Bachelor in

Applied Data Science

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Modeling Climate Change: The Role of GDP, Energy Consumption, and Greenhouse Gases

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Acknowledgements

Abstract

This study analyzes the relationships between surface temperature, socioeconomic and environmental indicators. The analysis was driven by the motivation to understand human activity influencing climate change and their contribution to warming the Earth's surface. This includes correlations between Greenhouse gas emissions, energy production, consumption, gross domestic product (GDP) and population. Using comprehensive datasets and applying models like Autoregressive Distributed Lag (ARDL), cointegration tests and panel regression techniques to investigate both short- and long-term dynamics. The analysis begins with unit root testing to examine stationarity, followed by multicollinearity diagnostics and model selection. Based on these methods, results show long-run cointegration among the variables. GHG emissions and non-renewable energy consumption are shown as key drivers of temperature increase. This study highlights the importance of robust data, historical perspective and geographical variety in understanding the climate and its future behavior. The observed association in the analysis offers support for targeted mitigation strategies. These findings contribute to a deeper understanding of climate change and highlight the necessity of global cooperation, clean energy transitions and data driven climate policy.

Time-Series Analysis, China, United States of America, Surface Temperature

Contents

List of Figures

List of Tables

CHAPTER 1

Introduction

1.1 Introduction

The entire planet is impacted by global warming. Efforts to limit warming to 1.5 ℃ above pre-industrial levels require reducing greenhouse gas emissions (on Climate Change, 2018). The understanding of how socioeconomic indicators, such as GDP, energy consumption, population relate to temperature changes in the short and long run is still limited. Nevertheless, working with large climate and socioeconomic datasets requires "data empathy", by looking into how data were collected, processed, and the biases they might carry (Faghmous & Kumar, 2014). Without it, analyses can mislead decision makers who need reliable, regionally tailored insights to meet targets such as limiting warming to 1.5 ℃ above pre-industrial levels.

Theoretical analyzes indicating the connection between air temperature and the presence of CO_2 in the atmosphere were made in the mid-19th century Foote, 1856. The analysis concludes that an increase in the CO_2 content in the atmosphere must be associated with an increase in the global surface temperature in geological historical periods. In later years, Guy Stewart Callendar demonstrated the existence of a correlation between CO_2 concentration and temperature in the 1930s (Callendar, 1938). Additionally, he estimated that if the content of CO_2 in the air were to double, the climate would warm up by 2 ℃. These observations were only the beginning of the analysis of the impact CO_2 concentration has on surface temperature, in more recent years the advancement of technology has aided the research in this field, allowing a more enhanced understanding of the global climate system.

The recent intensification of extreme weather events has occurred alongside rising global temperatures. Identifying the links between them is essential for understanding climate dynamics and prediction. Improving data quality has significantly enhanced the accuracy of climate analysis.

Cutting GHG emissions is complicated and not an easy task. The Convention on Climate Change (UNFCCC) was put into effect on The United Nations Conference on Environment and Development (UNCED). It is also known as the 'Earth Summit'. The essence of the Earth Summit that took place in Rio de Janeiro on June 1992 was to advocate for sustainable development (UN, 1992). All countries had integrate social, economic, and environmental factors. The Kyoto Protocol that was established in 1997. Nations around the world gathered to reduce GHG emissions according to regulations of UNFCCC (UNFCC, 2025). In 2015, 189 nations signed the Paris Agreement to take drastic measures to reduce GHG emissions. The essence was that each country had to reduce their GHG emissions. How they assess GHG emission reduction relied on each country's geopolitical scenario, location, and economic development level. Nations with lower GDP are more vulnerable to the adverse consequences of climate change (UN, 2022).

1.2 Problem Statement

This paper investigates the problem of climate change, in specific land surface temperatures and identifying predictive and causal factors that contribute to this. Understanding the interdependent relationship between these factors and how they affect surface land temperature is key to being able to fight climate change.

1.3 Aims and Objectives

Climate change, as a global phenomenon, affects almost every area of the earth's functioning. The aim for this paper is to look at global surface temperature and its development throughout the years and how the use of non-renewable energy sources by mankind has affected global warming.

As part of the analysis, predictions between the relationship between key variables and change in temperature will be examined. The following variables will be considered; renewable and non-renewable energy consumption, energy production, gross domestic product (GDP) and population.

1.4 Scope and Limits

In terms of impact on the global community, climate change affects health issues, economic activity, agriculture, political issues, availability of natural resources such as drinking water, to mention a few. In terms of impact on the biosphere, climate change primarily affects the reduction of biodiversity due to the rapid pace of changes to which living organisms are unable to adapt through evolution. The impact of climate change on the geosphere occurs both directly through weather impacts, changes in the hydrosphere and atmosphere.

