD$	40.938	No Causality
$lnGDP \rightarrow lnCO2$	61.842**	One-way Causality from GDP to CO2
$lnCO2 \rightarrow lnGDP$	40.150	No Causality
$lnGDP \rightarrow lnGERD$	66.617*	Two-way Causality from GDP to GERD
$lnGERD \rightarrow lnGDP$	78.840**	Two-way Causality from GERD to GDP

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Table A6: Panel Causality for Lower middle-income countries from the top 50 list

Hypothesis	Fisher Statistic	Conclusion
$lnResearchOutput \rightarrow lnCO2$	24.861*	One-way Causality from Research Output to CO2
$lnCO2 \rightarrow lnResearchOutput$	16.044	No Causality
$lnGDP \rightarrow lnResearchOutput$	16.728	No Causality
$lnResearchOutput \rightarrow lnGDP$	13.859	No Causality
$lnResearchOutput \rightarrow lnGERD$	27.466	No Causality
$lnGERD \rightarrow lnResearchOutput$	6.594	No Causality
$lnGERD \rightarrow lnCO2$	9.381	No Causality
$lnCO2 \rightarrow lnGERD$	8.180	No Causality
$lnGDP \rightarrow lnCO2$	16.946	No Causality
$lnCO2 \rightarrow lnGDP$	6.187	No Causality
$lnGDP \rightarrow lnGERD$	12.249	No Causality
$lnGERD \rightarrow lnGDP$	10.401	No Causality

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

Table A7: Individual cross-section Wald stat. and p-value

Country	Optimal lag length/ k_i	$lnGDP \rightarrow lnResearchOutput$		$lnResearchOutput \rightarrow lnGDP$		Developed/Developing	H/UM/LM
		w_i	p_i	w_i	p_i		
United States of America	1	0.206	0.650	0.021	0.885	Developed	H
China	4	0.883	0.927	11.366	0.023**	Developing	UM
Germany	3	0.910	0.823	7.035	0.071*	Developed	H
United Kingdom	3	1.429	0.699	6.016	0.111	Developed	H
Japan	2	3.074	0.215	1.159	0.560	Developed	H
Canada	3	5.203	0.157	5.425	0.143	Developed	H
France	1	0.374	0.541	0.099	0.754	Developed	H
Australia	4	30.260	0.000***	8.159	0.086*	Developed	H
Italy	1	0.569	0.450	0.001	0.982	Developed	H
Spain	3	2.320	0.509	2.480	0.479	Developed	H
India	3	0.321	0.956	3.698	0.296	Developing	LM
Netherlands	1	0.008	0.930	0.540	0.462	Developed	H
South-Korea	3	6.472	0.091*	1.271	0.736	Developed	H
Russia	1	0.006	0.936	0.078	0.780	Developing	UM
Sweden	4	7.625	0.106	1.409	0.843	Developed	H
Switzerland	2	0.738	0.691	2.729	0.256	Developed	H
Brazil	4	0.684	0.953	9.970	0.041**	Developing	UM
Poland	1	0.008	0.928	0.240	0.624	Developing	H
Norway	1	0.000	0.985	0.663	0.416	Developed	H
Denmark	4	1.133	0.889	4.768	0.312	Developed	H

