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Abstract

In order to estimate both short run and long run effects on CO_2 Emissions of several variables including FDI Inflows, Per Capita GDP, Gross Capital Formation, Trade Openness, Fossil Fuels Consumption, Renewable Energy, Population Density and Oil Price, we make use of a Dynamic Fixed Effects estimator (ARDL) for a dataset of 43 countries during the period 1980-2019. Our main results show that Fossil Fuels Consumption and Economic Growth significantly favors Carbon Dioxide Emissions, although this conclusion is inverted once we account for subsamples. Moreover, mitigation evidence from Renewable Energy sources is confirmed for the full sample. We develop as well a non-linear causality model, which tends to overcome the classical Granger approach while working with complex systems, to correctly assess causality between our variables. However, from our estimations, evidence of nonlinearity is ruled out for a set of variables. Hence, we address causality with the classical Granger Approach. With this technique, evidence of a two-way relation between Renewable Energy Sources and Carbon Emissions is confirmed.

Resumen

Con el objetivo de estimar tanto efectos de corto plazo como de largo plazo en las Emisiones de CO_2 de diferentes varables incluyendo Flujos de IED, PBI Per Cápita, Formación Bruta de Capital, Apertura Comercial, Consumo de Combustibles, Energía Renovable, Densidad Poblacional y Precio del Petróleo, hacemos uso de un estimador Dinámico de Efectos Fijos (ARDL) para una base de datos de 43 países durante el período 1980-2019. Nuestros resultados principales muestran que el Consumo de Combustibles Fósiles y el Crecimiento Económico favorecen significativamente a las Emisiones de Dióxido de Carbono, aunque esta conclusión se invierte una vez que se analiza por submuestras. Asimismo, evidencia de mitigación por parte de Fuentes de Energías Renovables es confirmada para la muestra en su conjunto. A su vez, desarrollamos un modelo de causalidad no linear, el cual tiende a superar el enfoque clásico de Causalidad "á la" Granger al analizar sistemas complejos, para constatar correctamente causalidad entre las variables. A pesar de ello, a partir de nuestras estimaciones, evidencia de no linearidad es rechazada para un conjunto de variables. Por tal motivo, estimamos causalidad a través del clásico Enfoque de Granger. Con esta técnica, evidencia de una relación dual entre Fuentes de Energías Renovables y Emisiones de Carbono es confirmada.

Keywords— emissions, panel data, dynamic model, short run and long run effects, ARDL.

Palabras clave— emisiones, modelos en panel, modelo dinámico, efectos de corto y largo plazo, ARDL.

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1 Introduction

Carbon Dioxide Emissions and Environmental Issues are a recurring theme both in the economic, social and political space, as well as in the Academy. For the last 30 years and particularly today, CO_2 Emissions and Reduction Policies are a hot topic for policy makers and the society as a whole.

Two separate analyses from the Scripps Institution of Oceanography and the National Oceanic and Atmospheric Administration has showed that levels of carbon dioxide in the air averaged 419 parts per million in May 2021 (annual peak), a thrilling number considering that it represents about half a percent higher than the previous high of 417 parts per million, set in May 2020. Carbon dioxide is the most important greenhouse gas driving global warming and researchers have estimated that there has not been this much proportion of CO_2 in the atmosphere for millions of years.

According to the United Nations Environment Programme (UNEP), even though The Covid-19 Crisis has produced a significant slowdown in Greenhouse Emissions, the world is still directed to a pervasive rise in global temperature of 3°C, if no environmental action is taken. This means that although many countries have accepted The Kyoto's Protocol in 1997 and The Paris Agreement in 2015, to this day no serious or fundamental environmental change has been developed by policy makers and companies from all over the globe, as already stated by the Climate Action Tracker in 2020.

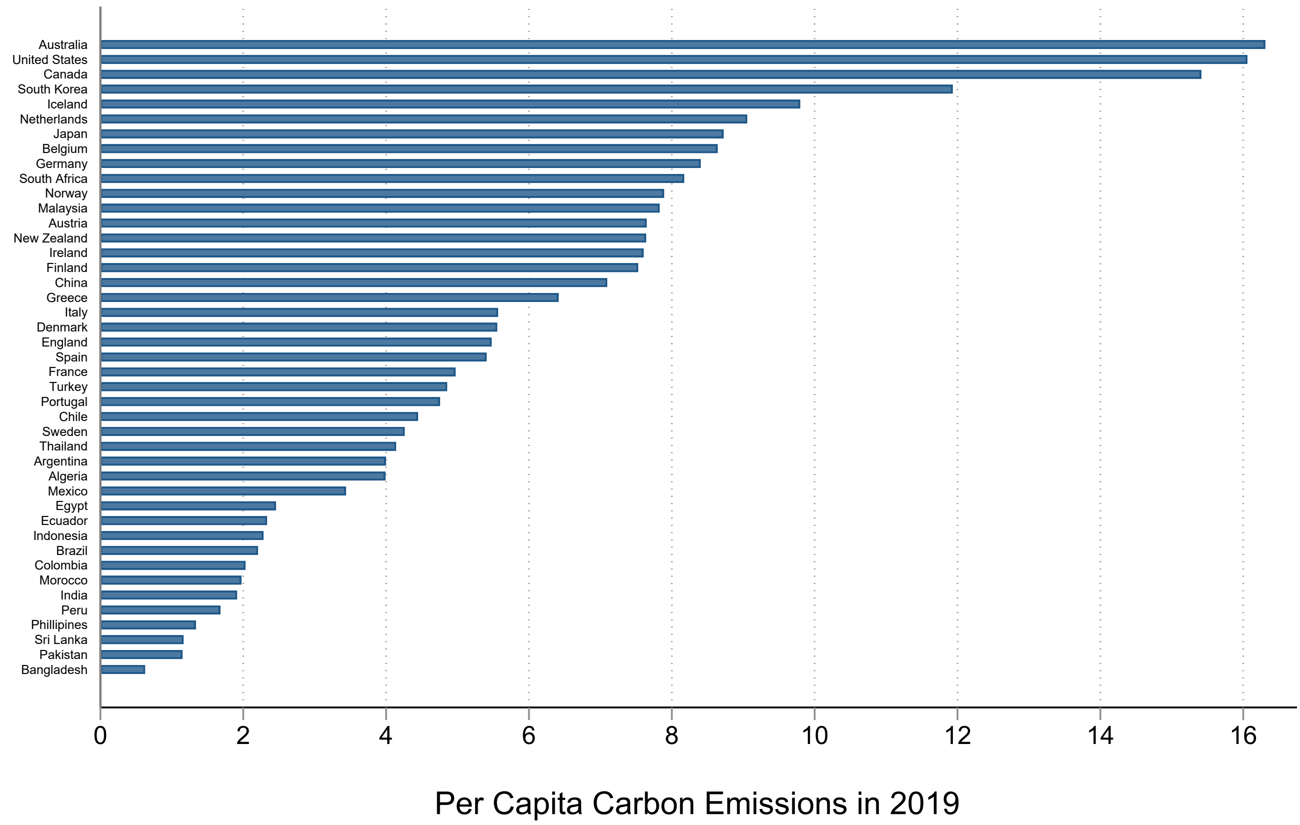
Moreover, the FootPrint Network Organization has estimated that the World consumes the equivalent to 1.6 Earths to provide the resources we use. This means that it takes the Earth one year and eight months to regenerate what we use in a full year. In other words, we use more ecological resources and services than nature can regenerate through overfishing, overharvesting forests, and emit more carbon dioxide into the atmosphere than forests can sequester.

Carbon Dioxide Emissions Mitigation reports have also scalated due to the unprecedented levels in pollution. The annual United Nations (UN) Environment Emissions Gap Report presented an assessment of current national reducing efforts and the targets that the countries have presented, which constitute the foundation of the Paris Agreement. Despite growing global awareness of the dangers posed by climate change, fossil CO2 emissions from energy use and industry rose for three consecutive years to aprroximately 52.4 GtCO2e[1] ($\pm$5,2 bound).

1. GtCO2e stands for Gigatonnes of CO_2 equivalent.

We believe studying Environmental Topics is necessary to make a change and contribute to mitigate Climate Change. Carbon Dioxide Emissions have been increasing for the last 40 years and are currently in worrying levels (see Figure 1).

Figure 1: Per Capita Carbon Emissions in year 2019.



Note. Own elaboration based on data from Our World in Data.

Analyzing the impact of several economic variables in Carbon Dioxide Emissions is key to correctly address policies. Most countries, specially developing economies, are facing a current dilemma: how to grow and overcome poverty traps without sacrificing the Environment. In other words, how to accomplish Sustained Development. And this conclusion needs to be specific of every economy and every country, otherwise, applying and establishing policies that worked for developed economies to poorer countries most likely will not to the job.

To help enrich this debate, we analyze a Panel Dataset of 43 countries from 1980 to 2019. We develop a Dynamic Fixed Effects Model to estimate the magnitude and sign of both short and long run effects of several variables including FDI Inflows, Per Capita GDP, Gross Capital Formation, Trade Openness, Fossil Fuels Consumption, Renewable Energy, Population Density and Oil Price on

Carbon Dioxide Emissions.

In doing so, we contribute to the Literature of Environmental Policies in analyzing different models between groups of countries ordered by income and geographic locations, a feature that was missing in other papers and works. This is, we differentiate models between Low Income, Middle Income and High Income countries, and we also adapt results between American, European, Asian, African and Oceanian economies, in order to account and address for specific country region and income effects.

This paper has the following structure. In Section II we ilustrate the state of the arts in terms of other works and Literature related to Environemental Policies and Economic variables, both for EKC Hypothesis and for the econometric methodology used in this paper. In Section III we present our data and develop the mathematical and econometric framework used in this research. In section IV we present our results for the whole dataset and differentiating between groups of countries and regions. Finally, in Section V we conclude our paper calling for action and developing several policies that ought to contribute to CO_2 Emissions Mitigation and facilitate Sustained Development.

2 Literature Review

2.1 EKC and Economic Environmental Approach

Although Environmental Debates seem to be a recent topic in the Political and Social spectrum, in the Academy has been a present theme for more than 50 years. The first and most influential paper in this literature, which had nothing to do with Environmental topics, was the seminal work by Simon Kuznets in 1955. The author analyzed the interrelationship between Income Distribution (and specifically Income Inequallity) and Economic Growth. He set up a model and ilustrated that income per capita and income inequality exhibits an inverted-U shape curve relation: initially, as per capita income rises, equality increases as well. However, after a turning point (peak), it begins to decline. In other words, in the initial stages of development (poor economies), income growth is related to equality, while at the later stages of development (rich economies), it is related to inequality. This formulation was thereafter named ”Kuznets Curve”.

Figure 2: Kuznets Curve.

Regardless of the work by Vernon et al. (1981), which is considered one of the first investigation in terms of environmental and economic relation, it was not until the 1990s that the Kuznets Curve was estimated and contextualized in conjunction with Environmental topics. Despite the fact that the term "Environmental Kuznets Curve" (or EKC from here onwards) was first coined in 1993 by Panayotou, the first work to address Kuznets Curve model with Pollution and Emissions was the paper developed by Grossman & Krueger (1991). The authors empirically tested and demonstrated the existence of an inverted U-shaped curve between Income and Environmental Pollution[2].

A year later, Shafik & Bandyopadhyay assessed a report in cooperation with the World Bank where they explored the relationship between Economic Growth and Environmental Quality by analyzing patterns of environmental transformation for countries at different income levels. Not only did the authors expand the works in terms of economic variables effects on pollution, but they also deepened the knowledge with respect to panel data approach. Their report concluded that as revenues increase, the demand for improving the quality of the environment as well as the resources available for investment, will go up. This result is supported by Beckerman's paper (1992), which states that although economic growth usually contributes to environmental degradation in the first stages, it ultimately represents the best and optimal path to achieve an adequate quality of the environment in most countries.

Since the aforementioned papers, the amount of literature related to the EKC Curve and the effects of several economic variables in CO_2 Emissions has increased considerably. We present a table which consists of the most influential and relevant papers related to the subject in matter and then we include several works that have influenced this paper:

2. The authors analyzed SO_2 and Smoke.

Table 1: Literature Related

Authors	Period & Regions	Methodology	Main Results
Asafu-Adjayel, J. (1999)	1971-1995: 4 Asian Countries	Cointegration, VEC Model	Energy and Income have a unidirectional causal relation for India and Indonesia.
Alam & Sabihudinn (2002)	1960-1998: Pakistan	Cointegration, VEC Model	In the short run there exists a one way causality between Energy Consumption and Economic Growth.
Soytas & Sari (2003)	1950-1992: G7-E Countries	Cointegration, VEC Model	There is bidirectional causality between Energy Consumption and GDP in Argentina.
Ang, J. B. (2008)	1971-1999: Malaysia	Cointegration Model	Energy use and Output perceives a Long Run relation with Pollution and Economic Growth.
Chebbi & Boujelbene (2008)	1971-2004: Tunisia	VEC Model, IR Functions	In the short run, Economic Growth exerts a positive effect on Energy Consumption.
Halicioglu, F. (2008)	1960-2005: Turkey	Cointegration Model	In the long run, Income and Foreign Trade have a positive effect over Carbon Emissions.
Choi et al. (2010)	1971-2006: China, Korea, Japan	VAR, VEC Model	GDP and Trade Openness have a positive relationship with CO2 Emissions.
Hossain, S. (2011)	1971-2007: NI Countries	Cointegration Model	Economic Growth and Trade Openness have a positive short run effect over Carbon Emissions.
Arouri et al. (2012)	1981-2005: 12 MENA Countries	Cointegration, CCE-MG Model	Energy Consumption has a positive long run impact in CO2 Emissions.
Omri, A. (2013)	1990-2011: 14 MENA Countries	2SLS, GMM Estimators.	Results support bidirectional causality between Economic Growth and CO2 Emissions.
Fakhri et al. (2015)	1990-2010: 12 MENA Countries	DOLS, FMOLS Models	Energy Consumption and per capita GDP have a positive effect on CO2 Emissions.
Kasperowicz, R. (2015)	1995-2012: 18 EU Countries	Panel VEC Model.	In the short run there exists a positive relation between GDP and CO2 Emissions.
Saidi & Hammami (2015)	1990-2012: 58 Countries	GMM Estimator	Evidence shows a positive impact of CO2 emissions on Energy Consumption.
Ghouali, Y. Z. (2015)	1990-2012: BRICS	DOLS, FMOLS Model	Results confirm a long run relation between the variables included in the model.
Magazzino, C. (2016)	1960-2013: 6 GCC Countries	Cointegration Model	Results reject that Energy Use is neutral to Economic Growth.
Dogan & Aslan (2017)	1995-2011: EU Countries	FE, DOLS, FMOLS Model	There exists a one-way causality from Tourism to Carbon Emissions.
Ivanovic et al. (2017)	1997-2014: 17 Countries	DOLS, FMOLS Model	Existence of a long run relationship between CO2 Emissions and Real GDP is confirmed.
Goodness & Prosper (2017)	1971-2013: Developing Countries	DP Threshold Model	Economic Growth has different effects on CO2 Emissions depending on bounds.