Weather phenomena are shaped by a number of factors with both local and global influences. Local conditions such as topography affect precipitation and temperature. The broader phenomena, such as ocean currents and volcanic activity, can influence entire regions. These variables fluctuate seasonally and cyclically, adding complexity to climate expectations.

The scope of the work includes both theoretical and practical aspects related to the study of climate change with an emphasis on identifying and predicting factors that influence changes in temperature. The analysis will examine the relationship between these factors and temperature changes. However, it is important to note that while these complex relationships might correlate and support temperature predictions, establishing direct casual links is beyond the scope of this paper. Combined with the literature review, the analysis aims to build upon and further the arguments presented by previous researchers.

CHAPTER 2

Literature Review

The wide scope of the impact of climate change generates enormous social, political and scientific interest, which translates into numerous literature both in the field of popular science literature, as well as a significant number of scientific works. Both national and international organizations are being created with the goal of researching and mitigating climate change. The scientific approach and motivation of these organizations and researchers vary depending on their aim.

2.1 Earth Zones

Due to the complex systems of relationships between individual earth zones, most publications usually involve a fragmentary analysis of a relatively narrow range of interactions. When analyzing the issue of the earth's surface temperature and the occurring climatic phenomena, four main research areas analyzed in the literature can be distinguished: land, ocean, glaciers and atmosphere.

2.1.1 Oceans and glaciers

Oceans cover vast areas of the globe and are a crucial factor looking at climate change since they regulate the globe's temperature by absorbing excess heat. The warming of the oceans has been clear in polar and subpolar regions because of the weak layering of the ocean's depths helps enabling heat exchanges from deep ocean to the surface. This eventual heat exchange from the deep ocean to the atmosphere is irreversible climate change that has already begun because of heat the ocean already has absorbed (Oh et al., 2024).

There may also be periodic trends of no to minor temperature increases or even negative temperature change of the ocean surface. Research based on climate models indicates that during these intervals the heat of the ocean's surface is absorbed by the deeper ocean levels below 300m. This is proven to be a natural behavior of the globes system and does not help the argument against climate change (Meehl et al., 2011).

Glacial areas exhibit seasonal and long-term fluctuations (Calov & Ganopolski, 2005). Studies show a consistent decline in ice coverage, contributing to global warming through reduced albedo effect (Mandal et al., 2025). Albedo effect is when ice melts, darker surfaces are exposed, and it absorbs more heat which accelerates warming (Calov & Ganopolski, 2005). Climate models such as NEMO and FESOM are used to simulate interactions between ice, ocean currents, and the atmosphere, helping forecast future melt rates (Xie et al., 2023).

2.1.2 Land and Atmosphere

Land areas are warming faster than oceans, about 1.3℃ compared to 0.8℃, due to greenhouse gas emissions (Byrne et al., 2024). Heat builds up more quickly because there's less moisture to absorb and release it. Known as a positive feedback loop, water evaporates faster, and without enough to replenish it, the land dries and heats even more. The sun heats the equator the most, causing the warm air to rise. This cools and spreads toward the poles. The air sinks again around 30° and flows back towards the equator as wind (Kalvig, 2007). This atmospheric circulation shapes our weather and climate as it moves heat, moisture, and air. When patterns like warmer oceans change or more greenhouse gases, it causes more intense rain, stronger storms, or even shifts in temperature (Kossin et al., 2013). Climate change doesn't happen in one place. As it's part of how the Earth moves heat around, clouds play a big role too. About 60% of the Earth is covered by clouds and keeps the Earth cooler than it would otherwise be (Kalvig, 2007). Without clouds, the atmosphere would be warmer. Clouds cause the biggest uncertainty regarding climate in the future, because even though they reflect the sun back to space, some clouds absorb the heat from the land and in this way contribute to higher temperatures.

2.2 Intergovernmental Panel on Climate Change (IPCC) report

The overall picture of climate change and a summary of the phenomena taking place are usually presented in various reports of climate organizations and institutes. One of the most important studies in this area are the reports published by the Intergovernmental Panel on Climate Change (IPCC). The IPCC does not conduct its own research, make climate measurements or deal with modeling climate phenomena. Therefore, the source of data contained in the reports are primarily peer-reviewed scientific papers. Supplementary sources of data include, among others, government reports, studies of industrial organizations and research institutions, international, and possibly conference materials.

The sixth edition of the report published has main conclusions that average global temperature 1850 to 1900 has increased, GHG emissions are continuing to increase and average sea levels are increasing at a steady rate (see table 2.1). In addition to direct data resulting from observations, the report also includes an analysis of the indirect effects of climate change, such as the impact of global warming on human health, the impact of warming on human life and the impact on food production (Intergovernmental Panel On Climate Change (Ipcc), 2023).