Belgium	1	0.501	0.479	0.240	0.624	Developed	H
Iran	1	0.360	0.548	0.160	0.689	Developing	UM
Finland	3	1.933	0.586	1.849	0.604	Developed	H
Turkey	1	0.011	0.916	1.848	0.174	Developing	UM
Austria	3	0.983	0.805	5.511	0.138	Developed	H
Portugal	4	3.016	0.555	2.906	0.574	Developed	H
Malaysia	4	4.223	0.377	1.579	0.812	Developing	UM
Greece	2	0.970	0.616	3.851	0.146	Developed	H
South-Africa	4	5.112	0.276	2.626	0.622	Developing	UM
Mexico	3	0.660	0.883	4.099	0.251	Developing	UM
New Zealand	3	1.744	0.627	5.446	0.142	Developed	H
Czech Republic	2	0.781	0.677	1.136	0.567	Developed	H
Singapore	1	0.940	0.332	0.810	0.368	Developed	H
Saudi-Arabia	2	0.255	0.881	1.749	0.417	Developing	H
Israel	1	0.003	0.959	3.086	0.079*	Developed	H
Romania	4	7.595	0.108	24.639	0.000***	Developing	UM
Thailand	3	6.319	0.097*	6.050	0.109	Developing	UM
Ireland	1	0.009	0.926	0.005	0.945	Developed	H
Argentina	2	1.551	0.460	1.377	0.502	Developing	UM
Chile	1	0.053	0.819	0.970	0.325	Developing	H
Egypt	3	12.973	0.005***	9.611	0.022**	Developing	LM
Indonesia	4	10.208	0.037**	4.779	0.311	Developing	LM
Pakistan	4	12.377	0.015***	1.353	0.852	Developing	LM
Hungary	4	15.000	0.005***	3.741	0.442	Developing	H
Colombia	4	14.278	0.006***	30.388	0.000***	Developing	UM
Ukraine	2	0.179	0.914	1.151	0.563	Developing	LM
Slovakia	1	0.066	0.797	0.161	0.688	Developed	H
Slovenia	2	5.149	0.076*	0.170	0.919	Developed	H
Serbia	4	3.288	0.511	20.874	0.000***	Developing	UM
United Arab Emirates	2	3.757	0.153	2.927	0.231	Developed	H

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used.

H-High income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

Table A8: Individual cross-section Wald stat. and p-value

Country	Optimal lag length/ k_i	$lnCO2 \rightarrow lnResearchOutput$		$lnResearchOutput \rightarrow lnCO2$		Developed/Developing	H/UM/LM
		w_i	p_i	w_i	p_i		
United States of America	3	5.102	0.165	4.135	0.247	Developed	H
China	2	1.197	0.550	2.382	0.304	Developing	UM
Germany	2	12.103	0.002***	3.419	0.181	Developed	H
United Kingdom	2	4.188	0.123	0.423	0.809	Developed	H
Japan	2	1.708	0.426	1.707	0.426	Developed	H
Canada	1	0.000	0.988	0.844	0.358	Developed	H
France	1	0.087	0.767	0.018	0.893	Developed	H
Australia	1	1.157	0.282	0.008	0.927	Developed	H
Italy	2	5.560	0.062*	0.902	0.637	Developed	H
Spain	1	0.014	0.905	0.568	0.451	Developed	H
India	1	3.348	0.067*	1.293	0.255	Developing	LM
Netherlands	1	0.047	0.829	0.858	0.354	Developed	H
South-Korea	4	8.206	0.084*	10.719	0.030**	Developed	H
Russia	4	1.342	0.854	12.088	0.017**	Developing	UM
Sweden	1	0.025	0.874	0.012	0.911	Developed	H
Switzerland	4	1.839	0.765	2.550	0.636	Developed	H
Brazil	1	0.146	0.702	0.289	0.591	Developing	UM
Poland	3	2.927	0.403	0.718	0.869	Developing	H
Norway	4	7.627	0.106	2.841	0.585	Developed	H
Denmark	1	0.000	0.999	2.258	0.133	Developed	H
Belgium	1	1.916	0.166	1.752	0.186	Developed	H
Iran	2	2.071	0.355	1.516	0.469	Developing	UM
Finland	1	0.069	0.793	0.015	0.903	Developed	H
Turkey	1	0.046	0.830	1.923	0.166	Developing	UM
Austria	4	5.236	0.264	2.469	0.650	Developed	H
Portugal	4	5.126	0.275	5.761	0.218	Developed	H
Malaysia	3	6.098	0.107	1.635	0.652	Developing	UM
Greece	4	0.581	0.965	2.091	0.719	Developed	H
South-Africa	4	9.677	0.046**	59.389	0.000***	Developing	UM
Mexico	3	2.287	0.515	2.882	0.410	Developing	UM
New Zealand	1	0.002	0.969	0.022	0.882	Developed	H
Czech Republic	1	0.290	0.590	0.407	0.524	Developed	H
Singapore	1	1.127	0.288	1.847	0.174	Developed	H
Saudi-Arabia	2	2.350	0.309	1.023	0.600	Developing	H
Israel	1	0.000	0.999	0.229	0.633	Developed	H
Romania	1	2.049	0.152	0.063	0.802	Developing	UM
Thailand	4	11.010	0.026**	7.969	0.093*	Developing	UM
Ireland	4	2.480	0.648	3.634	0.458	Developed	H