Jardón et al. (2017)	1971-2011: LAC Countries	GM-FMOLS, D-GMOLS	Under cross-sectional independence, the existence of a EKC is confirmed.
Apergis et al. (2017)	1995-2010: American Countries	DOLS, FMOLS Model	Tourism, Renewable Energy and FDI contribute to Carbon Emissions mitigation.
Shahbaz et al. (2019)	1990-2015: MENA Countries	GMM Estimator	Evidence of feedback effect between Economic Growth and CO2 Emissions is confirmed.
Zhang et al. (2019)	1995-2017: Developing Countries	FMOLS Model	Energy Consumption has positive and significant effects on Carbon Emissions.
Manta et al. (2020)	2000-2017: CEE Countries	FMOLS, VEC Model	Bidirectional causality arises between Financial Development and GDP.
Moessner et al. (2021)	1971-2016: 121 Countries	Dynamic Panel Model	Carbon Emissions rise with Economic Development and Urbanization.

2.2 Dynamic Panel Approach Literature

Related to this paper and its methodology, we have included some investigations that served as a base framework. The first work included in this section was carried out by Islam et al. (2014). The authors examine the short run and long run impacts of Carbon Dioxide emissions on agricultural productivity in Southeast Asian countries. They investigate the dynamic relationship between CO_2 emissions (along with other control-variables) and agricultural output using a dynamic panel ARDL Model, based on a Pooled-Mean Group Estimator. Results show that increased Carbon emissions result in higher agricultural productivity due to the fact that farmers quickly adapt to climate change. In addition, use of capital machineries significantly increases agricultural yield and reduces dependency on human capital. Moreover, chemical fertilizers increase productivity in the short-run but display harmful impact in the long-run.

Two years later, Byrne et al. analyzed the nexus between economic growth and fossil and non-fossil fuel consumption for 53 countries (divided into four categories including developed exporters, developed importers, developing exporters and developing importers) between 1990 and 2012 employing a Pooled-Mean Group Dynamic ARDL approach. The investigators found evidence of bi-directional causality between fossil fuel consumption and real GDP across all subsamples. Moreover, two-way causality between non-fossil fuel use and real GDP is found in the short and long run for developed importers, while two-way causality is observed only in the long run for developed exporters. Likewise, evidence of negative long-run causality from real GDP to non-fossil fuels is confirmed for developing exporters. Finally, long-run causality from non-fossil fuel use to real GDP is observed for developing importers.

Fauzel (2016), in turn, explores long run and short run impact of FDI (disaggregated into manufacturing and non- manufacturing sector), on Carbon Dioxide emission in Mauritius for the period 1980-2012. In his work, the author uses a bounds testing approach to cointegration. The main findings of his study is that foreign direct investment in the manufacturing sector is harmful for the environment, whereas in non-manufacturing sectors it is not. Moreover, results show that growth is also seen to increase levels of CO_2 emissions. Finally, the estimations conclude that Energy Use positively accelerates emissions.

Furthermore, Yazdi, S. K. & Dariani A. G. (2019) inspect the dynamic causal relationships between Carbon Dioxide emissions, energy consumption, economic growth, trade openness and urbanisation for the period 1980–2014 using the Pooled-Mean Group Estimator and panel Granger causality tests for several Asian countries. From the results, a long-run relationship among the variables is confirmed, and evidence that urbanisation increases energy consumption and CO2 emissions is concluded.

In that year, Ullah, S. & Awan, M. S. study the association between environmental quality and economic growth alongside income inequality within Environmental Kuznet Curve (EKC) framework by using three environmental quality variables (CO_2, SO_2 emission and PM2.5 concentration), for a panel dataset of Developing Asian countries for the period 1973-2016. Results confirm the presence of EKC for all environmental quality indicators in the long run. However, this conclusion does not hold in the short run. Moreover, the findings reveal that income inequality is positively related to Carbon Dioxide and Sulfur Dioxide emission and PM2.5 concentrations in the atmosphere. Furthermore, population density, urban population, foreign direct investment and trade openness are also positively related with all environmental quality variables.

To end with this section, we include the paper developed by Oikonomou et al. (2021). The scientists attempt to evaluate the energy and carbon footprint within the framework of international environmental treaties and the efforts made by 11 large polluting countries to mitigate climate change during the period 1996-2019. To do so, the authors make use of an ARDL approach employing dynamic panel data techniques. The main empirical finding suggests that the reduction in CO2 emissions might be achieved without a slowdown in economic activity for the sample countries, i.e, evidence of

Sustainable Development is established.

3 Data and Methodology

3.1 Variables

In this paper we aim to establish short run and long run effects on CO_2 for a set of Economic variables for a panel dataset of 43 economies and 40 years during the period 1980-2019. The election of the countries and the period included in this paper responds to data availability. We differentiate results between country region, i.e., America, Europe, Africa, Asia and Oceania; and between Income, this is, Low Income, Middle Income and High Income[3] (see the Appendix for more information).

The main objective of this paper is to address short and long run effects of several economic variables in Carbon Dioxide Emissions. In mathematical expression, we investigate the following relation:

$CO2_{\text{it}} = f(pcGDP_{\text{it}}, FDI_{\text{it}}, Trade_{\text{it}}, Renew_{\text{it}}, OilCons_{\text{it}}, OilPrice, GCF_{\text{it}}, Density_{\text{it}})$

where i=1,2...N are the cross section units observed over t=1,2...T periods of time.

All data has been recovered from three different sources:

- emispc: Per Capita Carbon Dioxide Emissions generated by the burning of fossil fuels from energy and cement production [4] measured in tonnes of CO_2. We use this variable as proxy of Environmental Pollution or Degradation. We have obtained data related to this variable from Our World in Data site.
- pcgdp: Per Capita Gross Domestic Product in current U$S obtained from the World Bank dataset. We utilize this variable as proxy of Economic Development or Growth.
- gcf: Gross Capital Formation as GDP percentage, tracked down from the World Bank site. We chose this variable to proxy for Financial Investment.
- fdi: Foreign Direct Investment Inflows as GDP percentage, also obtained from the World Bank dataset. We include this variable to control for Financial Investment and Financial Development.

3. The criteria utilized in Income Groups has been that of the author's decision.
4. Land use change is not included.

- renew: Percentage of Total Energy Produced by Renewables sources. This variable was collected from Our World in Data website, used to proxy for Renewable Development or Green Energy Use.

- oilcons: Per Capita Fossil Fuels Consumption, understood as the average consumption of energy from coal, oil and gas per person, measured in megawatt-hours. It is meant to proxy for Non-renewable of Fossil Fuel Energy Use. Data was obtained from the Our World in Data site.

- trade: Foreign Trade as GDP percentage, measured as the sum of exports and imports divided by country's GDP. It proxies for Foreign Trade Development. Data was collected from the World Bank page.

- density: Population Density measured as people per squared kilometer of land area. It is utilized as a proxy for Country Growth. Data was obtained from the World Bank Dataset.

- oilprice: Price of an Oil Barril in U$S. It is chosen to control for foreign effects on a specific country. Data was collected from the EIA webpage.

Summary and Descriptive Statistics are presented in the following table:

Table 2: Descriptive Statistics

Variables	*Statistics*	*Low Income*	*Middle Income*	*High Income*	*Africa*	*America*	*Asia*	*Europe*	*Oceania*	*Full Sample*
emispc	*mean*	*2.112*	*3.355*	*9.812*	*3.786*	*6.019*	*3.089*	*8.283*	*12.409*	*6.253*
	sd	*2.234*	*1.564*	*3.839*	*3.048*	*6.596*	*3.349*	*2.539*	*4.895*	*4.796*
	max	*9.950*	*8.073*	*21.292*	*9.950*	*21.291*	*12.408*	*14.240*	*19.276*	*19.276*
	min	*0.095*	*1.266*	*2.732*	*0.773*	*0.912*	*0.095*	*1.710*	*5.233*	*5.233*
	median	*1.353*	*3.544*	*9.223*	*2.498*	*3.391*	*1.372*	*8.287*	*11.940*	*11.940*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
pcgdp	*mean*	*2070.711*	*6022.342*	*28253.640*	*2640.434*	*11440.180*	*5835.305*	*27182.080*	*26459.710*	*16109.920*
	sd	*1868.068*	*3589.243*	*17459.560*	*1650.572*	*13758.860*	*10262.580*	*18437.690*	*16467.090*	*17758.930*
	max	*10216.630*	*15924.790*	*102913.500*	*8007.413*	*65297.520*	*48603.480*	*102913.500*	*68150.110*	*102913.500*
	min	*194.805*	*1246.825*	*1715.429*	*498.551*	*729.876*	*194.805*	*1246.825*	*6713.760*	*194.805*
	median	*1446.624*	*4994.635*	*24807.230*	*2436.659*	*5960.762*	*1446.743*	*24013.990*	*20210.060*	*8862.836*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*

gcf	*mean*	*0.249*	*0.215*	*0.236*	*0.248*	*0.205*	*0.269*	*0.228*	*0.247*	*0.237*
	sd	*0.070*	*0.051*	*0.043*	*0.064*	*0.031*	*0.073*	*0.039*	*0.027*	*0.056*
	max	*0.467*	*0.436*	*0.438*	*0.431*	*0.304*	*0.467*	*0.438*	*0.299*	*0.467*
	min	*0.125*	*0.120*	*0.102*	*0.125*	*0.120*	*0.125*	*0.102*	*0.175*	*0.102*
	median	*0.241*	*0.210*	*0.231*	*0.247*	*0.207*	*0.259*	*0.227*	*0.246*	*0.229*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
fdi	*mean*	*0.015*	*0.027*	*0.031*	*0.014*	*0.024*	*0.014*	*0.035*	*0.021*	*0.025*
	sd	*0.015*	*0.021*	*0.075*	*0.016*	*0.020*	*0.015*	*0.084*	*0.019*	*0.055*
	max	*0.094*	*0.117*	*0.866*	*0.093*	*0.117*	*0.088*	*0.866*	*0.070*	*0.866*
	min	*-0.028*	*-0.0002*	*-0.396*	*-0.008*	*-0.005*	*-0.028*	*-0.395*	*-0.038*	*-0.396*
	median	*0.011*	*0.022*	*0.014*	*0.011*	*0.020*	*0.009*	*0.014*	*0.019*	*0.013*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
density	*mean*	*190.200*	*41.562*	*139.646*	*45.578*	*26.891*	*300.006*	*134.369*	*8.639*	*140.138*
	sd	*243.142*	*26.415*	*146.380*	*25.062*	*16.032*	*248.825*	*122.120*	*6.332*	*180.814*
	max	*1252.347*	*108.372*	*529.719*	*100.851*	*69.951*	*1252.347*	*512.906*	*18.540*	*1252.347*
	min	*8.070*	*10.194*	*1.912*	*8.070*	*2.734*	*41.997*	*2.276*	*1.912*	*1.912*
	median	*112.591*	*35.004*	*92.938*	*45.818*	*23.632*	*251.407*	*99.882*	*7.555*	*79.935*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
oilcons	*mean*	*7382.102*	*13387.500*	*40084.570*	*12607.620*	*24129.310*	*12539.270*	*34020.550*	*47523.430*	*25091.220*
	sd	*6876.047*	*7030.716*	*15776.870*	*8459.729*	*26911.660*	*14500.880*	*12090.020*	*15430.080*	*19754.360*
	max	*28579.710*	*36219.410*	*83345.760*	*28579.710*	*83345.760*	*60159.880*	*65873.160*	*69810.910*	*83345.760*
	min	*427.938*	*4962.738*	*10674.120*	*2730.583*	*3195.381*	*427.938*	*5857.847*	*22305.230*	*427.938*
	median	*4882.413*	*13509.950*	*35849.430*	*10340.990*	*13232.500*	*4679.874*	*32734.270*	*46484.790*	*23304.180*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
oilprice	*mean*	*38.237*	*38.237*	*38.237*	*38.237*	*38.237*	*38.237*	*38.237*	*38.237*	*38.237*
	sd	*26.768*	*26.768*	*26.768*	*26.768*	*26.768*	*26.768*	*26.738*	*26.738*	*26.738*
	max	*95.990*	*95.990*	*95.990*	*95.990*	*95.990*	*95.990*	*95.990*	*95.990*	*95.990*
	min	*10.870*	*10.870*	*10.870*	*10.870*	*10.870*	*10.870*	*10.870*	*10.870*	*10.870*
	median	*26.455*	*26.455*	*26.455*	*26.455*	*26.455*	*26.455*	*26.455*	*26.455*	*26.455*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*
trade	*mean*	*0.519*	*0.554*	*0.686*	*0.558*	*0.402*	*0.605*	*0.751*	*0.477*	*0.610*
	sd	*0.227*	*0.462*	*0.341*	*0.121*	*0.172*	*0.416*	*0.344*	*0.109*	*0.342*
	max	*1.404*	*2.204*	*2.392*	*0.880*	*0.830*	*2.204*	*2.392*	*0.685*	*2.392*
	min	*0.122*	*0.115*	*0.160*	*0.302*	*0.115*	*0.122*	*0.171*	*0.286*	*0.115*
	median	*0.493*	*0.390*	*0.623*	*0.539*	*0.373*	*0.496*	*0.666*	*0.471*	*0.546*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*