Table 2.1: **IPCC report sixth edition**

Average land temperature increase (1850-1900)	1.59 ℃
Average ocean temperature increase (1850-1900)	0.88 ℃
Average global temperature increase (1850-1900)	1.1 ℃
Greenhouse gas emissions	Upward trend, although the rate of increase has decreased.
The average global sea level increase (1901-2018)	0.20m. At the same time, a steadily increasing rate of sea level rise is observed.

2.3 Prediction factors of surface temperature

In summary, climate change has serious consequences for ecosystems and humanity. Studies confirm that warmer climate affects temperatures, sea levels and human health. Initiatives such as the Paris Agreement emphasize the need for action to reduce climate change. The following previously identified variables will be looked at closer in relation to how they impact the climate; renewable and non-renewable energy consumption, energy production, gross domestic product (GDP), emissions and population.

2.3.1 GHG emissions

Climate change is also related to direct changes occurring in the atmosphere, hydrosphere and lithosphere. The main cause and source of the observed changes is primarily carbon dioxide, or more broadly greenhouse gases (GHG) such as methane (CH_4), freons (CFC), ozone (O_3), nitrous oxide (N_2O), halon or other industrial gases (HFC, PFC, SF_6). The complex interactions and dependencies between the spheres are a commonly researched field, ranging from direct measurements of individual spheres to paleoclimate studies to climate computational models. In the case of positive feedback these mutual dependencies can rapidly accelerate climate change. This emphasizes the importance of understanding these complex relationships in order to counteract climate change (Intergovernmental Panel On Climate Change (Ipcc), 2023).

Numerous studies have looked at the link between CO_2 and climate change in the form of temperature increase. *Carbon Dioxide and Climate* (1979), projected that a doubling of atmospheric CO_2 would result in a temperature increase of approximately 3 ℃, with a standard deviation of 0.375 ℃. It is also highlighted that water and oceans on the globe can help absorb some of the temperature increase, resulting in a delayed change in temperature but also a more rapid change once it has occurred. Emphasizing that it is possible that thresholds of CO_2 concentrations in the atmosphere can be reached before significant change in temperature has been acknowledged (*Carbon Dioxide and Climate*, 1979).

Hansen et al. (2023) looked at a collection of research on this topic and argue that the estimated earth sensitivity that the Ad Hoc study group (*Carbon Dioxide and Climate*, 1979) set was too low compared to more recent studies and also identified that the study group did not include glaciers in their scenario. Hansen et.al. states with a greater urgency the importance of mitigating GHG emissions and along with reiterating the need to identify the time required to reach a new equilibrium, it also states the need to identify point of no return (Hansen et al., 2023).

2.3.2 GDP

Climate change and economic growth are linked in the long term, typically no change as of the current period but will have long term effects and slow down economic growth (Fankhauser & S.J. Tol, 2005). The overall wealth that looks at fuel consumption in relation to oil prices as a common ground of correlation. There is also a benefit to be made when complying with limitations such as the Paris agreement, resulting economic benefits along with stable temperatures as researched by Kompas et al. (2018). Short term analysis of GDP isn't a big factor to emission changes, but oil prices have impacts on emissions (Zou, 2018). Mikayilov et al. (2018) showed that there is a long-term relation using cointegration between emissions and GDP in Europe. In turn, a predictable pattern that economic growth has a strong relation with emissions increase. Mehmood et al. (2024) investigated the largest emitters of Co2 being China and United states in relation to the GDP using a Bootstrap Autoregressive Distributed Lag model (BARDL) model. The study finds that the United States of America shows decoupling between GDP and emissions over time due to coal weakening. In contrast, China's heavy reliance on coal making decoupling harder.

Panayotou (1993) among others has researched if the inverted U-shape relationship between economic growth and income disparities proven by Kuznets (Kuznets, 1985) could be applicable to economic growth and environmental degradation. Their result was that in line with inequality studied by Kuznets, the same theory can be applied to environmental degradation. There is a trend of it worsening before improving.

More recently Zhang and Zhang (2018) validated the environmental Kutznets curve (EKT) in China for the impact economic growth has on carbon emissions. The study looked at GDP, trade structure, exchange rate and foreign direct investments and developed an ARDL model and tested the cointegration of these variables on emissions. The relationship was tested using a Granger causality test, and they were able to show an undirected causality from the independent variables and emissions.