Argentina	4	7.134	0.129	3.855	0.426	Developing	UM
Chile	3	2.937	0.230	3.295	0.193	Developing	H
Egypt	3	4.380	0.223	20.172	0.000***	Developing	LM
Indonesia	3	4.418	0.220	1.827	0.609	Developing	LM
Pakistan	1	0.132	0.717	0.575	0.448	Developing	LM
Hungary	1	1.101	0.294	0.630	0.427	Developing	H
Colombia	1	2.227	0.136	7.081	0.008***	Developing	UM
Ukraine	1	3.727	0.054*	0.398	0.528	Developing	LM
Slovakia	1	0.581	0.446	1.835	0.176	Developed	H
Slovenia	2	2.782	0.249	1.245	0.537	Developed	H
Serbia	1	0.534	0.465	1.743	0.187	Developing	UM
United Arab Emirates	4	41.723	0.000***	6.104	0.192	Developed	H

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used

High-income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

Table A9: Individual cross-section Wald stat. and p-value

Country	**Optimal lag length/ k_i**	$lnGERD \rightarrow lnResearchOutput$		$lnResearchOutpu \rightarrow lnGERD$		**Developed/Developing**	**H/UM /LM**
		w_i	p_i	w_i	p_i		
United States of America	2	0.225	0.894	0.068	0.966	Developed	H
China	4	12.549	0.014**	2.819	0.588	Developing	UM
Germany	1	1.498	0.221	6.070	0.014**	Developed	H
United Kingdom	4	0.641	0.958	6.182	0.186	Developed	H
Japan	2	2.822	0.244	0.012	0.994	Developed	H
Canada	2	0.357	0.836	6.435	0.040**	Developed	H
France	4	3.289	0.511	5.607	0.230	Developed	H
Australia	2	0.702	0.704	0.604	0.739	Developed	H
Italy	1	2.432	0.119	0.002	0.968	Developed	H
Spain	4	11.270	0.024**	9.274	0.055*	Developed	H
India	1	0.901	0.343	3.129	0.077*	Developing	LM
Netherlands	1	0.004	0.950	0.092	0.761	Developed	H
South-Korea	4	8.813	0.066*	4.567	0.335	Developed	H
Russia	2	1.069	0.301	0.003	0.954	Developing	UM
Sweden	4	6.721	0.151	8.542	0.074*	Developed	H
Switzerland	4	12.627	0.013**	4.588	0.332	Developed	H
Brazil	1	1.960	0.161	0.365	0.546	Developing	UM
Poland	2	1.607	0.448	1.743	0.418	Developing	H
Norway	3	6.207	0.102	1.526	0.676	Developed	H
Denmark	1	0.392	0.531	0.038	0.845	Developed	H
Belgium	2	2.334	0.311	6.087	0.048**	Developed	H
Iran	4	3.025	0.554	11.533	0.021**	Developing	UM
Finland	4	5.843	0.211	3.688	0.450	Developed	H