	mean	*0.093*	*0.174*	*0.168*	*0.027*	*0.204*	*0.077*	*0.176*	*0.210*	*0.144*
	sd	*0.089*	*0.127*	*0.197*	*0.029*	*0.117*	*0.072*	*0.208*	*0.166*	*0.162*
renew	*max*	*0.362*	*0.450*	*0.828*	*0.130*	*0.450*	*0.362*	*0.828*	*0.456*	*0.828*
	min	*0.0005*	*0.001*	*0.0005*	*0.0005*	*0.001*	*0.003*	*0.0005*	*0.036*	*0.0005*
	median	*0.059*	*0.132*	*0.075*	*0.017*	*0.212*	*0.052*	*0.094*	*0.198*	*0.075*
	N	*560*	*280*	*880*	*160*	*360*	*440*	*680*	*80*	*1720*

3.2 Panel Unit Roots

In this section, we will assess the quality of our variables. Before estimating our model, we transform all variables into logarithmic form to reduce variation and skewness, with the exception of FDI due to the presence of negative values.

As already stated, our panel dataset includes 43 countries for a period of 40 years, this is, large N, large T dataset. The asymptotics of this type of panels are different from that of large N, small T panels. Small T panel estimation usually relies on fixed or random-effects estimators, or a combination of fixed-effects and instrumental-variable estimators, such as the Arellano and Bond (1991) GMM estimator. These methods require pooling individual groups and allowing only the intercepts to differ across the groups. However, one of the central findings from the large N, large T literature is that the assumption of homogeneity of slope parameters is often inappropriate. This point has been made by Pesaran and Smith (1995); Im, Pesaran, and Shin (2003); Pesaran, Shin, and Smith (1997, 1999); and Phillips and Moon (2000).

Moreover, with large N, large T dynamic panels, nonstationary variables is also a concern. Not appropiately accounting for the presence of unit roots might invalidate our estimations due to spurious regressions. To do so, we will employ a series of unit root tests[5], owing to their higher power when compared to conventional unit root tests. These tests differ significantly on whether they control for cross-sectional dependence and whether they allow for common roots or individual roots, such as the ones proposed by Im et al. (2003) (hereafter IPS) and Pesaran (2007), Phillips and Sul (2003) and Moon and Perron (2004).

As presented by Burret et al. (2015), the aforementioned tests are based on the mean of individual ADF t-statistics of each unit in the panel, and it eliminates cross-sectional dependence by augmenting

5. Known as second generation unit root tests.

the ADF regression with the lagged cross-sectional mean and its first differences of the individual series (CADF statistics) to capture cross-sectional dependence (CD from here onwards) by a single factor model.

Since the lag length significantly influences the results (and therefore the conclusions) of the test, we carefully determine the number of lags using the well-known Newey and West's (1984) Approach: $4 * (T/100)^{2/9} \approx 3$.

Once we have accounted for cross-sectional dependence (see Table 2 in Appendix), we proceed to present information regarding unit root for all variables included in our model:

Table 3: Second Generation Panel Unit Root Tests

Variables	***Levels***				***First Differences***			
	trend		***without trend***		***trend***		***without trend***	
	CADF	***IPS***	***CADF***	***IPS***	***CADF***	***IPS***	***CADF***	***IPS***
lemispc	***-2.587****	***-2.838******	***-1.418***	***-1.708***	***-3.016******	***-5.817******	***-2.835******	***-5.668******
lpcgdp	***-2.229***	***-2.208***	***-2.221******	***-2.377******	***-3.274******	***-5.162******	***-2.905******	***-4.945******
lrenew	***-2.609*****	***-3.291******	***-1.759***	***-2.548******	***-3.564******	***-5.897******	***-3.450******	***-5.611******
lgcf	***-2.417***	***-2.388***	***-1.834***	***-1.938***	***-2.888******	***-5.094******	***-2.864******	***-5.161******
lfdi	***-2.349***	***-4.112******	***-2.246******	***-3.753******	***-3.355******	***-6.225******	***-3.357******	***-5.464******
ltrade	***-2.148***	***-1.882***	***-2.119******	***-1.972***	***-3.200******	***-5.109******	***-2.839******	***-4.972******
ldensity	***-2.120***	***-2.767******	***-1.792***	***-1.754***	***-2.840******	***-2.767******	***-2.447******	***-2.950******
loilcons	***-2.828******	***-2.622*****	***-1.333***	***-1.579***	***-2.959******	***-5.654******	***-2.840******	***-5.464******

Note. *, ** and *** denotes 10%, 5% and 1%, respectively. Because no variable is found stationary in levels for all tests, we will convert all variables to their differences.

As already presented, no variable is found to be stationary in levels for the CADF and IPS test with and without trend. For that reason, we will proceed to transform all variables in differences in order to establish stationarity. We also include First Generation Unit Root Tests in the Appendix for loilprice and conclude that this variable is not stationary in levels and consequently transformed in differences.

3.3 Panel ARDL

In this section, we present the theoretical framework of the econometrical approach used in this paper. The ARDL Model is utilized to address cointegration between variables. Following Engle and Granger (1987), if two time series x_t, y_t are integrated of order 1 (I(1)), but there exists a combination of them such as $x_t + \beta_t * y_t$ that is I(0), then it is said that x_t, y_t are mutually cointegrated.

Cointegration is a technique widely used in the Economic Literature because it permits asserting Long Run relationships between variables. And in Economy, most relations are specifically important in the long run. However, ARDL is a type of cointegration approach that overcomes those developed by Engle and Granger and Johansen (1991, 1995) due to its flexibility: while the latter require all variables be integrated of the same order (e.g. I(1)), the former does not, this is, it permits different order of integration. Moreover, ARDL is useful to present both short run and long run effects of variables and their significance over time. Assume a dynamic panel autoregressive distributive lag (ARDL) (p, q_1, . . . , q_k) of the form,

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{p} \delta'_{ij} x_{i,t-j} + \mu_i + \epsilon_{it} \tag{1}$$

where the number of groups i = 1, 2, . . . , N; the number of periods t = 1, 2, . . . , T; X_{it} is a k × 1 vector of explanatory variables; δ_{it} are the k × 1 coefficient vectors; λ_{ij} are scalars; and μ_i is the group-specific effect. T must be large enough such that the model can be fitted for each group separately. Time trends and other fixed regressors may be included.

A principal feature of cointegrated variables is their responsiveness to any deviation from the long-run equilibrium. This feature implies an error correction model in which the short-run dynamics of the variables in the system are influenced by the deviation from equilibrium. Thus, it is common to reparameterize (1) into the error correction equation

$$\Delta y_{it} = \phi_i(y_{i,t-1} - \Phi'_i x_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta^{*'}_{ij} \Delta x_{i,t-j} + \mu_i + \epsilon_{it} \tag{2}$$

where $\theta_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$ is the error-correcting speed of adjustment term (if $\phi_i = 0$, there would be no evidence for a long-run relationship); $\Phi = \sum_{j=0}^{q} \delta_{it}/(1 - \sum_k \lambda_{ik})$ contains the long-run relationships between the variables, $\lambda^*{}_{\mathrm{ij}} = -\sum_{m=j+1}^{p} \lambda_{\mathrm{im}}$, j = 1, 2, . . . , p—1; and $\delta^*{}_{\mathrm{ij}} = -\sum_{m=j+1}^{q} \delta_{\mathrm{im}}$, j = 1, 2, . . ., q—1.

In order to assess cross-sectional dependence and to robust our estimations, following Pesaran and Smith (1995) and Pesaran et al. (199), we make use of three different estimators to analyze short run and long run effects:

(i) Pooled Mean Group or PMG Estimator: it permits the existence of short run relationships, where coefficients, the speed of adjustment and the error variances are allowed to be heterogenous; while it assumes that the long-run coefficients are the same (i.e., identical and homogenous) for all the countries in the panel, as developed by Shaari et al. (2020). This method relies on a combination of pooling and averaging coefficients.

(ii) Mean Group or MG Estimator: Under this technique, heterogeneity is assumed both in the short and long run, while the results are consistent even if the regressors are I(1), as shown by Pesaran et al. (1999). This procedure relies on estimating N time-series regressions and averaging the coefficients, as shown by Blackburne III and Frank (2007).

(iii) Dynamic Fixed Effects or DFE Estimator: This technique is similar to the PMG estimator, providing consistency to long run estimations. Furthermore, it restricts the adjustment coefficient giving reliable results in the short run.

In this work, we use the Panel ARDL model and improve its power of prediction by adding a dynamic component that has been incorporated by recent Environmental Literature (see Persyn & Westerlund (2008, Menegaki (2019)) this is, it incorporates in the equation the lag of the dependent variable as a variable of interest. Following Juergen (2019), we formally present the main equation of the model:

$$
\begin{aligned}
\Delta \ln y_{\text{it}} = \alpha_{\text{i}} + \sum_{j=1}^{p} \alpha_{1,\text{ ij}} \Delta \ln y_{\text{i,t-j}} + \sum_{j=0}^{q_1} \alpha_{2,\text{ ij}} \Delta \ln pcGDP_{\text{i,t-j}} + \\
\sum_{j=0}^{q_2} \alpha_{3,\text{ ij}} \Delta \ln FDI_{\text{i,t}} + \sum_{j=0}^{q_3} \alpha_{4,\text{ ij}} \Delta \ln GCF_{\text{i,t}} + \sum_{j=0}^{q_4} \alpha_{5,\text{ ij}} \Delta \ln Trade_{\text{i,t}} + \\
\sum_{j=0}^{q_5} \alpha_{6,\text{ ij}} \Delta \ln OilCons_{\text{i,t}} + \sum_{j=0}^{q_6} \alpha_{7,\text{ ij}} \Delta \ln Renew_{\text{i,t}} + \sum_{j=0}^{q_7} \alpha_{8,\text{ ij}} \Delta \ln Density_{\text{i,t}} + \\
\sum_{j=0}^{q_8} \alpha_{9,\text{ ij}} \Delta \ln oilprice_{\text{i,t}} + \phi_{\text{i}} ECM_{\text{i,t}} \beta_{1,\text{ ij}} \Delta \ln pcGDP_{\text{i,t}} + \\
\beta_{2,\text{ ij}} \Delta \ln FDI_{\text{i,t}} + \beta_{3,\text{ ij}} \Delta \ln GCF_{\text{i,t}} + \beta_{4,\text{ ij}} \Delta \ln Trade_{\text{i,t}} + \\
\beta_{5,\text{ ij}} \Delta \ln OilCons_{\text{i,t}} + \beta_{6,\text{ ij}} \Delta \ln Renew_{\text{i,t}} + \beta_{7,\text{ ij}} \Delta \ln Density_{\text{i,t}} + \epsilon_{\text{it}}
\end{aligned} \tag{3}
$$

where $\alpha_1 - \alpha_9$ are the short run coefficients, $\beta_1 - \beta_7$ the long run coefficients, and ϕ_{i} represents the coefficient of the ECM which measures the speed of adjustment that is made every year towards long-run equilibrium.

We will show results for the Dynamic Fixed Effects Estimator and compare them to those from PMG and MG, because the former is robust to the number of regressors used, while the latter do not work properly when the number of variables included are considerable[6].

4 Results

4.1 Full Sample

Before estimating our model, we ought to make sure that evidence of cointegration is confirmed. To address this purpose, we use Kao's, Pedroni's and Westerlund's Cointegration Tests in order to assert robust results and to assess for the aggregation (or not) of time trends. From the aforementioned tests, we observe that the cointegration hypothesis is confirmed for all statistics, at least at the classical 95% Confidence Value (see Table A4 in the Appendix).

Once we have accounted for cointegration, we estimate short run and long run coefficients on Carbon Dioxide Emissions. We first address results both for the whole sample (see Table 4), and then we proceed to estimate for different geographic and income groups to better understand the relation

6. MG and PMG Estimator do not work with more than 9 regressors for a matrix size of 800.

between our variables. We also subdivide for 4 periods of time in order to aggregate a historical component (see table 5).