Kinyar and Bothongo (2024) investigated how the GDP amongst other variables affects the carbon emissions in the UK. The study used an ARDL bounds test with FMOLS and

DOLS robustness checks and a Granger causality test and were unable to verify an EKC curve trend in the UK from 1988 to 2020. The nature of the relationship between GDP and emissions has inconsistent results, but there is a majority of research that has been able to support the EKT theory (Bilgili et al., 2016).

2.3.3 Energy

Energy Consumption

Energy consumption refers to the total amount of energy used within a country. It's often driven by industrialization, population growth, and economic activity. Non-renewable energy sources, such as coal, oil, and gas, are major contributors to greenhouse gas (GHG) emissions due to their carbon-intensive nature (Akhmat et al., 2014). Coal remains one of the most consumed and polluting energy sources globally. Bilgili et al. (2016) examined the Environmental Kuznets Curve (EKC) across 17 countries from 1977 to 2010, finding a significant negative correlation between renewable energy consumption and GHG emissions using FMOLS and DOLS methods. Similarly, Kinyar and Bothongo (2024) analyzed the UK and found renewable energy, eco-innovation, and process eco-innovation significantly reduce emissions in both the short and long term. These findings suggest that transitioning from fossil fuels to renewable energy can play a vital role in climate mitigation.

Energy Production

Energy production measures the total primary energy extracted domestically from natural sources like fossil fuels, hydropower, wind, solar, and nuclear power. It excludes imports and exports and is typically measured in Quadrillion British Thermal Units (QBTUs) (Newell et al., 2019). Unlike consumption, which reflects demand, production highlights a country's supply capacity and energy independence. Production structure significantly influences a country's emission levels and climate policies. Countries relying on fossil fuel production face more complex decarbonization pathways than those investing in renewable infrastructure (Dogan et al., 2020). Moreover, energy production carries broader implications for economic and geopolitical stability. In empirical climate analyzes, distinguishing between consumption and production provides a clear understanding of national energy systems and their impact on emissions. This distinction is critical for time-series and panel data models examining the drivers of global temperature change.

2.3.4 Population

High consumption levels in industrialized nations are the main contributors to greenhouse gas (GHG) emissions. Expanding populations in developing regions suffer the most from the effects of climate change. The world population will surpass 9.1 billion by 2050 (Stephenson et al., 2010). Much of this growth is concentrated in low- and middle-income countries. According to United Nations World Population Prospects, this demographic poses complex challenges for climate adaptation, human development, and environmental sustainability.

Countries with high fertility have contributed minimally to the global GHG emissions historically. However, it is still expected to rise, because of economic development they need to reduce poverty (Stephenson et al., 2010). Population growth alone does not lead to climate change but rather interacts with energy consumption and energy production because it impacts a country's infrastructure. Urbanization amplifies these interactions, especially in rapidly growing cities where planning, service provision, and resilience may lag the pace of growth.

Rapid growth can strain a government's ability to provide basic services and integrating resources from family planning to improving health outcomes, to ease the demographic pressure on the environment. This intersects the climate adaptation and mitigation, because fertility, migration, and household structure are rarely incorporated into mainstream climate models or national mitigation strategies. The Intergovernmental Panel on Climate Change acknowledges the importance of demographic trends, but comprehensive integration into scenario modeling and policy planning remains limited (Stephenson et al., 2010).

Larger populations can place pressure on natural resources and energy systems, potentially increasing emissions. Densely populated areas are also more exposed to climate risks, including extreme heat, poor air quality, and public health challenges (Guzman et al., 2009).

CHAPTER 3

Methodology

The topic for this paper is to explore the relationship between climate change and global temperature variations over time.

3.1 Data Overview

Earth surface temperature data set that Berkeley has posted on Kaggle website was used for the analysis (Earth, 2018). The data set provides an overview of the average, minimum and maximum temperatures of land, land-and-ocean average temperature and land average temperature along with uncertainty measures. It also provides datasets where temperature measurements are divided up by country, state, major cities and cities. The temperature datasets range from 1750-2015. Temperature data does show changes in climate regarding surface temperature, but to further elaborate and support the research topic of climate change, additional datasets for the analysis are greenhouse gas (GHG) emissions, GDP (Gross Domestic Product) population and energy consumption and production (see table in subsection 3.1.1).

The global Greenhouse Gas (GHG) emissions dataset was collected from the European Commission and contains yearly emissions by country from 1970 to 2024. Economic output, measured via Gross Domestic Product (GDP) has data from over 200 countries. The GDP dataset is collected from the world bank and ranges from 1960 to 2020. Energy consumption and production is collected from US energy information administration (EIA) and has both global and country specific data. The dataset ranges from 1980-2023 with yearly entries. Lastly, the population dataset was collected from the UN and covers population numbers from 1950 to 2023 and is divided by countries.