Turkey	3	8.493	0.037**	13.635	0.003***	Developing	UM
Austria	2	0.736	0.692	0.130	0.937	Developed	H
Portugal	3	0.380	0.944	4.265	0.234	Developed	H
Malaysia	4	7.974	0.093*	5.345	0.254	Developing	UM
Greece	4	6.972	0.137	1.816	0.770	Developed	H
South-Africa	3	0.615	0.893	1.223	0.748	Developing	UM
Mexico	4	7.484	0.112	1.913	0.752	Developing	UM
New Zealand	4	3.432	0.488	2.954	0.566	Developed	H
Czech Republic	2	2.312	0.315	3.835	0.147	Developed	H
Singapore	1	1.822	0.177	0.830	0.362	Developed	H
Saudi-Arabia	2	2.149	0.342	0.286	0.867	Developing	H
Israel	2	3.409	0.182	6.489	0.039**	Developed	H
Romania	1	4.342	0.037**	1.802	0.179	Developing	UM
Thailand	4	3.130	0.536	6.803	0.147	Developing	UM
Ireland	4	21.396	0.000***	1.795	0.773	Developed	H
Argentina	2	3.738	0.154	0.005	0.997	Developing	UM
Chile	3	1.681	0.641	9.816	0.020**	Developing	H
Egypt	3	1.378	0.711	4.198	0.241	Developing	LM
Indonesia	3	2.068	0.558	10.097	0.018**	Developing	LM
Pakistan	4	2.886	0.577	20.868	0.000***	Developing	LM
Hungary	2	0.554	0.457	1.596	0.206	Developing	H
Colombia	2	3.513	0.173	4.351	0.114	Developing	UM
Ukraine	2	2.686	0.261	1.297	0.523	Developing	LM
Slovakia	1	3.725	0.054*	1.071	0.301	Developed	H
Slovenia	3	0.369	0.947	7.154	0.067*	Developed	H
Serbia	3	10.520	0.015**	8.691	0.034**	Developing	UM
United Arab Emirates	3	17.620	0.001***	3.637	0.303	Developed	H

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used

High-income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

Table A10: Individual cross-section Wald stat. and p-value

Country	**Optimal lag length/ k_i**	$lnGERD \rightarrow lnCO2$		$lnCO2 \rightarrow lnGERD$		**Developed/Developing**	**H/UM/LM**
		w_i	p_i	w_i	p_i		
United States of America	4	10.522	0.032**	42.582	0.000***	Developed	H
China	3	7.978	0.046**	4.681	0.197	Developing	UM
Germany	1	1.343	0.247	0.896	0.344	Developed	H

United Kingdom	1	0.170	0.680	0.963	0.326	Developed	H
Japan	1	0.762	0.383	0.726	0.394	Developed	H
Canada	1	0.000	0.998	0.728	0.394	Developed	H
France	1	1.098	0.295	0.399	0.527	Developed	H
Australia	3	6.752	0.080*	1.597	0.660	Developed	H
Italy	1	0.063	0.801	0.009	0.925	Developed	H
Spain	1	0.680	0.410	5.507	0.019**	Developed	H
India	1	0.384	0.535	0.039	0.843	Developing	LM
Netherlands	1	0.217	0.641	10.373	0.001***	Developed	H
South-Korea	4	14.844	0.005***	3.003	0.557	Developed	H
Russia	1	0.032	0.858	5.063	0.024**	Developing	UM
Sweden	1	0.189	0.664	0.975	0.324	Developed	H
Switzerland	2	0.219	0.896	0.143	0.931	Developed	H
Brazil	4	0.004	0.948	2.811	0.590	Developing	UM
Poland	3	0.353	0.552	11.041	0.012**	Developing	H
Norway	1	0.199	0.656	0.638	0.424	Developed	H
Denmark	1	0.141	0.707	1.226	0.268	Developed	H
Belgium	1	0.303	0.582	0.037	0.847	Developed	H
Iran	2	0.243	0.622	0.120	0.942	Developing	UM
Finland	1	0.254	0.614	2.353	0.125	Developed	H
Turkey	2	4.772	0.029	2.097	0.350	Developing	UM
Austria	4	18.421	0.001***	3.096	0.542	Developed	H
Portugal	4	14.379	0.006***	2.684	0.612	Developed	H
Malaysia	4	3.162	0.531	10.498	0.033**	Developing	UM
Greece	1	0.076	0.783	0.140	0.709	Developed	H
South-Africa	1	0.006	0.941	1.069	0.301	Developing	UM
Mexico	2	0.967	0.325	0.130	0.718	Developing	UM
New Zealand	4	1.221	0.269	1.677	0.795	Developed	H
Czech Republic	1	1.429	0.232	0.182	0.669	Developed	H
Singapore	1	0.000	0.999	1.843	0.175	Developed	H
Saudi-Arabia	2	0.126	0.723	0.568	0.753	Developing	H
Israel	3	4.700	0.030**	0.845	0.358	Developed	H
Romania	1	1.419	0.234	0.045	0.832	Developing	UM
Thailand	1	1.609	0.205	1.531	0.216	Developing	UM
Ireland	4	0.714	0.398	10.197	0.037**	Developed	H
Argentina	1	2.191	0.139	4.888	0.027**	Developing	UM
Chile	2	0.232	0.630	2.331	0.312	Developing	H
Egypt	1	0.068	0.794	0.162	0.687	Developing	LM
Indonesia	2	3.115	0.211	0.606	0.739	Developing	LM
Pakistan	2	7.459	0.024**	0.246	0.884	Developing	LM
Hungary	4	0.004	0.950	1.999	0.736	Developing	H
Colombia	3	4.094	0.129	15.221	0.002***	Developing	UM
Ukraine	4	0.694	0.952	4.049	0.399	Developing	LM
Slovakia	1	0.146	0.703	15.133	0.000***	Developed	H
Slovenia	1	0.549	0.459	0.060	0.807	Developed	H
United Arab Emirates	1	1.053	0.305	0.521	0.470	Developed	H