Table 4: Results for the whole sample

Variables	PMG Estimator	MG Estimator	DFE Estimator
		Short Run Coefficients	
$dlemispc_t$			
$dlemispc_{t\text{-}1}$	-0.1254^{***} (0.0289)	-0.1922^{***} (0.0275)	-0.1919^{***} (0.0217)
$dlpcGDP_t$	0.0272 (0.0217)	0.0051 (0.0147)	0.0639^{***} (0.0143)
$dlpcGDP_{t\text{-}1}$			0.0324^{***} (0.0118)
$dlGCF_t$	0.0529^{**} (0.0229)	0.0595^{***} (0.0223)	0.1061^{***} (0.0183)
$dlFDI_t$	0.0302 (0.1198)	-0.0458 (0.1283)	-0.0044 (0.0312)
$dlrenew_t$	-0.0197 (0.0376)	-0.0728^{***} (0.0236)	-0.0264^{***} (0.0046)
$dlrenew_{t\text{-}1}$			-0.0185^{***} (0.0043)
$dldensity_t$	-0.6196 (0.5366)	-1.7116 (1.4582)	0.3774 (0.2655)
$dloilcons_t$	0.6913^{***} (0.0590)	0.6555^{***} (0.0563)	0.2595^{***} (0.0156)
$dltrade_t$	-0.0117 (0.0157)	-0.0349^{*} (0.0191)	0.0119 (0.0202)
$dloilprice$	0.0037 (0.0051)	0.0106^{***} (0.0041)	0.0063 (0.0057)
ECM_t	0.4168^{***} (0.0401)	0.7929^{***} (0.0450)	0.3213^{***} (0.017)
		Long-Run Coefficients	
$lemispc_t$			
$lpcGDP_t$	0.0138^{***} (0.0046)	0.0658^{*} (0.0377)	0.0867^{***} (0.013)
$lGCF_t$	-0.0557^{***} (0.0109)	-0.0527 (0.0546)	-0.1094^{***} (0.0293)
FDI_t	-0.1122^{***} (0.0297)	0.0930 (0.3016)	-0.0458 (0.0972)
$lrenew_t$	-0.0122^{***} (0.0025)	-0.0840 (0.0554)	-0.0484^{***} (0.0093)
$ldensity_t$	-0.0359 (0.0245)	0.0386 (0.2608)	-0.1033^{**} (0.0483)
$loilcons_t$	1.0219^{***} (0.0110)	0.7548^{***} (0.0716)	0.8191^{***} (0.0246)
$ltrade_t$	-0.0384^{***} (0.0074)	-0.0304 (0.0356)	-0.0100 (0.023)

Note. *, ** and *** denotes 10%, 5% and 1%, respectively.

First of all, we observe as a general rule that most standard deviations for each coefficient are not considerably different for the PMG, MG and DFE Estimators. In all three models there exists significant evidence of partial dynamic adjustment from Carbon Emissions, that is, all coefficients from $dlemispc_{t\text{-}1}$ are negative, which indicates a mean reverting component. Results show as well that the ECM Estimation is positive and significant. In particular, our model estimates an outcome of 0.3213, which signifies the capability of the model to witness 32.13% speed of adjustment to verify the alignment to equilibrium in the long run due to the effect of the regressors.

It is also evident from our results that in the short run, per capita GDP rises Carbon Dioxide Emissions, although this result is found to be statiscally significant only for our selected estimator. In particular, a 1% Economic Growth augments CO_2 Emissions in 6.39 %. This result is particularly permanent over time because the lag of per capita GDP is found to have positive effects on Carbon Dioxide Emissions. This observation is key to understand most environmental claims done by institutions, social and environmental groups, scientists, and economic and political agents, that Economic Growth has pervasive negative effects on Environmental Quality. In this sense, policy makers should carefully address this issue in order to achieve a real Sustainable Development.

We observe as well that the change in Fossil Fuels Consumption has significant positive effects on Carbon Dioxide Emissions, despite the fact that results are not homogenous: while the PMG and MG Estimators respectively show a 69.13 and a 65.55 percentage growth in Carbon Emissions, the DFE estimation is less outstanding, reaching a 25.95% increase. Our observations are similar to previous studies such as Arouri et al. (2012), Issaoui et al. (2015) and Chontanawat (2020). Likewise, it is noted that Gross Capital Formation has possitive and significant effects on Carbon Dioxide Emissions, a result contrary to that estimated by Adebayo et al. (2021), who conclude statiscally not significant coefficients. Finally, we also find as expected and documented by studies such as Heshmati et al. (2014), Koengkan & Fuinhas (2017) and Karimi et al. (2021), that Renewable Production has significant effects on Carbon Emissions mitigation and that these effects are sustained over time.

We then proceed to interpret long run coefficients. With the exception of Foreign Direct Investments and Trade Openness, all variables are found to be statistically significant at the 5% significance level. We observe that in the long run, as presented before in the short run, per capita GDP growth rises Carbon Emissions by approximately 8.67%. Same conclusion arises with Fossil Fuels Consumption: a 1% increase accelerates Carbon Dioxide Emissions by 81.91%. Finally, we found as well that Renewable Sources of Energy have the expected negative effects on Carbon Emissions.

Remarkably, we notice that the variable GCF changes its coefficient with respects to the short run, i.e., the variable becomes negative. This result might imply that over time, economies are able to obtain technologies or develop procedures that are eco-friendly through capital formation, generating a positive environmental policy. Moreover, it is also noted that Population Density has a negative impact on CO_2 Emissions on 10.33%, a considerable and significant coefficient. This result might suggest that favoring population density by achieving centralization and re-designing urban cities has a positive effect on carbon mitigation. The idea is simple and straight-forward: public transport generates a lesser amount of emissions that would be produced by individual transportation; buildings such as apartments consume less electric energy and gas, and less water than what individual houses do, and so on. Bare in mind though that our results are obtained in the long run, so urban cities should be carefully designed in the short run so as to favour carbon mitigation onwards.

4.2 Subsamples

In this section, we proceed to estimate our dynamic FE approach differentiating between geographic and income criteria in order to correctly address public environmental policies.

From our results, some interesting findings arise. Trade Openness is not statistically significant in the long run for the majority of the subsamples, with the exception of Middle and High Income Groups. This conclusion might suggest that trade openness favors Carbon Emissions in the Long Run due to Imports of Technologies or Machinery that contributes to the Environmental degradation, although it depends on income levels.

Then, it is observed that the use of Renewable sources of Energy reduces Carbon Dioxide Emissions for all different subsamples in the Short Run, with the exception of America, Europe and Africa, and Middle and High Income; and in the Long Run, with the exception of America, Asia, Oceania and Africa, and Middle Income Economies. These results evidence that for the case of Africa, Renewable Energy Sources might not be an important public policy for Carbon Emissions mitigations, due to pervasive coal and fossil fuels energy usage; whereas for the case of Middle and High Income, it might evidence that when eco-friendly energy use is already relevant[7], Environmental Policies should focus on different technologies and practices other than Renewable Sources of Energy.

Moreover, evidence of Long Run Unsustainable Development is confirmed for America, Asia, Oceania, Low Income Economies, and over time for the 4 historical periods. In particular, it is clear that through the course of the years, Economic Growth has deepened Carbon Emissions, from a 14.68%

7. There exists a correlation between Income and Renewable Sources of Energy.

between 1980-89, to a worrying 41.41% rise in CO_2 Emissions between 2010-19. This uncovering is specially important because it supports the evidence that over the last years, classical Economic Growth has been favored over Sustainable Development, worsening and aggravating Environmental degradation. And this finding is relevant to Global Environmental debates due to the fact that it notably affects poorer economies. We believe Developed and Rich Economies must help Low Income Countries achieve a sustainable and "greener" Economic Growth, mostly through financial borrowing.

We have found as well that Oil Price has negative effects on Emissions during the last years, i.e., increased costs of production tend to reduce Emissions, favoring the use of other eco-friendly technologies that rely more on Renewable sources of Energy instead of classical Oil, Coal or Gas sources. Finally, it is also observed that Fossil Fuels Consumption is extremely detrimental to Environmental Quality both in the Long and Short Run, for all subsamples, as stated by the vast majority of the Literature. Policies should focus on this fact, giving incentives to incorporate different sources of technology that rely less on environmental degradation. Likewise, for all subsamples, the Error Correction Coefficient is positive and significant at the 99% Confidence level (see Table 5).

Table 5: Results for subsamples

Variables	Region					Income			Years			
	America	**Europe**	***Asia***	***Oceania***	***Africa***	***Low***	***Middle***	***High***	***80-89***	***90-99***	***00-09***	***10-19***
						Short Run Coefficients						
$dlemispc_t$												
$dlemispc_{t\text{-}1}$	−0.3547*** (0.0407)	−0.0893*** (0.0236)	−0.0992** (0.0469)	−0.2993** (0.1205)	−0.1599** (0.0734)	−0.2150*** (0.0388)	−0.2199*** (0.0442)	−0.0966*** (0.0223)	−0.2818*** (0.0171)	−0.2589*** (0.0317)	−0.3279*** (0.0473)	−0.3138*** (0.0434)
$dlpcGDP_t$	0.0080 (0.0307)	0.0068 (0.0132)	0.1569*** (0.0332)	0.0675 (0.0446)	0.0346 (0.0607)	0.1058*** (0.0365)	0.0245 (0.0214)	0.0118 (0.0123)	0.0713*** (0.0177)	0.1148*** (0.0249)	0.1682*** (0.0471)	0.1515*** (0.0408)
$dlpcGDP_{t\text{-}1}$	0.0576** (0.0238)	−0.0005 (0.0112)	0.0128 (0.0287)	0.0492 (0.0363)	0.0261 (0.0492)	0.0798*** (0.0308)	0.0427*** (0.0160)	−0.0021 (0.0104)	0.0393*** (0.0132)	0.0267 (0.0164)	0.0615* (0.0321)	0.0708** (0.0280)
$dlGCF_t$	0.0576 (0.0457)	−0.0238 (0.0161)	0.1822*** (0.0408)	0.0547 (0.0573)	0.0775 (0.0709)	0.1572*** (0.0459)	0.0892*** (0.0282)	−0.0013 (0.0155)	0.0965*** (0.0194)	0.0779*** (0.0258)	0.0387 (0.0403)	0.0854** (0.0383)
$dlFDI_t$	0.2875 (0.2648)	−0.0359** (0.0176)	0.0883 (0.3423)	−0.0972 (0.1761)	0.2021 (0.4319)	0.0752 (0.3270)	0.0302 (0.2000)	−0.0329* (0.0175)	0.0065 (0.0294)	−0.0136 (0.0294)	0.0150 (0.0406)	0.0204 (0.0404)
$dlrenew_t$	−0.0151 (0.0114)	−0.0012 (0.0055)	−0.0556*** (0.0133)	−0.1984*** (0.0622)	0.0002 (0.0137)	−0.0379*** (0.0115)	−0.0100 (0.0072)	−0.0057 (0.0053)	−0.0319*** (0.0050)	−0.0435*** (0.0065)	−0.0551*** (0.0123)	−0.0522*** (0.0115)
$dlrenew_{t\text{-}1}$	−0.0092 (0.0087)	−0.0227*** (0.0052)	−0.0162 (0.0125)	−0.1207*** (0.0638)	−0.0174 (0.0115)	−0.0348*** (0.0102)	−0.0006 (0.0056)	−0.0230*** (0.0051)	−0.0192*** (0.0045)	−0.0281*** (0.0058)	−0.0307*** (0.0098)	−0.0302*** (0.0093)
$dldensity_t$	1.9521*** (0.5268)	−0.3221 (0.2237)	−1.5521 (1.0125)	−0.2331 (0.5611)	3.4984 (2.5127)	1.2754** (0.5704)	1.7241 (1.3748)	−0.4206** (0.2064)	0.2793 (0.2661)	−0.4803 (0.4242)	−0.7960 (0.5274)	−0.7521 (0.5193)
$dloilcons_t$	0.5858*** (0.0731)	0.9297*** (0.0284)	0.1097*** (0.0190)	0.2518** (0.1021)	0.5755*** (0.1444)	0.1780*** (0.0243)	0.7080*** (0.0582)	0.8280*** (0.0256)	0.2239*** (0.0160)	0.1495*** (0.0168)	0.0534*** (0.0188)	0.0649*** (0.0184)
$dltrade_t$	−0.0497 (0.0416)	0.0092 (0.0254)	0.0767** (0.0354)	0.0064 (0.0787)	−0.0075 (0.0722)	−0.0095 (0.0402)	0.0004 (0.0313)	0.0099 (0.0215)	0.0186 (0.0239)	0.0852*** (0.0319)	0.0965* (0.0543)	0.0901* (0.0486)
$dloilprice$	0.0111 (0.0134)	0.0115** (0.0054)	−0.0049 (0.0115)	−0.0110 (0.0137)	−0.0116 (0.0243)	0.0025 (0.0140)	−0.0015 (0.0098)	0.0083* (0.0046)	−0.0004 (0.0066)	−0.0178* (0.0101)	−0.0359** (0.0141)	−0.0302** (0.0131)
ECM_t	0.6090*** (0.0420)	0.1591*** (0.0217)	0.2121*** (0.0306)	0.2937*** (0.1039)	0.4566*** (0.0787)	0.3808*** (0.0323)	0.3624*** (0.0466)	0.1594*** (0.0191)	0.3635*** (0.0194)	0.2989*** (0.0227)	0.3307*** (0.0387)	0.3417*** (0.0344)
						Long Run Coefficients						
$lemispc_t$												
$lpcGDP_t$	0.1122*** (0.0211)	−0.0161 (0.0272)	0.1516*** (0.0402)	0.2788*** (0.1114)	0.0132 (0.0685)	0.1789*** (0.0278)	0.0353 (0.0273)	0.0169 (0.0246)	0.1468*** (0.0194)	0.2301*** (0.0285)	0.3905*** (0.0926)	0.4141*** (0.0773)
$lGCF_t$	−0.0952** (0.0477)	−0.2254*** (0.0603)	−0.1057 (0.0918)	−0.2219 (0.1492)	−0.0454 (0.0794)	−0.0959* (0.0535)	−0.0350 (0.0497)	−0.2241*** (0.0571)	−0.1242*** (0.0311)	−0.1019* (0.0522)	−0.3176*** (0.1047)	−0.2103** (0.0861)
FDI_t	−0.3245 (0.4168)	−0.2733** (0.1196)	0.0855 (1.4146)	0.4924 (0.9154)	0.7567 (1.0905)	−0.0283 (0.8014)	−1.6320*** (0.5480)	−0.1844 (0.1153)	0.0119 (0.0837)	−0.0727 (0.1119)	0.0153 (0.1469)	0.0248 (0.1387)
$lrenew_t$	−0.0136 (0.0235)	−0.0393*** (0.0133)	−0.0623 (0.0410)	−0.1751 (0.1069)	−0.0427 (0.0292)	−0.1052*** (0.0249)	−0.0207 (0.0246)	−0.0394*** (0.0127)	−0.0743*** (0.0111)	−0.0932*** (0.0186)	−0.1325*** (0.0379)	−0.1091*** (0.0329)
$ldensity_t$	−0.4155*** (0.0764)	0.3581** (0.1825)	0.2253* (0.1339)	−0.8797*** (0.4168)	−0.0813 (0.1914)	−0.2275*** (0.0729)	−0.3180** (0.1368)	0.1356 (0.1439)	−0.1779*** (0.0657)	−0.5336*** (0.1421)	0.1586 (0.3028)	−0.0223 (0.2484)
$loilcons_t$	0.7830*** (0.0420)	0.9640*** (0.0555)	0.6586*** (0.0751)	0.8091*** (0.2031)	0.9781*** (0.1022)	0.6906*** (0.0484)	1.0122*** (0.0516)	0.8058*** (0.0465)	0.7526*** (0.0301)	0.5930*** (0.0513)	0.1852** (0.0774)	0.2117*** (0.0714)