3.1.1 Data Sources

Variable	Symbol	Measurement	Time-period	Source
Global land surface temperature	GLST	Global average earth surface temperature and temperature anomaly in Celsius	1750–2013 (2015)	Berkley (Earth, 2018)
Temperature	Temp	Temperature anomaly in Celsius	1980-2020	NOAA (for Environmental Information, 2025)
Greenhouse gas emissions	GHG	Global total greenhouse gas emissions by year	1970–2024	EDGAR (for Global Atmospheric Research) Community, 2024)
Gross domestic product	GDP, GDP(PPP)	Global total gross domestic product. PPP is based on purchasing power parity. US Dollars	1960–2020	Our World in Data through Kaggle (Kaggle & zgrcemta, 2022)
Gross domestic product	GDP per capita	Per capita is the sum of value added to the economy of a country divided by the population. US Dollars	1980-2020	UN Trade and Development (on Trade {and} Development (UNCTAD), n.d.)
Population	POP	Global population by year	1950–2023	UN (Roser et al., 2023)
Non-renewable energy consumption	NREC	Global total non-renewable energy consumption by year. QBTU	1980–2023	US EIA (Administration, 2024)
Renewable energy consumption	REC	Global renewable energy consumption by year. QBTU	1980–2023	US EIA (Administration, 2024)
Energy Consumption	EC	Global energy consumption by year. QBTU	1980–2023	US EIA (Administration, 2024)
Energy production	EP	Global energy production by year. QBTU	1980–2023	US EIA (Administration, 2024)

3.1.2 Data challenges and scope limitations

Some of the major difficulties that were handled during the analysis were firstly, finding good datasets from reputable sources. It was a struggle to get datasets that covered a reasonable timeframe. One of the main challenges during the analysis was the struggle to align datasets due to structural inconsistencies: some were country-level, others global, some had one entry per year, while others had multiple or aggregate totals.

To do correlation and regression analysis all datasets had to be cleaned and transformed to ensure consistency in time and country. This required standardizing timeframes and converting all year fields into numeric formats for accurate merging.

General issues with analysis for this topic are the vast number of aspects and variables that can be included when looking at temperature change and climate change. For this report the scope was narrowed down to include temperature, GHG emissions, GDP, population data and energy consumption with a special focus on renewable energy.

3.1.3 Data preparations

The datasets were prepared by examining for missing values, which were none present in the relevant columns. Then the date column was transformed into datetime objects, and day, month and year was extracted into separate columns.

3.2 A collaborative analytical design

This study was conducted collaboratively by the team, each focusing on a distinct scope of analysis to explore the multifaceted relationship between climate change and temperature dynamics:

1. **Global-Level Analysis**

   One team member focused on compiling and analyzing global datasets to enable the investigation of overall global effect the variables have on GLST. Techniques such as Variance Inflation Factor (VIF), ADF and PP unit root testing and ARDL modeling with bounds tests were used to explore short and long-run relationships for all variables.

2. **Panel Data (Country-Level) Analysis**

   Another team member prepared a panel dataset consisting of country-year observations, by using fixed and random effect models to examine variations within-country over time, and how changes in socioeconomic variables affect the temperature. This analysis captures how different countries compare to each other (inter-country effects), and how each country changes over time (intra-country effects).

3. **Case Studies: Country Specific Environmental Economics**

   The third team member centered on an independent case study between two major economies: China and the United States. These countries were selected due to their high levels of emissions, economic size, and data availability. The goal was to observe how these countries use energy, and how emissions and GDP relate to temperature.

3.2.1 Global-Level Analysis

Based on the literature review and numerous references, the variables that are selected should have a relationship with temperature. To further analyze these relationships, the cointegration between these variables was checked to see if there exists a long-term relationship that influences the temperature over time. An ARDL dynamic regression model was fitted with the variables:

Dependent variable: GLST

Independent variables: GHG, REC, NREC, POP, GDP

The methodology will follow similar approaches done by several other researchers to test the relationship between economic and environmental variables (Kinyar & Bothongo, 2024; Zhang & Zhang, 2018).

Given that this is a global analysis, total GDP (PPP) was used to represent the overall purchasing power of the global economy, as it provides a more accurate comparison across countries than nominal GDP or measures of money supply.

Data Preparation

Prior to merging, year fields were standardized as numeric types to ensure consistency across datasets. Merging was conducted using an inner join on the year column to ensure alignment of observations. Datasets like the GHG, POP, NREC and REC had only yearly entries, therefore in order to compare emissions to temperature, a yearly average had to be calculated for the average temperature before merging these tables with an inner join by year.