Serbia	1	0.347	0.556	1.492	0.222	Developing	UM

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used

High-income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

Table A11: Individual cross-section Wald stat. and p-value

Country	**Optimal lag length/ k_i**	$lnGDP \rightarrow lnCO2$		$lnCO2 \rightarrow lnGDP$		**Developed/ Developing**	**H/UM/LM**
		w_i	p_i	w_i	p_i		
United States of America	4	1.424	0.840	0.493	0.974	Developed	H
China	4	16.565	0.002***	0.464	0.977	Developing	UM
Germany	1	0.848	0.357	0.989	0.320	Developed	H
United Kingdom	1	0.147	0.701	1.086	0.297	Developed	H
Japan	1	0.953	0.329	0.031	0.860	Developed	H
Canada	1	1.813	0.178	0.002	0.969	Developed	H
France	1	0.426	0.514	0.105	0.745	Developed	H
Australia	3	0.516	0.472	0.017	0.896	Developed	H
Italy	1	0.169	0.681	0.313	0.576	Developed	H
Spain	2	4.433	0.109	0.067	0.967	Developed	H
India	1	0.000	0.991	0.674	0.412	Developing	LM
Netherlands	1	0.025	0.874	0.274	0.600	Developed	H
South-Korea	1	0.041	0.839	3.959	0.047**	Developed	H
Russia	1	0.072	0.788	0.067	0.795	Developing	UM
Sweden	1	1.643	0.200	1.406	0.236	Developed	H
Switzerland	1	0.063	0.802	0.091	0.763	Developed	H
Brazil	3	0.463	0.927	32.312	0.000***	Developing	UM
Poland	4	6.490	0.165	16.431	0.002***	Developing	H
Norway	1	1.303	0.254	1.383	0.240	Developed	H
Denmark	1	0.086	0.770	0.143	0.705	Developed	H
Belgium	1	0.112	0.738	0.427	0.514	Developed	H
Iran	2	0.639	0.726	0.762	0.683	Developing	UM
Finland	1	3.688	0.055*	1.512	0.219	Developed	H
Turkey	1	0.659	0.417	0.265	0.607	Developing	UM
Austria	1	1.404	0.236	0.277	0.598	Developed	H
Portugal	4	4.452	0.348	15.496	0.004***	Developed	H
Malaysia	2	7.492	0.024**	2.582	0.275	Developing	UM
Greece	2	4.170	0.124	0.852	0.653	Developed	H
South-Africa	1	5.834	0.016**	0.001	0.976	Developing	UM
Mexico	2	5.552	0.062*	0.298	0.862	Developing	UM
New Zealand	3	16.553	0.001***	0.945	0.815	Developed	H
Czech Republic	2	5.461	0.065*	2.377	0.305	Developed	H
Singapore	1	0.836	0.361	0.399	0.528	Developed	H
Saudi-Arabia	1	0.101	0.751	1.738	0.187	Developing	H
Israel	1	2.089	0.148	1.342	0.247	Developed	H
Romania	1	0.050	0.823	2.255	0.133	Developing	UM
Thailand	1	4.011	0.045**	0.121	0.728	Developing	UM
Ireland	4	11.756	0.019**	8.459	0.076*	Developed	H
Argentina	1	0.642	0.423	3.431	0.064*	Developing	UM