$ltrade_t$	−0.0211 (0.0322)	0.0606 (0.0659)	0.0867 (0.0549)	−0.0710 (0.1661)	−0.0577 (0.0877)	0.0196 (0.0419)	−0.0013 (0.0379)	0.0189 (0.0516)	0.0013 (0.0235)	0.0186 (0.0447)	0.2732 ** (0.1210)	0.2616 ** (0.0999)

Note. *, ** and *** denotes 10%, 5% and 1%, respectively.

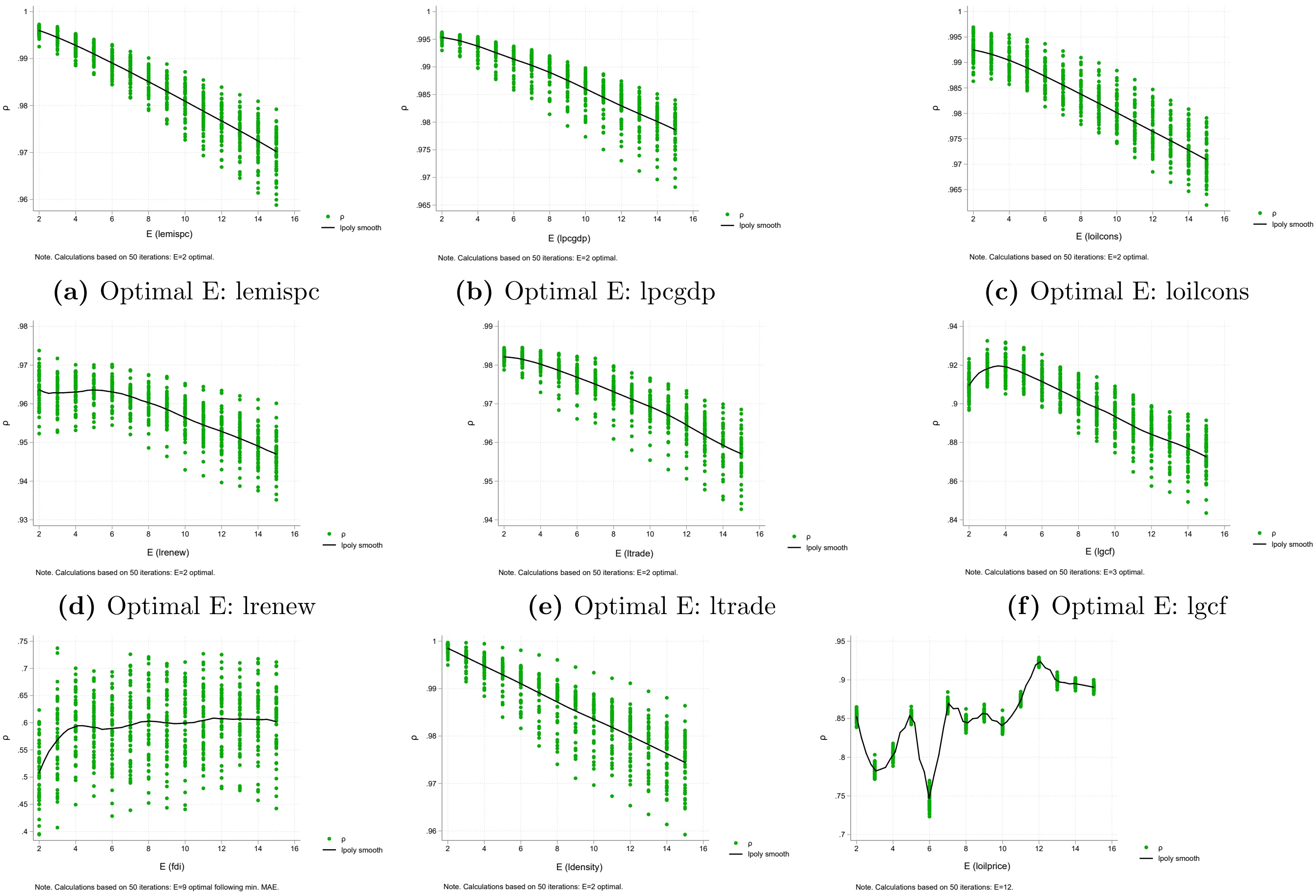
4.3 Non-linear Causality: Empirical Dynamic Modelling

Causal identification is a difficult task in many social and environmental contexts, including and specially when studying complex dynamical systems wherein experiments or model-based regressions might not be appropriate. Dealing with the complexity of real phenomenons requires tools that are able to characterize and correctly test causality in dynamical systems. One remarkable method that we will use in this section is called empirical dynamic modeling or EDM (for an introduction see Chang et al. 2017). It is an emerging data-driven framework for modeling nonlinear dynamic systems, based on the mathematical theory of reconstructing system attractors from time series data. This technique allows us to characterize a dynamical system including its complexity, predictability, and nonlinearity, as well as distinguish causation, while making minimal assumptions from its characteristics related to nonlinearity, stability, and equilibrium (see Sugihara and May 1990, Casdagli et al. 1991, Sauer et al. 1991, Sugihara et al. 2012 and Li et al. (2021)).

The logic of EDM is based on the fact that a dynamical system producing observed time series or panel data can be modeled by reconstructing the states of the underlying system as it evolves over time, as developed by Takens (1981) and Li et al. (2021) (see the Appendix for the mathematical and theoretical framework developed in Li et al. (2021)).

In this section, we will estimate nonlinear causality between our variables included in the model, following the investigation carried out by Liu et al. (2019). The more straightforward approach to estimate it is to first establish the dimensionality of the system, which can be understood as approximating the number of independent variables needed to reconstruct the underlying attractor manifold M that defines the system (Sugihara and May 1990; Sugihara et al. 2012). Next, one must check the nonlinearity characteristic of the candidate time series, in order to finally apply the CCM algorithm.

We begin by estimating optimal E, often selected based on the highest ρ (i.e., the E where the peak ρ is located) or lowest MAE between the predicted and the observed values, while attempting to keep the model somewhat parsimonious. These two measures generally agree but if they do not, then the one indicating the lowest embedding dimension E should be used (Glaser et al. 2011). We explore all dimensions between 2 and 15 using simplex projection to identify the optimal E. As the library set is randomly selected, we replicated the method 50 times (see Figure 3).



(a) Optimal E: lemispc **(b)** Optimal E: lpcgdp **(c)** Optimal E: loilcons

(d) Optimal E: lrenew **(e)** Optimal E: ltrade **(f)** Optimal E: lgcf

(g) Optimal E: FDI **(h)** Optimal E: ldensity **(i)** Optimal E: loilprice

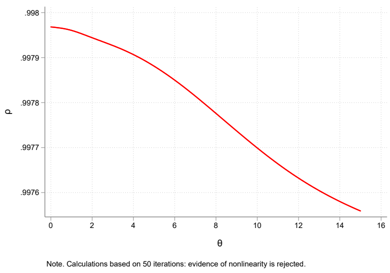
Figure 3: Selection of Optimal E.

After we have selected the optimal E, we progress by checking for nonlinearity between variables by using S-maps or sequentially locally weighted global linear maps (Sugihara 1994; Hsieh et al. 2008). Following Liu et al. (2019), linearity exists if the trajectory on a manifold M is invariant with respect to a system's current state, whereas nonlinearity exists if system evolution is state-dependent. This is evaluated by taking the optimal E peviously chosen and estimating a type of regression model that varies the weight of nearby observations (in terms of system states rather than time) with a distance decay parameter Θ.

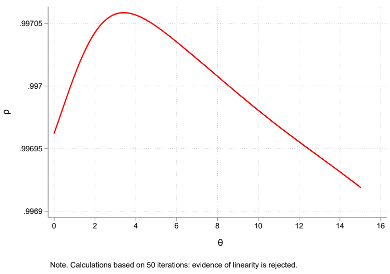
In this work, we explore possible Θ values between 0 and 15 with an increment of 0.05. Additionally, we include all observations for the local prediction. This allows for more stable results with low E or in low data-density regions of M_Y. When $\Theta = 0$, there is no differential weighting of neighbors on M_X, so the S-map reduces to a type of autoregressive model with a random 50/50 split of library versus prediction data. However, as Θ increases, predictions become more sensitive to the nonlinear behavior of a system by drawing more heavily on nearby observations to make predictions. In other words, predictions become more state-dependent. Again, using ρ and MAE and forming ρ-Θ and MAE - ρ plots, the nonlinearity of the system can be evaluated. If nonlinearity or state-dependence is observed in the form of larger ρ and smaller MAE when $\Theta > 0$, EDM tools are needed to model system behavior. If the system is linear, ρ would not increase as Θ goes above zero, and hence, models with linearity assumptions might be more appropriate.

4.4 Comparing CCM Causality Modelling with Granger Causality

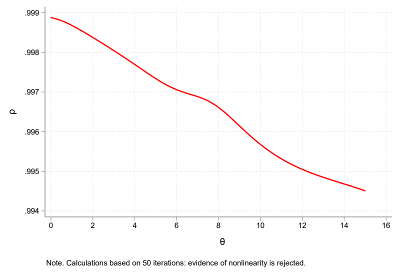
After testing for nonlinearity, many of our variables are found to be linear (see Figure 6). Hence, Granger Causality approach ought to be a more appropriate model to estimate causality between our variables. This procedure was mainly developed for linear stochastic processes, and its core idea is that if a time series variable x "Granger causes" y, then the past values of x should increase the predictability of y (Granger, 1969).



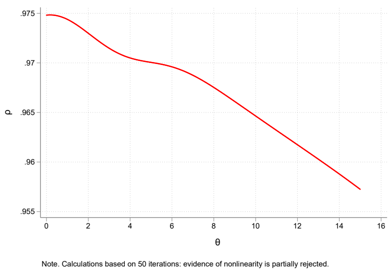
(a) Nonlinearity: lemispc



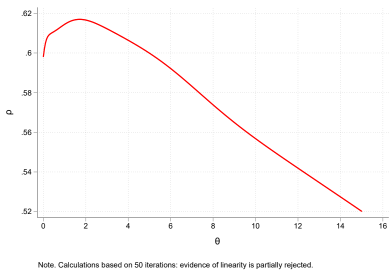
(b) Nonlinearity: lpcgdp



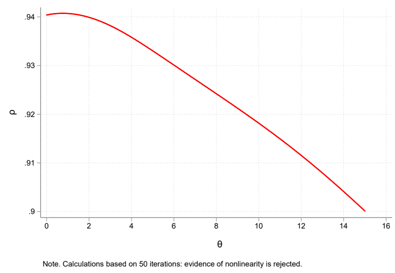
(c) Nonlinearity: loilcons



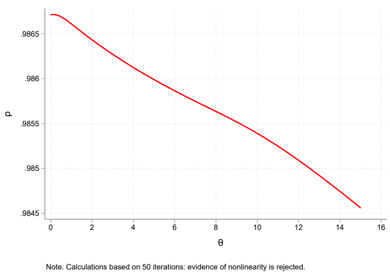
(d) Nonlinearity: lrenew



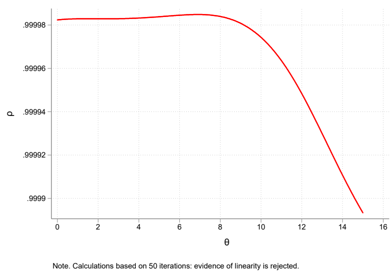
(e) Nonlinearity: FDI



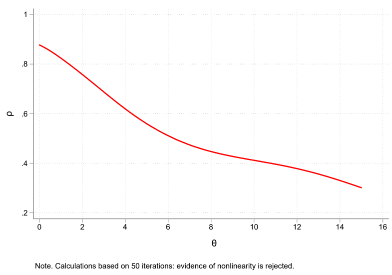
(f) Nonlinearity: lgcf



(g) Nonlinearity: ltrade



(h) Nonlinearity: ldensity



(i) Nonlinearity: loilprice

Figure 4: Testing for nonlinearity of variables.