In order to explore the long-term relationship between the dependent and independent variables, multicollinearity was a major concern and also the stationary state of the data. These factors that are contributors to the state of the climate are globally heavily related, leading to multicollinearity in the data that could result in incorrect predictions and correlation results.

As preparation for analysis of the intersect dataset it needed to be transformed and go through checks to ensure the validity of the results. Due to the large variation of values for the different variables the datapoints were transformed to the natural logarithmic of the values to ensure that the variables are comparable.

Unit Root testing

To check for stationarity in the dataset using both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root testing was performed. This follows previous analysis by other researchers on similar topics (Akhmat et al., 2014; Kinyar & Bothongo, 2024). These tests check the data for any underlying trends or seasonal patterns in the dataset. In the case of the variables being non-stationary any prediction or correlation analysis will potentially show misleading strong relationships due to the underlying trends. Therefore, to proceed with the analysis, it is important to check and validate or potentially correct the variables. Both ADF and PP tests are based on the following hypotheses:

Null hypothesis H_0: time series has a unit root (non-stationary), it has some time dependent structure

Alternative hypothesis H_1: time series does not have a unit root (stationary), does not have time dependent structure

The test was performed for the data as is ($I(0)$, and at first differencing ($I(1)$) because an ARDL is dependent on variables being at most $I(1)$.

VIF analysis

As mentioned, multicollinearity must be taken into consideration for the analysis to avoid misleading results. A Variance Inflation Factor (VIF) test is a method to check whether the independent variables are strongly correlated with each other. This is done by measuring the strength of the correlation between the variables and how much the variance is increased because of collinearity. A VIF score should ideally be below 5, 10 at most, to be considered appropriate to use.

ARDL bound test

Variables such as GDP, POP, REC, NREC and GHG are all a part of an intricate global system where one would expect there will be underlying seasonal trends and other underlying trends from the global market. Because of the nature of the data, it is assumed that at least the chosen variables for this test will need to be differentiated in order to make them stationary.

This would mean that any prediction and co-integration testing would need to be able to accept variables with a mix of $I(0)$ and $I(1)$ nature. Following the methods used by similar research (Kinyar & Bothongo, 2024) an ARDL bound test is an appropriate dynamic regression model that is flexible with variables that are mixed in differentiation ($I(0)$ and $I(1)$). The initial regression equation 3.1 is set as follows:

$$
\begin{aligned}
\Delta \ln \mathsf{GLST}_t = \beta_0 &+ \sum_{i=0}^{k} \beta_1 \Delta \ln \mathsf{GHG}_{t-i} + \sum_{i=0}^{k} \beta_2 \Delta \ln \mathsf{REC}_{t-i} + \sum_{i=0}^{k} \beta_3 \Delta \ln \mathsf{NREC}_{t-i} \\
&+ \sum_{i=0}^{k} \beta_4 \Delta \ln \mathsf{POP}_{t-i} + \sum_{i=0}^{k} \beta_5 \Delta \ln \mathsf{GDP}_{t-i} + \gamma_1 \ln \mathsf{GHG}_{t-1} \\
&+ \gamma_2 \ln \mathsf{REC}_{t-1} + \gamma_3 \ln \mathsf{NREC}_{t-1} + \gamma_4 \ln \mathsf{POP}_{t-1} \\
&+ \gamma_5 \ln \mathsf{GDP}_{t-1} + \epsilon_t
\end{aligned} \tag{3.1}
$$

where:

- Δ : first difference operator
- β_0 : the intersect, constant
- β : coefficients (regressors)
- γ : lagged regressors
- ϵ_t : error term

To generate the best-fit ARDL model, the AIC (Akaike's information criteria) score was considered when selecting the most suitable number of lags for the model.

The best-fit ARDL model will also be tested for long-term cointegration after fitting.

This test has the hypotheses:

Null hypothesis H_0: There is not a statistically significant long-run relationship between the dependent variable GLST and the independent variables GHG, GDP, POP, NREC and REC.

Alternative hypothesis H_1: There is a statistically significant long-run relationship between the dependent variable GLST and the independent variables GHG, GDP, POP, NREC and REC.

This is conducted by calculating a *f*-score based on comparing the non-restricted model against a restricted model that assumes the lag of all variables equals zero. The *f*-statistic will be checked against the ARDL bounds test table for significance (Pesaran et al., 2001). If the *f*-statistic value is greater than both the inner and outer bound values, then co-integration is proved.