Chile	1	0.023	0.878	0.029	0.865	Developing	H
Egypt	2	2.769	0.250	0.890	0.641	Developing	LM
Indonesia	4	7.543	0.110	3.331	0.504	Developing	LM
Pakistan	4	11.329	0.023**	1.865	0.761	Developing	LM
Hungary	4	2.611	0.625	1.992	0.737	Developing	H
Colombia	1	0.109	0.742	2.406	0.121	Developing	UM
Ukraine	2	2.207	0.332	1.604	0.448	Developing	LM
Slovakia	1	0.495	0.482	0.390	0.532	Developed	H
Slovenia	1	3.429	0.064*	3.266	0.071*	Developed	H
United Arab Emirates	1	0.164	0.685	0.938	0.333	Developed	H
Serbia	1	0.718	0.397	1.230	0.267	Developing	UM

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used

High-income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

Table A12: Individual cross-section Wald stat. and p-value

Country	**Optimal lag length/ k_i**	$lnGDP \rightarrow lnGERD$		$lnGERD \rightarrow lnGDP$		**Developed/Developing**	**H/UM/LM**
		w_i	p_i	w_i	p_i		
United States of America	3	20.958	0.000***	0.729	0.866	Developed	H
China	4	25.225	0.000***	4.851	0.303	Developing	UM
Germany	4	9.314	0.054*	3.803	0.433	Developed	H
United Kingdom	1	2.499	0.114	0.233	0.630	Developed	H
Japan	2	1.029	0.598	0.544	0.762	Developed	H
Canada	1	0.251	0.617	0.038	0.845	Developed	H
France	1	1.790	0.181	0.144	0.705	Developed	H
Australia	2	1.053	0.591	0.936	0.626	Developed	H
Italy	1	0.703	0.402	0.629	0.428	Developed	H
Spain	3	6.429	0.093*	3.203	0.361	Developed	H
India	4	6.312	0.177	10.365	0.035**	Developing	LM
Netherlands	4	22.243	0.000***	0.897	0.925	Developed	H
South-Korea	4	14.451	0.006***	1.280	0.865	Developed	H
Russia	3	4.958	0.175	6.799	0.079*	Developing	UM
Sweden	3	11.502	0.009***	4.248	0.236	Developed	H
Switzerland	2	4.842	0.089*	1.039	0.595	Developed	H
Brazil	1	1.968	0.161	4.879	0.027**	Developing	UM
Poland	1	9.067	0.003***	0.620	0.431	Developing	H
Norway	1	1.749	0.186	0.040	0.841	Developed	H
Denmark	1	6.131	0.013**	0.776	0.378	Developed	H
Belgium	3	1.287	0.732	3.269	0.352	Developed	H
Iran	3	1.614	0.204	0.186	0.666	Developing	UM