Granger causality is tested by estimating statistical models using the variables of interest. After estimating the model, variables are excluded to see how it statistically effects the predicting power of other variables, this is, Granger causality Approach requires variables to be separable, which implies that when the causative variable x is totally removable from the model or system, only then it can be robustly tested whether it has a causative effect on y (Granger, 1969; Dumitrescu and Hurlin (2012)).

For presentation purposes, we estimate both models, comparing side to side our results. From the table below, we observe from the CCM Approach that all variables perceive a two-way relation with respect to lemispc. This result suggests that all variables have a causation effect over our main variable, i.e., that all variables might be relevant with respect to studying environmental topics. However, this procedure works with fixed and predetermined parameters, and does not evaluate convergence (which implies an increase in ρ as the library size L increases). Hence, we develop a convergence approach and test it to robust our prior results. From these tests, we conclude that our estimations are robustly estimated (see the Appendix).

Nevertheless, when looking at the Granger Causality Framework, different conclusions arise. We observe that there exists only one two-way relation between lemispc and lrenew. This result suggests that a decline in CO_2 Emissions favors the use of Renewable Energy sources, which in turn accelerates Environmental improvement. Our estimations suggest as well no evidence of any neutral relation. Finally, we have found several one way relation, in particular from lpcgdp to lemispc, this is, Economic Growth causes our variable Carbon Emissions, as sustained by Apergis and Payne (2010), Li et al. (2011) and Litavcová and Chovancová (2021); from lemispc to loilcons, which is supported by the studies carried out by Lean and Smyth (2010) and Farhani and Rejeb (2012); from lgcf to lemispc, which implicates the existence of a potential Carbon Mitigation policy, as estimated by Abul et al. (2020); from ltrade to lemispc, as found by Omri et al. (2015), Shahbaz et al. (2016) and Sun et al. (2019); and finally from lemispc to ldensity, which indicates that population density might not be a relevant variable to undergo a Carbon Emissions Mitigation Policy, or it might indicate that population density is not a significant variable in relation with Environmental Issues. This finding is contrary to the results assessed by Rahman (2017) and Rahman and Vu (2021) (see Table 6).

Table 6: CCM and Granger Causality Estimations

Variables	Relation	CCM	Conclusion	Ho: no causality	Conclusion
lemispc—lpcgdp	lemispc → lpcgdp	0.8353 *** (0.0028)	*Two-way relation*	4.2471	*One-way relation*
	lpcgdp → lemispc	0.8465 *** (0.0105)	*(E=2)*	8.2202**	*(lags=2)*
lemispc—loilcons	lemispc → loilcons	0.9875 *** (0.0028)	*Two-way relation*	9.4695**	*One-way relation*
	loilcons → lemispc	0.9879 *** (0.0025)	*(E=2)*	6.4676	*(lags=2)*
lemispc—lrenew	lemispc → lrenew	0.3718 *** (0.0362)	*Two-way relation*	14.8412***	*Two-way relation*
	lrenew → lemispc	0.3774 *** (0.0397)	*(E=4)*	8.1499***	*(lags=2)*
lemispc—ltrade	lemispc → ltrade	0.1347 *** (0.0492)	*Two-way relation*	3.6671	*One-way relation*
	ltrade → lemispc	0.3807 *** (0.0349)	*(E=2)*	9.6071**	*(lags=1)*
lemispc—lgcf	lemispc → lgcf	0.1317 ** (0.0515)	*Two-way relation*	4.3588	*One-way relation*
	lgcf → lemispc	0.2792 *** (0.0404)	*(E=4)*	4.7023**	*(lags=1)*
lemispc—fdi	lemispc → fdi	0.1739 *** (0.0388)	*Two-way relation*	6.8948***	*One-way relation*
	fdi → lemispc	0.3649 *** (0.0535)	*(E=9)*	0.1653	*(lags=1)*
lemispc—ldensity	lemispc → ldensity	0.6448 *** (0.0295)	*Two-way relation*	11.6130***	*One-way relation*
	ldensity → lemispc	0.5178 *** (0.0338)	*(E=2)*	11.6334	*(lags=1)*
lemispc—loilprice	lemispc → loilprice	0.1294 ** (0.0576)	*Two-way relation*	6.0378	*One-way relation*
	loilprice → lemispc	0.6611 *** (0.0158)	*(E=2)*	22.0252***	*(lags=1)*

Note. *, ** and *** denotes 10%, 5% and 1%, respectively. We have chosen lags=2 based on AIC lags criteria selection. Jacknife standard errors for CCM and bootstrap errors (100 replications) for Granger Tests.

5 Conclusions and Debate

We have developed a Dynamic Fixed Effects Estimator from a Panel ARDL Procedure for a dataset of 43 countries during the period 1980-2019. We estimated short run and long run effects on Carbon Dioxide Emissions for a set of variables including Renewable Energy sources, Fossil Fuels Consumption, Gross Capital Formation, Foreign Direct Investment, per capita GDP, Trade Openness, Oil Price and Population Density.

From our results, we find for the full sample that GDP, GCF and Oil Consumption have positive and significant short run effects on CO_2 Emissions, whereas Renewable Energy has the expected significant negative effects on Carbon Emissions. Moreover, in the long run, we find that GDP and Oil Consumption have positive and significant effects on Carbon Dioxide Emissions, while GCF, Renewable Energy and Population Density perceive significant negative effects on our main variable. We also build estimates for different income and geographic subsamples in order to assess more appropiately conclusions and understand deeply the intrinsic relations between variables.

Likewise, we develop a nonlinear approach to estimate causality between our variables. After establishing existence of linearity for most of the variables, we compare CCM results with those from the Classical Granger approach. While the former suggests the existence of bidirectional causality between Carbon Emissions and all variables included in our model, the latter suggests the existence of only one two-way relation between Emissions and Renewable Energy and unidirectional relation between Carbon Emissions and the rest of the variables of interest. We have also estimated several convergence tests to robust our estimations.

From our results, some important conclusions for environmental policies arise. First, it is evident that general claims regarding Unsustainable Development over the past years are supported: whereas for the period 80-89 a 1% rise in Economic Growth generated an acceleration on Environmental Degradation of 7.13%, for the period 10-19 this effect deepens to a worrying 15.15%. Nonetheless, this claim is sensitive to Geographic locations because it is found that only for the case of Asian countries, Economic Growth has significant and positive effects on Carbon Dioxide Emissions. However, in the long run, the aforementioned effects are even more substantial. Whereas in the period 80-89 the positive effect of GDP on Carbon Emissions was approximately 14.68%, in the last 10 years it has growth to a dramatic 41.41%.

Our estimations support as well the idea that Gross Capital Formation worsens Environmental Quality, although this effect turns out to be reversed in the long run. This observation requires a detailed environmental public policy because it suggests that society might need to accept a rise in Carbon Dioxide Emissions in the short run so as to generate a reinforcing reduction on the latter in the long run. This mitigation policy, however, might only work for American and European countries, as suggested by our results.

Fossil Fuels Consumption and Renewable sources of Energy have the expected positive and negative effects (respectively) on CO_2 Emissions, both in the short and long run. For the former, across the years, the magnitude of its effects have been reducing, going from a 22.39% increase in Carbon Emissions for the period 80-89, to a 6.49% rise for the period 10-19, in the short run. In the long run, the magnitude effects changed from a worrying 75.26% to a 21.17% increase in Carbon Emissions. However, for the latter variable, we fortunately find that in the last years its effects have become more significant, ranging from a -3.19% and -7.43% in the short and long run respectively (for the period 1980-89), to a -5.22% and -10.91% respectively (for the period 2010-19). Nevertheless, this conclusion should be carefully taken into account due to the difference in our estimations for geographic locations: in the short run, it is found to be significant for Asia and Oceania, while in the long run it is found to be significant only for Europe. This observation suggests that these continents have acquired renewable technologies that favor Environmental Quality, whereas the rest of the countries have fallen short of it.

To conclude, we believe that Environmental policies should be addressed and developed in a global and holistic manner, i.e., we think it is an obligation countries should impose themselves because Environmental Degradation affects all countries and all societies equally. In this sense, we truly believe that developed economies should contribute economically or technologically (either through financial aid or economic borrowing, or through technological transfer), so as to help developing economies accomplish a more eco-friendly growth. We assume this is key to achieve 2030 Environmental Target, which includes at least a 40% cut in greenhouse gas emissions (from 1990 levels), at least a 32% share of renewable energy and at least a 32.5% improvement in energy efficiency. However, this Environmental effort should not only be addressed in a macro perspective. Within each country, policy makers, companies and investors, social groups and citizens must work together to generate reinforcing positive policies. Otherwise, Sustainable Development will become an even more difficult and problematic task than it already is.

In our opinion, policies should include teaching Environmentalism in all educational levels, including topics such as recycling, a Social Economic approach to Development in order to shed light to Sustainable Development, costs of deforestation, and many other subjects; building ESG areas in all companies in order to generate a conscious green policy in the private sector; facilitating and encouraging "access to clean, reliable and affordable energy services for cooking and heating, lighting, communications and productive uses" (AGECC 2010: 13); defining property rights, which tends to be a major problem in developing economies where certain industries take advantage of their economic position to develop their activities without considering their effects on others (negative externalities).

Another important policy must be taking into account the interests and rights of local populations when designing and implementing global governance mechanisms, as developed by Boncheva et al. (2020). The authors show that recent analyses of the energy and greenhouse gas performances of alternative bio-fuels, have ignited a controversy that might be resolved by applying two simple principles: society cannot afford to miss the global greenhouse-gas emission reductions and the local environmental benefits and societal access when bio-fuels are correctly establish; but society also cannot accept the undesirable impacts of bio-fuels. Naive "win–win–win" discourses ought to be replaced with more realistic "trade-offs" embedded in each environmental and economic policy.

Finally, we believe another relevant policy for Environmental Improvement must be addressing an Independent Environmental Board to evaluate policies carried out by each government (similar to the UN Environemental Assembly but within each country).

If we want to change our present to give our children a better future, we must analyze our past in order to correctly address policies and efforts. And we must begin now.

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Appendix

A Additional Tests and Estimators.

Table A1: Countries divided into Income Groups

Income Group	*Criteria: per capita GDP*	*Countries*
Low Income	*<USD* 5250	*Algeria, Bangladesh, China, Ecuador, Egypt, India, Indonesia, Morocco, South Africa, Sri Lanka, Pakistan, Peru, Phillipines and Thailand*
Middle Income	*>USD* 5250 *&* *<USD* 13500	*Argentina, Brasil, Chile, Colombia, Malaysia, Mexico and Turkey.*
High Income	*>USD* 13500	*Australia, Austria, Belgium, Canada, Denmark, England, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, and United States.*

Each country included in each Income Group has been established based on Average Income, that is why we incorporate China as a Low Income Country when it is usually considered a Middle Income Economy.

Table A2: Tests for Cross Sectional Dependence

Tests	*Information*	*Estimates*
Pesaran's Test	*Its statistic follows a Standard Normal Distribution*	*4.157****
Friedman's Test	*Its statistic follows a Chi-squared Distribution*	*73.089****
Frees' Test	*Its statistic follows a T-asymptotically Distribution*	*4.818****

Note. *, ** and *** denotes 10%, 5% and 1%, respectively. All tests reject cross sectional independence.

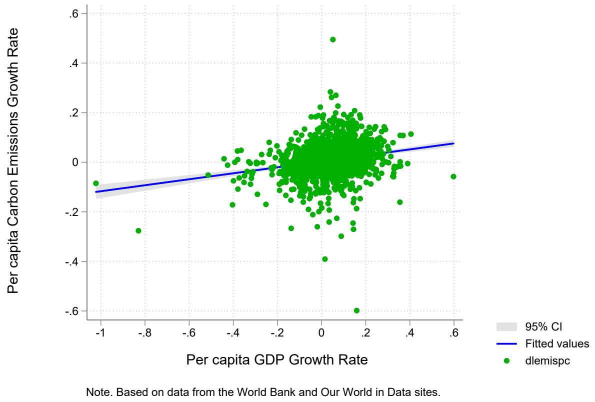
Table A3: Second Generation Panel Unit Root Tests

Variables	*Levels*		*Differences*	
	LLC	*HT*	*LLC*	*HT*
loilprice	*-0.6069*	*-0.3643*	*-37.2658****	*-42.8216****

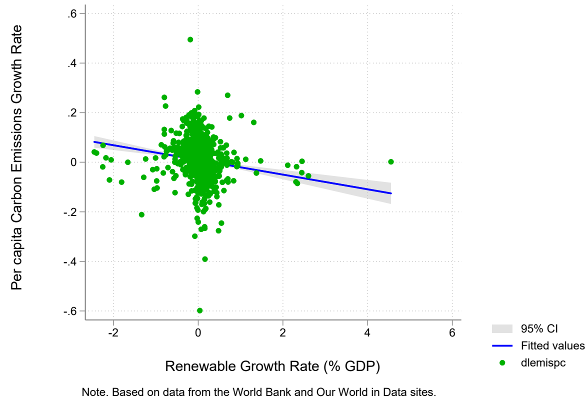
Note. *, ** and *** denotes 10%, 5% and 1%, respectively. No test rules out stationary in levels, so we use loilprice in differences.