3.2.2 Panel Data (Country-Level) Analysis

The datasets used for panel analysis were GHG emissions, energy consumption, energy production and population. These were compiled into a comprehensive panel dataset. It covers across countries and years and reshaped from wide to long format and melted into Country and Year (Torres-Reyna, 2007). An Object-Oriented Framework was utilized for reproducibility. Energy consumption and energy production that provided Quadrillion

British Thermal Units (QBtu), (Newell et al., 2019) by the U.S. Energy Information Administration (EIA), required extensive reshaping and extraction due to the dataset's structure. In order to structure the data for consistency and melted into a panel format, it needed support of guidance paper from Princeton Edu, (Torres-Reyna, 2007) and ChatGPT.

Exploratory Data Analysis (EDA) was conducted to assess the structure of the data after merging all data sets. It involved mean, standard deviation, min, and max, to assess the shape of the distribution. Dispersion metrics such as inter-quartile range, total range, and coefficient of variation were added. With skewness and kurtosis, it showed positive skewness and heavy-tailed distributions and justified the use of logarithmic transformations to improve normality and reduce extreme outliers.

Spearman correlation analysis was performed (equation 3.2) to assess the relationships among the log-transformed variables.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \tag{3.2}$$

Strong positive correlations were observed among GHG emissions, GDP, energy consumption, energy population, and population, while the temperature showed weak negative correlations. This might be influenced by geographic and development differences.

Next, Variance Inflation Factor (VIF) analysis was performed to assess multicollinearity among the independent variables. To ensure stationarity, the Augmented Dickey-Fuller (ADF) test was applied to determine the presence of unit roots and stationarity, before proceeding with the Fixed Effects (FE) and Random Effects (RE) for panel analysis.

Each country has unique characteristics, such as geography, climate zone, or economy, that don't change much over time. Fixed-effect (FE) model for panel regression was used to ensure that the analysis focused on changes within each country over time. This could reduce bias, caused by important differences between countries that don't change over time, leading to more accurate results, (Dell & Jones, 2009).

This fixed-effects formulation (Torres-Reyna, 2007), where unobserved heterogeneity is addressed through country-specific and year-specific effects:

$$Y_{it} = \alpha_i + \beta X_{it} + \delta_t + u_i + \epsilon_{it} \tag{3.3}$$

where:

- Y_{it} : dependent variable
- βX_{it} : log-transformed independent variables
- α_i : country fixed effects over time
- δ_t : year t fixed effects
- u_i : inter-entity error term

- ϵ_{it} : overall error term

By contrast, the random effects was also included for unobserved, country-specific influences that are random and not correlated with the independent variables (Torres-Reyna, 2007).

For this analysis, all variables are in logarithmic form to reduce the influence of extreme values.

The model specification includes country-specific constant terms (α_i) to control for time-invariant characteristics unique to each country, such as geography, or historical factors. In addition, year-specific effects (δ_t) are incorporated to capture global events, such as global financial crises, or major climate events.

The model is:

$$Temp_{it} = \alpha_i + \beta_1 lnGDP_{it} + \beta_2 lnGHG_{it} + \beta_3 lnPOP_{it} + \beta_4 lnEC_{it} + \beta_5 lnEP_{it} + \delta_t + \epsilon_{it} \quad (3.4)$$

By contrast, the random effects was also included for unobserved, country-specific influences that are random and not correlated with the independent variables (Torres-Reyna, 2007). It has almost the same equation as the FE effects, except that the country in FE is fixed as α_i, while in u_i it is random. βX_{it} correlates with the α_i in FE, while the u_i is not correlated with the βX_{it}.

$$Temp_{it} = \alpha_i + \beta_1 lnGDP_{it} + \beta_2 lnGHG_{it} + \beta_3 lnPOP_{it} + \beta_4 lnEC_{it} + \beta_5 lnEP_{it} + \delta_t + u_i + \epsilon_{it} \quad (3.5)$$

To determine the most reliable model, the Hausman test compared the obtained coefficients from both models (Torres-Reyna, 2007).

The Vector Autoregression (VAR) model is useful because it treats all variables as connected. It allows them to potentially influence one another. Instead of looking at each variable in isolation, VAR looks at how temperature is affected not just by its own past values, but also by the past values of the other variables. This helps capture possible time-lagged effects, where changes in one factor might influence another only after some time. VAR(2) Stationary Model captures short-run temporal dynamics and delayed interactions (Zivot & Wang, 2006):