Finland	4	0.906	0.924	2.274	0.685	Developed	H
Turkey	3	5.736	0.125	10.196	0.017**	Developing	UM
Austria	2	4.040	0.133	1.066	0.587	Developed	H
Portugal	4	1.072	0.899	4.509	0.341	Developed	H
Malaysia	3	9.933	0.019**	9.024	0.029**	Developing	UM
Greece	2	2.040	0.361	0.704	0.703	Developed	H
South-Africa	2	9.315	0.009***	0.494	0.781	Developing	UM
Mexico	1	1.328	0.249	0.038	0.846	Developing	UM
New Zealand	2	12.875	0.002***	0.807	0.668	Developed	H
Czech Republic	2	0.319	0.852	0.550	0.760	Developed	H
Singapore	2	3.220	0.200	3.020	0.221	Developed	H
Saudi-Arabia	1	1.010	0.315	2.970	0.085*	Developing	H
Israel	4	6.898	0.141	3.279	0.512	Developed	H
Romania	2	4.288	0.117	2.015	0.365	Developing	UM
Thailand	1	11.635	0.001***	3.749	0.053*	Developing	UM
Ireland	3	9.279	0.026**	5.126	0.163	Developed	H
Argentina	1	3.249	0.071*	1.611	0.204	Developing	UM
Chile	2	4.688	0.096*	0.396	0.820	Developing	H
Egypt	1	0.125	0.724	0.001	0.971	Developing	LM
Indonesia	4	4.203	0.379	1.752	0.781	Developing	LM
Pakistan	2	0.535	0.765	0.727	0.695	Developing	LM
Hungary	4	0.504	0.973	4.075	0.396	Developing	H
Colombia	2	9.695	0.008***	1.366	0.505	Developing	UM
Ukraine	1	0.480	0.488	0.668	0.414	Developing	LM
Slovakia	2	4.209	0.122	1.517	0.468	Developed	H
Slovenia	2	0.256	0.880	4.931	0.085*	Developed	H
United Arab Emirates	1	0.071	0.789	1.194	0.274	Developed	H
Serbia	2	2.002	0.368	11.038	0.004***	Developing	UM

Granger causality carried out using a maximum of 4 lags. * (**) (***) denote statistical significance at the 10% (5%) (1%) level of significance. Lag orders ki is selected by AIC. 100 Bootstrap replications were used

High-income countries, UM-Upper-middle income countries and LM-Lower-middle income countries.

<u>Research Output and CO2 emissions</u>

Results showed that the null hypothesis of Research Output does not Granger cause CO2 was rejected only by South-Korea, Russia, South-Africa, Thailand, Egypt and Colombia. This means that these countries are good at absorbing and applying the research in the climate change field they produce in the real world towards lowering emissions, whether it’s through new policies or technology brought about.

The null hypotheses of CO2 does not Granger cause Research Output was rejected by Germany, Italy, India, South-Korea, South-Africa, Thailand, Ukraine and UAE. Intuitively it makes sense that a country's overall climate change-related research output will be linked with the performance of lowering emissions by a country. These countries are all high emitters of CO2 emissions and this fact alone could push these countries to put more emphasis on climate change-related research, hence we can say that CO2 emissions alone are a driver in increasing climate change-related research output with these countries.

<u>GDP and Research Output</u>

The null hypothesis of GDP does not Granger cause Research Output is rejected by Australia, South-Korea, Thailand, Egypt, Indonesia, Pakistan, Hungary, Colombia and Slovenia. This implies that an economies level of growth is a major determinant to overall climate change-related research output. This makes intuitive sense because the more these economies grow, the higher their investments into R&D will be, hence bringing about an increase in research output.

Looking at the opposite relationship, of Research Output does not Granger cause GDP, China, Germany, Australia, Brazil, Israel, Romania, Egypt, Colombia and Serbia reject it. This illustrates that there is a link between Climate Change Research Output and GDP level in these countries. Based on the results these countries strongly consider and utilize its climate change research output when it comes to funding allocation in the country. This is supported by the fact that China, Germany, Australia and Brazil are amongst the countries that invested most heavily into clean energy in 2019 (Statista, 2020).

<u>Research Output and GERD</u>

Lastly, looking at the null hypothesis of Research Output does not Granger cause GERD is rejected by Germany, Canada, Spain, India, Sweden, Belgium, Iran, Turkey, Israel, Chile, Indonesia, Pakistan, Slovenia and Serbia. It makes intuitive sense that a country's quality of research output will be a driver that influences the amounts of funds going into it every year, seeing that a country will be more willing to invest heavily into R&D if it consistently produces high-quality research output and vice-versa.