We present in this section some correlation graphs to give a first insight on how the economic variables included in our model affect our variable of interest Per capita Carbon Emissions Growth Rate:

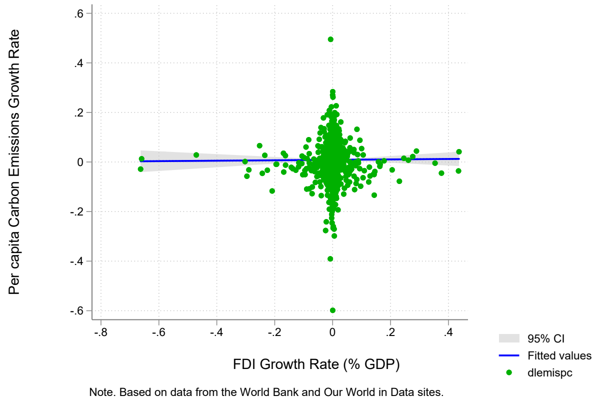
Figure 5: Correlation between Per capita Carbon Emissions Growth Rate and several economic variables included in our model.



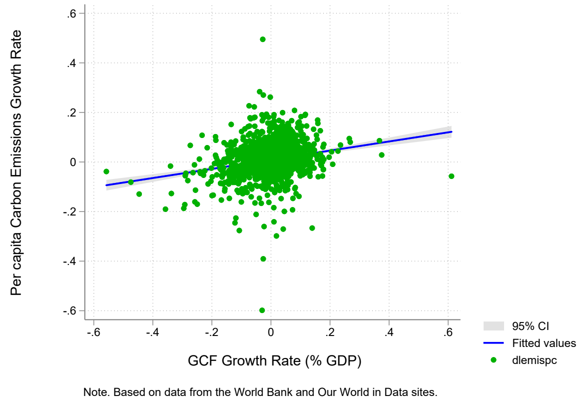
(a) Correlation dlemispc-dlpcgdp$_2$



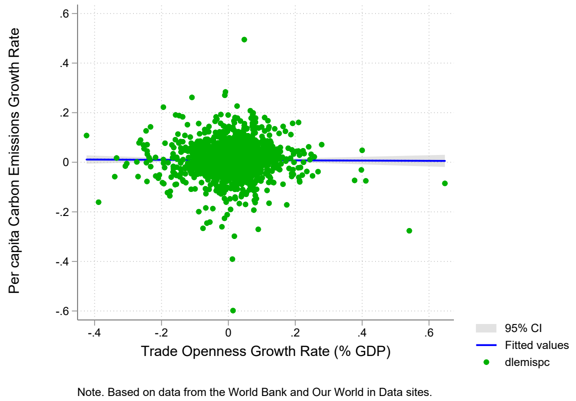
(b) Correlation dlemispc-dlrenew



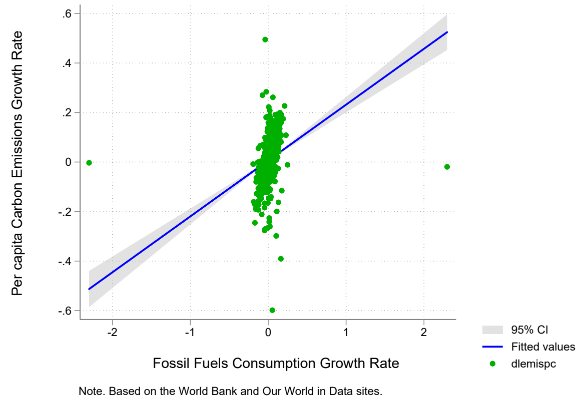
(c) Correlation dlemispc-dfdi



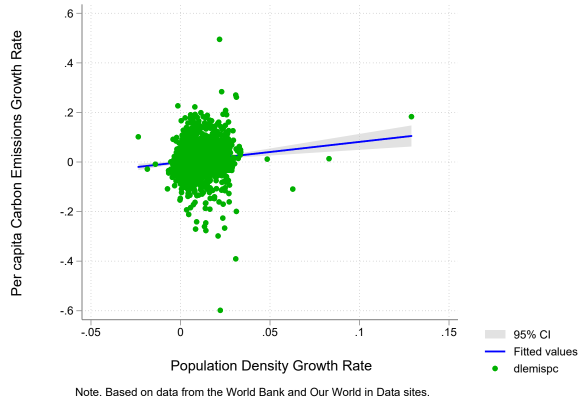
(d) Correlation dlemispc-dlgcf



(e) Correlation dlemispc-dltrade



(f) Correlation dlemispc-dloilcons



(g) Correlation dlemispc-dldensity

Table A4: Test for Cointegration

Model	***Test***	***Statistic***
Kao	*Modified DF t*	*-20.1123****
	Dickey-Fuller t	*-15.3345****
	Augmented DF t	*-3.7597****
	Unadjusted MDF t	*-34.6563****
	Unadjusted DF t	*-18.0210****
Pedroni	*Modified PP t*	*2.0276****
	Phillips-Perron t	*-9.7359****
Westerlund	*Variance Ratio*	*-2.6300****

Note. *, ** and *** denotes 10%, 5% and 1%, respectively. All tests validate cointegration at the 95% confidence.

B Empirical Dynamic Modelling: Mathematical Framework

Following Li et al. (2021), consider a system that is characterized by D variables, which chart a trajectory of system states as they change over time (see Figure 6). As the economies or individuals evolve, the trajectories of these variables will trace a D-dimensional 'manifold' M in a D-dimensional state space over the course of different periods. The aforementioned manifold M represents the system's trajectory on all D variables as they change, so that at any time t the system's state is a single point on M that reflects the D system variables. The main idea is that if the variables are deterministically related, i.e., if they cause each other, M will reflect a set of typically unknown differential equations that generate an 'attractor' along which the points on M tend to fall. This being said, the attractor may be chaotic rather than a fixed point equilibrium or set of points equilibria to which system states tend to converge. The term dynamical refers to systems that function in this way.

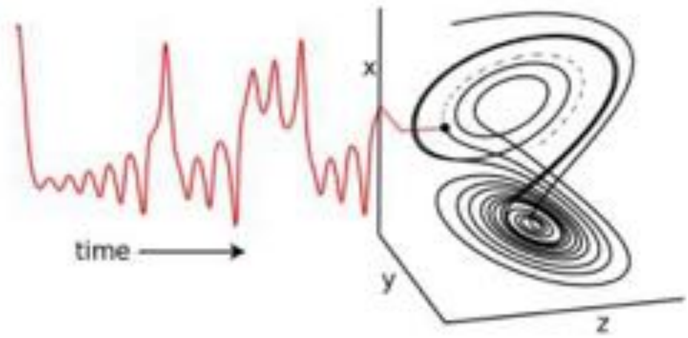


Figure 6: Time Series Projection from the Lorenz Attractor.

If the underlying equations of M are known, it is elementary to characterize the complexity and nonlinearity of the system, describe its deterministic and stochastic features and identify causal effects among the D variables. However, in practice M is unknown and all D variables are not measured. Therefore, M must be reconstructed with an observed variable X from time-series (single entity N = 1) or panel data (multiple entities N > 1) with sufficient time length. Then, if X is a projection, this is, measure of M as in Figure 6, Takens's theorem proves that the deterministic behavior of the entire system might often be reconstructed using merely the lags of the variable X to form an E-dimensional shadow manifold $\mathrm{M_X}$ (where $\mathrm{D} < \mathrm{E} \leq 2\mathrm{D} + 1$; see Takens 1981; Sauer et al. 1991); this logic also applies to the multivariate case, such as if a stochastic input is also needed to reconstruct a system (Deyle and Sugihara 2011). Figure 5 illustrates this reconstruction process using E = 3 lags of X from Figure 6. As Figure 7 illustrates, a set of E-length vectors formed by E lags of X are used to reconstruct the original manifold as the shadow manifold $\mathrm{M_X}$ (i.e., vectors of data on X at each t, $\mathrm{t} - \mathrm{T}$, . . . , $\mathrm{t} - (\mathrm{E} - 1)\tau$, where the 'time delay' parameter $\tau > 0$).

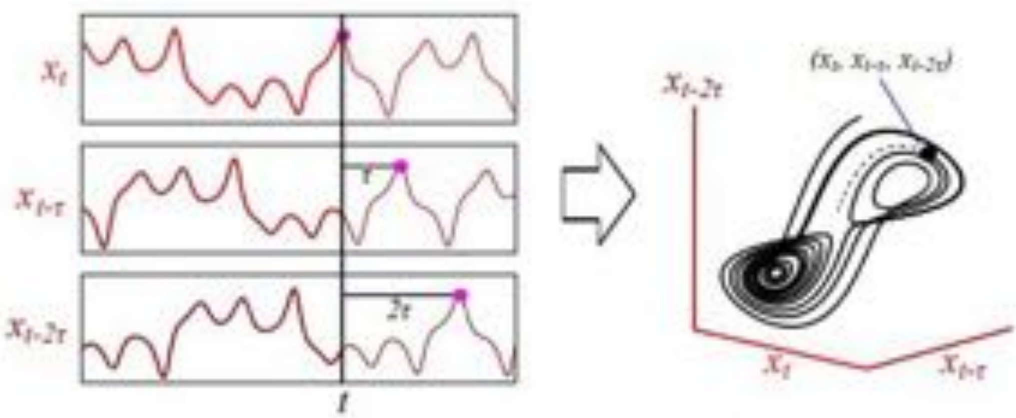


Figure 7: An example of manifold reconstruction.

In this paper, we follow the method established by Clark et al. (2015), wherein E-length vectors of lags on X are taken for each panel separately (so any given point on M_X does not mix data and/or lags drawn from different panels). Then, all of the E-length vectors are pooled in analyses, which makes the assumption that all of the panels share the same underlying dynamic system while each panel's longitudinal trajectory contributes to the reconstruction of different sections of the manifold.

Using lags to reconstruct a manifold is a 'delay embedding' or 'lagged coordinate embedding' approach to state space reconstruction, wherein E-length vectors of lags on X define points on M_X, and the quality of the reconstruction is evaluated by the correlation ρ between out-of-sample observed and predicted values, the hallmark of deterministic systems is prediction. The measure ρ reflects the extent to which the underlying system can be recovered by a deterministic manifold reconstructed as M_X. If the original D-dimensional manifold M is properly unfolded as M_X in E-space, then predictive ability ρ will be maximized, and thus ρ across different values of E (this is, different numbers of lags for the embedding) can be used to infer about the underlying system M.

In addition to understanding EDM framework, we develop simplex projection as well. Simplex projection is a method for investigating the dimension of M and the extent to which a system appears to behave deterministically (Sugihara and May 1990). Even if data appear to be stochastic using typical methods such as autocorrelation, simplex projection can help show if they are driven by deterministic processes causing chaotic behavior that can masquerade as stochastic. This is done by forming an E-dimensional reconstructed attractor manifold M_X and assessing its characteristics. To reconstruct M as M_X, E lags of X are used to build an E-length vector of data that forms a single point on M_X, i.e., an embedding, which is done for each t $\geq$ E. In our approach, a random 50/50 split of the E-length vectors is used to first form a 'library' of training data to build M_X by default. It should be noted that this is a random split of vectors in the reconstructed manifold rather than the original time-series data. This approach avoids the possible problem of creating additional gaps in the original time-series data. The library of training data therefore becomes a randomly determined set of E-length vectors of lags on X that form points on a reconstructed E-dimensional manifold M_X.

The other half of the data form a 'prediction' or validation set, which contains E-length 'target' vectors falling somewhere on M_X. Information in the reconstructed manifold M_X can then be used to predict the future of each target. Specifically, for each target x_t in the prediction set, the $k = E + 1$ nearest neighbors (x_{t1}, . . . , x_{tk}) on M_X from the library set are found by Euclidean distances.

These k neighbors (x_{t1}, . . . , x_{tk}) form a simplex on M_X that is meant to enclose the target x_t in E-space. The simplex of neighbors enclosing the target is then 'projected' into the future ($x_{(t+1)_1}$, . . . , $x_{(t+1)_k}$) to compute a weighted mean that predicts the future value of the target x_{t+1}.

A weight ω_i associated with each neighbor i is determined by the Euclidean distance of the target to each neighbor and a distance decay parameter Θ. Specifically, the weight ω_i can be written as

$$\omega_i = \frac{\mu_i}{\sum_{j=1}^{k} \mu_j} \tag{4}$$

where

$$\mu_i = \exp(-\Theta \frac{||x_t - x_{ti}||}{||x_t - x_{t1}||}) \tag{5}$$

the Euclidean distance measure is denoted $||.||$, and x_{t1} is the nearest neighbor in the manifold (i.e., the most similar historical trajectory to the target). When $\Theta = 0$ the distances are ignored, and all neighbors are weighted equally. As Θ increases, the weight of nearby neighbors increases to represent more local states on M_X (i.e., more similar historical trajectories on X). By default, $\Theta = 1$ to reflect greater weighting of nearer neighbors and, thus, state-dependent evolution on the manifold M. Furthermore, in simplex projection Θ is typically not varied and, instead, is merely fixed to 1 for all analyses. Note that the current version of edm assumes the variables used in the mapping are continuously distributed but future versions will include updated algorithms to better suit alternative distributions (e.g., dichotomous variables).

The quality of predictions is evaluated by the correlation ρ of the future realizations of the targets in the prediction set with the weighted means of the projected simplexes. The mean absolute error (MAE) of the predictions, a measure that focuses more on the absolute gap between observed and predicted data instead of the overall variations like ρ, can also be used as a complement to ρ with the inverse property (i.e., higher value indicates poorer prediction) and will range between 0 and 1 when variables are pre-standardized (we implement a special z prefix for this as noted below). When ρ and MAE disagree, some authors have recommended using the lower of the two embedding dimensions E (Glaser et al. 2011), but this often occurs only with noisy data, including shorter time series where ρ might be more sensitive to outliers and thus MAE can be used (Deyle et al. 2013, S1). A familiar term ρ^2 might also be used as a type of coefficient of determination (akin to R^2). Whatever the measure of prediction accuracy, it should be noted that by default, predictions are out-of-sample due to the fact that data used to reconstruct a manifold and make predictions is unshared with the data being predicted (Sugihara and May 1990; Sugihara 1994; Sugihara et al. 2012; Ye et al. 2016).

To simplify prediction, only the first observation in each target vector's future realization (at t + 1) is used for ρ and MAE (rather than, for instance, multivariate correlation using the entire set of E observations). The resulting ρ and MAE offer insight into how well the reconstructed manifold $\mathrm{M_X}$ makes out-of-sample predictions of the future. When the original manifold M is properly unfolded in E-space as $\mathrm{M_X}$, the neighbors of a target point on $\mathrm{M_X}$ will provide information about the future of the target (Deyle and Sugihara 2011), meaning $\rho > 0$ at a given E.

To infer about the underlying system (e.g., its dimensionality D), ρ and MAE are evaluated at different values of E, and the functional form of the ρ – E and MAE – E relationships can be used to infer about the extent to which the system appears to be deterministic within the studied time frame (Sugihara and May 1990). Unlike typical regression methods, and in particular when working with low-dimensional systems, increasing the dimensionality of a reconstructed manifold by adding additional lags (i.e., larger E) will affect predictions because this adds extraneous information, thus making maximum ρ and minimum MAE useful for choosing E. In high-dimensional or stochastic systems with autocorrelation, however, this will not be the case and ρ may increase with E or appear to approach an asymptote as E increases, which is why the E – ρ and E–MAE relationship is diagnostically useful.

Ideally, a system might be described with less than 10 factors (i.e., less than 10 dimensions), such that prediction is maximized when E < 10. In this case, the system might be considered low-dimensional and deterministic to the extent that predictive accuracy is high (e.g., $\rho > 0.7$ or 0.8). In other words, deterministic low-dimensional systems should make good predictions that are maximized when E is relatively small. If prediction continues to improve or improves and then stabilizes as E increases, the system might be tentatively considered stochastic. This may be due to either stochasticity with autocorrelation (e.g., an AR process), or high-dimensional determinism which may be treated as stochastic. To describe such systems parsimoniously, an E which does not lose too much information compared to an E that maximizes predictions might be chosen (e.g., by hypothesis tests), because "it is also important not to over-fit the model, and in some cases it may be prudent to choose a smaller embedding dimension that has moderately lower predictive power than a higher dimensional model. We do this both to prevent over-fitting the model, and to retain a longer time series" (Clark et al. (2015)).

Finally, this general approach might also be made multivariate by including additional observations from different variables in each embedding vector (see Deyle et al. 2013, 2016a,b; Deyle and Sugihara 2011; Dixon et al. 1999, 2001). This is useful when an attractor manifold cannot be fully reconstructed with a single variable, such as with external forces stochastically acting on a system (Stark 1999; Stark et al. 2003). In such a case, simplex projection could be conducted by adding additional variables to the embedding and testing for improved predictive ability, with special considerations for producing similar prediction conditions, specifically by using the same number of nearest neighbors when including versus excluding the additional variable in the lagged embedding. Conveniently, if an additional variable participates in an alternative deterministic system, then only a single observation from the alternative system may need to be included in the embedding. If prediction does not improve, then no new information is being provided by the additional variable (as Takens's theorem implies for coupled deterministic systems). Notably, in any multiple-variable case, standardizing the variables helps ensure an equal weighting for all variables in the embedding (e.g., using z-scores).

Next, we analyze S-maps or 'sequential locally weighted global linear maps'. S-maps are tools for evaluating whether a system evolves in linear or nonlinear ways over time (Sugihara 1994; Hsieh et al. 2008). This is useful because linear stochastic systems such as VARs might be predictable due to autocorrelation, which would appear as a high-dimensional system with $\rho > 0$ using simplex projection. Therefore, a tool is needed to evaluate whether the system is actually predictable due to deterministic nonlinearity, even if it is high-dimensional. S-maps function as this tool.

A nonlinear system evolves in state-dependent ways, such that its current state influences its trajectory on a manifold M (i.e., an unstable process). Conversely, linearity exists if the trajectory on M is invariant with respect to a system's current state (as assumed in typical VAR and DPD models). This is evaluated by taking the E chosen from simplex projection and estimating a type of autoregression that varies the weight of nearby observations (in terms of system states rather than time) with a distance decay parameter Θ as in simplex projection. Of course, although we use the term 'autoregression', we are not describing a time-series or panel data model equation but, instead, the S-map procedure should be interpreted as reconstructing and interrogating a manifold (rather than modeling a series of predictor variables). As with simplex projection, S-maps use a 50/50 split of data into library and prediction sets of E-length embedding vectors by default. The library set represents a reconstructed manifold M_X, and the k nearest neighbors on the manifold in the library set are used to predict the future of each target vector in the prediction set. For S-maps, each of the k neighboring library vectors has E elements that can be thought of as akin to predictors—consider k rows of data with E columns of predictor variables—such that the predictor set includes k neighbors at E occasions t, t − ρ , . . ., t − (E − 1)ρ . With a constant term c included by default, this is similar to a local regression with E + 1 predictors and k observations, where E + 1 coefficients are computed to predict each target in the prediction set. Unlike simplex projection where the number of neighbors k = E + 1, in S-maps k is often chosen to include the entire library of points on M_X (i.e., the entire reconstructed manifold). Numerically, the predicted value y at point t (from the prediction set) is calculated as:

$$\hat{y}_{\mathrm{t}} = \sum_{j=0}^{E} C_{\mathrm{t}}(j) X_{\mathrm{t}}(j) \tag{6}$$

The coefficient vector C_t can be calculated using singular value decomposition in the form B = AC, where B is a k-dimensional vector of the weighted future value for all the neighboring points and A is a weight matrix of the k neighboring points from the library set (that will contain both past and future values from the original time-series used to form the randomly determined library used to reconstruct the manifold as M_X), as well as the constant term (Sugihara 1994). Mathematically, $B_i = \omega_i y_i$ and $A_i = \omega_i X_i$. The weight ω_i in S-map is defined as

$$\omega_{\mathrm{i}} = \exp(-\Theta \frac{|x_{\mathrm{t}} - x_{\mathrm{i}}|}{1/k \sum_{j=1}^{k} |x_{\mathrm{t}} - x_{\mathrm{j}}|}) \tag{7}$$

When $\Theta = 0$ in the weight function, there is no differential weighting of neighbors on M_X, so in the univariate case the S-map is simply an E-order autoregression with a random 50/50 split of training versus prediction data (i.e., the mapping is global rather than local). However, as the weight Θ increases, predictions become more sensitive to the nonlinear behavior of a system by increasing the weight on nearby neighbors to make predictions. In other words, predictions become more state-dependent by using more information from historical trajectories on M_X, which are more similar to targets in a prediction set. If a system evolves in state-dependent ways, more information from nearby neighbors should increase predictive ability.

Again, using ρ and MAE, and looking at the functional form of the $\rho - \Theta$ and MAE $- \Theta$ relationships, the nature of a system could be evaluated. If state-dependence is observed in the form of larger ρ and smaller MAE when $\Theta > 0$, then EDM tools are used to model the nonlinear dynamical behavior of the system. If nonlinearity is not observed, EDM tools can still be used to evaluate causal relationships in a nonparametric fashion using CCM (although CCM may be less efficient than more traditional methods in this case). Here again, S-maps may be useful diagnostically because a linear stochastic system with autocorrelation should show optimal predictions when $\Theta = 0$, if for no other reason than increasing local weighting as $\Theta > 0$ may increase sensitivity to local noise.

As with simplex projection, S-mapping can also be done in a multivariate fashion (see Deyle et al. 2013, 2016a,b; Dixon et al. 1999, 2001; Li et al. 2021). Here again, the interest is in determining whether additional information about a system is contained in other variables due to external forces acting on the system, and tests for improved predictions are possible to evaluate this observation. In the multivariate case, S-maps are more similar to autoregressive-distributed lag (ARDL) or DPD models, but strictly only when $\Theta = 0$. As Θ increases, it becomes a more local regression wherein neighbors are identified and predictions increasingly rely on the local information in a reconstructed manifold. As already stated, standardization might help ensure an equal weighting for the different variables in the model, but it should always be kept in mind that the S-map is again not a traditional regression model and, instead, is a reconstructed attractor manifold $\mathrm{M_X}$.

Alongside simplex projection and s-mapping, we ought to develop Convergent Cross Mapping or CCM. Convergent cross-mapping is a nonparametric method for evaluating casual association among variables, even if they take part in nonlinear dynamical systems (Sugihara et al. 2012). This method is based on the fact that if X is a deterministic driver of Y ($X \rightarrow Y$), then the states of Y must contain information that could contribute to recovering or 'cross-mapping' the states of X (Schiff et al. 1996). This method is an extension of simplex projection, such that an attractor manifold M is reconstructed using one variable and hence used to predict a different variable. If variables share an attractor manifold M, then predictions are made using the reconstructed manifold.

To elaborate, CCM is based on the fact that if variables X and Y participate in the same dynamical system with manifold M, reconstructed manifolds M_X and M_Y might be mapped to each other. In turn, it is possible to test whether X and Y share information about a common dynamical system and it is possible to test the extent to which the variables causally influence each other in a directional sense (i.e., $X \to Y$ and/or $Y \to X$). This is based on a counterintuitive fact: if $X \to Y$ in a causal sense, then historical information about X is contained in Y and thus it is possible to use M_Y to predict X via simplex projection (see Sugihara et al. 2012), which we symbolize as $X|M_Y$. This is counterintuitive because in typical time-series or panel data methods, causation is used to explain or predict outcomes rather than the reverse. However, in CCM, the outcome Y cross-maps or 'xmaps' the causal variable X, with a shadow manifold M_Y predicting X (i.e., $X_b = X|M_Y$, which heuristically is read left-to-right as implying a potential $X \to Y$ effect). The outcome is used to predict the causal variable because searching for causes requires starting with an outcome and seeing if its dynamical structure M_Y carries the signature of a cause X (Schiff et al. 1996). Counterintuitively, even if $X \to Y$ causality exists (i.e., $X_b = X|M_Y$ works well), if Y does not cause X then M_X will adjust poorly when predicting Y , because M_X will be a function of variables other than Y (i.e., $Y_b = Y|M_X$ will not work well; Sugihara et al. 2012).

B.1 Convergence Tests

The term 'convergent' in CCM describes the criterion by which causality is assessed. This term reflects the fact that if $X \to Y$ causality exists, then prediction accuracy (e.g., a correlation ρ among X and X_b) will improve as the library size L of points on M_Y increases. Larger libraries improve predictions in this case because they make the manifold M_Y denser, and therefore nearest neighbors improve predictions if causal information exists in the local manifold (Sugihara et al. 2012). However, if $X \to Y$ associations are merely statistical, then increasing L should not improve prediction accuracy because denser manifolds will not provide additional predictive information (see Ye et al. 2015b).

We test for convergence in order to robust our causality results. The main idea is to differentiate two model estimates: one with a library size of 10 and one with a library size of 150, replicated 100 times (200 replications in total). We observe that all variables perceive causality with the exception of ltrade. Therefore, we conclude that Trade Openness is not a variable to guide Carbon Mitigation

Policies (see Table 7).

Table A5: Tests for CCM Convergence

L	Model	Coefficient	Ho: diff.=0	Obs
10	**lemispc—lpcgdp**	*0.7853*	*-4.4979****	*200*
150	**lemispc—lpcgdp**	*0.8237*		*(E=2)*
10	**lemispc—loilcons**	*0.9335*	*-14.2554****	*200*
150	**lemispc—loilcons**	*0.9838*		*(E=2)*
10	**lemispc—lrenew**	*0.1268*	*-14.0926****	*200*
150	**lemispc—lrenew**	*0.2984*		*(E=4)*
10	**lemispc—lgcf**	*0.0247*	*-0.0170****	*200*
150	**lemispc—lgcf**	*0.8627*		*(E=4)*
10	**lemispc—fdi**	*0.0585*	*-4.3983****	*200*
150	**lemispc—fdi**	*0.1218*		*(E=9)*
10	**lemispc—ltrade**	*0.1922*	*3.3094****	*200*
150	**lemispc—ltrade**	*0.1444*		*(E=2)*
10	**lemispc—ldensity**	*0.2189*	*-13.0658****	*200*
150	**lemispc—ldensity**	*0.4666*		*(E=2)*
10	**lemispc—loilprice**	*0.4666*	*78.9637****	*200*
150	**lemispc—ldensity**	*0.0534*		*(E=2)*

Note. *, ** and *** denotes 10%, 5% and 1%, respectively. All tests validate causality evidence at the 99% confidence level, with the exception of ltrade and loilprice.