On the other hand, there is causality running from GERD to Research Output for China, Spain, South-Korea, Switzerland, Turkey, Malaysia, Romania, Ireland, Slovakia, Serbia and UAE. This result implies that the money spent on R&D in these countries will most likely lead to an outcome of research output published.

<u>GERD and CO2 emissions</u>

The null hypothesis of GERD does not Granger cause CO2 was rejected only by USA, China, Australia, South-Korea, Austria, Portugal, Israel and Pakistan. Showing that overall, R&D on climate change mitigating technology is not a driver in lowering CO2 emissions in most cases, indicating that these countries might be more research-intensive before applying any policies which will ultimately influence the country's emissions.

The null hypothesis of CO2 does not Granger cause GERD was rejected by the USA, Spain, Netherlands, Russia, Poland, Malaysia, Ireland, Argentina, Colombia and Slovakia. Although this only makes up a portion of the top 50 list, the overall Granger causality test shows that a causal relationship runs from CO2 to GERD. This makes intuitive sense because a country is more likely to increase or decrease their GERD based on the country's performance in trying to lower emissions.

<u>GDP and CO2 emissions</u>

GDP does not Granger cause CO2 is rejected by China, Finland, Malaysia, South-Africa, Mexico, New Zealand, Czech Republic, Thailand, Ireland, Pakistan and Slovenia which are mainly developing countries. This makes economic sense since these countries are still on the path to grow their economies and seeing that these are mainly coal and oil-rich nations, which will rely heavily on their resources to do so. GDP growth will therefore be a strong driver of CO2 emissions for these countries.

This will support the EKC hypothesis, seeing that these countries have not reached their respective peaks with emissions and still need time to grow.

Looking at the opposite relationship, CO2 does not Granger cause GDP, only China, South-Korea, Brazil, Poland, Portugal, Ireland, Argentina and Slovenia reject it. It doesn’t make intuitive sense that CO2 has a direct impact on GDP, unless it’s viewed from the perspective of more emissions, means higher overall production in your country. Seeing that all the countries that reject this null hypothesis are developing countries besides South-Korea, Portugal and Slovenia, it would make economic sense. This is because these countries would not have reached their respective peaks of their EKC and are still in the process of growing their economies to the point in which we will start to see a dip in their CO2 emissions. Hence, CO2 emission is a key indicator of growth performance for these countries. The same reasoning will apply to South-Korea, Portugal and Slovenia because they are fast-growing economies who haven’t reached their peaks in the EKC.

GDP and GERD

Lastly, looking at the individual cross-sections, the null hypothesis of GDP does not Granger cause GERD is rejected by USA, China, Germany, Spain, Netherlands, South-Korea, Sweden, Switzerland, Poland, Denmark, Malaysia, South-Africa, New Zealand, Thailand, Ireland, Argentina, Chile and Colombia. This implies that the more these economies grow, the higher their investments into R&D will be for technological developments.

On the other hand, there is no causality running from GERD to GDP for the most case, except with China, India, Russia, Brazil, Turkey, Malaysia, Saudi-Arabia, Thailand, Slovenia and Serbia. Four out of the five of the countries represent the BRICS nations. This illustrates that GERD has a much larger influence on a country’s GDP level, in your more emerging economies such as your BRICS nations and other countries like Turkey, Saudi Arabia, Malaysia, Thailand, Serbia and Slovenia that all rejected the null hypotheses. The BRICS nations and countries such as Saudi Arabia, Turkey, Malaysia, Mexico and

Serbia all form part of this groups, and knowing that the BRICS countries are all heavily coal and fossil dependent (Ndlovu & Inglesi-Lotz, 2019, 2020) for both energy supply and GDP growth, combined with the fact that Russia, Saudi-Arabia, Mexico and Malaysia are all major oil exporters, it supports the results shown that a change in CO_2 emissions is linked with growth in these countries.