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \epsilon_t \quad (3.6)$$

$$Y_t = \begin{pmatrix} Temp_t \\ \ln(GHG)_t \\ \ln(GDP)_t \\ \ln(EC)_t \\ \ln(EP)_t \\ \ln(POP)_t \end{pmatrix} \quad c = \begin{pmatrix} {}^{c}Temp \\ {}^{c}GHG \\ {}^{c}GDP \\ {}^{c}EC \\ {}^{c}EP \\ {}^{c}POP \end{pmatrix} \quad \epsilon_t = \begin{pmatrix} {}^{\epsilon}Temp,t \\ {}^{\epsilon}GHG,t \\ {}^{\epsilon}GDP,t \\ {}^{\epsilon}EC,t \\ {}^{\epsilon}EP,t \\ {}^{\epsilon}POP,t \end{pmatrix} \tag{3.7}$$

$$\Pi_1 = \begin{pmatrix} \pi_{11}^{(1)} & \pi_{12}^{(1)} & \pi_{13}^{(1)} & \pi_{14}^{(1)} & \pi_{15}^{(1)} & \pi_{16}^{(1)} \\ \pi_{21}^{(1)} & \pi_{22}^{(1)} & \pi_{23}^{(1)} & \pi_{24}^{(1)} & \pi_{25}^{(1)} & \pi_{26}^{(1)} \\ \pi_{31}^{(1)} & \pi_{32}^{(1)} & \pi_{33}^{(1)} & \pi_{34}^{(1)} & \pi_{35}^{(1)} & \pi_{36}^{(1)} \\ \pi_{41}^{(1)} & \pi_{42}^{(1)} & \pi_{43}^{(1)} & \pi_{44}^{(1)} & \pi_{45}^{(1)} & \pi_{46}^{(1)} \\ \pi_{51}^{(1)} & \pi_{52}^{(1)} & \pi_{53}^{(1)} & \pi_{54}^{(1)} & \pi_{55}^{(1)} & \pi_{56}^{(1)} \\ \pi_{61}^{(1)} & \pi_{62}^{(1)} & \pi_{63}^{(1)} & \pi_{64}^{(1)} & \pi_{65}^{(1)} & \pi_{66}^{(1)} \end{pmatrix} \quad \Pi_2 = \begin{pmatrix} \pi_{11}^{(2)} & \pi_{12}^{(2)} & \pi_{13}^{(2)} & \pi_{14}^{(2)} & \pi_{15}^{(2)} & \pi_{16}^{(2)} \\ \pi_{21}^{(2)} & \pi_{22}^{(2)} & \pi_{23}^{(2)} & \pi_{24}^{(2)} & \pi_{25}^{(2)} & \pi_{26}^{(2)} \\ \pi_{31}^{(2)} & \pi_{32}^{(2)} & \pi_{33}^{(2)} & \pi_{34}^{(2)} & \pi_{35}^{(2)} & \pi_{36}^{(2)} \\ \pi_{41}^{(2)} & \pi_{42}^{(2)} & \pi_{43}^{(2)} & \pi_{44}^{(2)} & \pi_{45}^{(2)} & \pi_{46}^{(2)} \\ \pi_{51}^{(2)} & \pi_{52}^{(2)} & \pi_{53}^{(2)} & \pi_{54}^{(2)} & \pi_{55}^{(2)} & \pi_{56}^{(2)} \\ \pi_{61}^{(2)} & \pi_{62}^{(2)} & \pi_{63}^{(2)} & \pi_{64}^{(2)} & \pi_{65}^{(2)} & \pi_{66}^{(2)} \end{pmatrix} \tag{3.8}$$

Where:

- Y_t is the vector of endogenous variables at time
- c is the vector of intercepts
- ϵ_t is the vector of errors
- Π_1 is 6x6 matrix of coefficients for lag 1
- Π_2 is the matrix of coefficients for lag 2

3.2.3 Case Studies: Country Specific Environmental Economics

This particular study segment is to examine whether rising temperatures are related to economic activity, energy, and emissions in two major economies. There already are relations between GDP, emissions and Oil prices as mentioned by Zou (2018). According to the International Monetary Fund (IMF), World Bank Group, and the United Nations show that United States, China and Japan/Germany rank the top and therefore will be investigating the top two countries. Additionally, China and United States were selected due to being the two largest economies, ideal for climate-economic studies (Kompas et al., 2018). Furthermore, there is available data accessible for analysis from recent time periods suitable for trend analysis.

The data collected from these sources include dates ranging from 1700 to 2023. To find the correct time period that will overlap and hold enough presence in the current time period is to investigate from 1980 to 2020. The data is accessed through a CSV file in which was merged from multiple sources into a single dataset. The data set will hold the year and variables as headers. To keep the data consistent, the unit of measurement will be converted into standardized measurement and comparability. Additionally, all variables

Table 3.1: **Case Studies: Variables Used**

Variable	Source	Unit of Measurement	Description
Temperature	NOAA and Berkley	Celsius	Temperature anomaly which shows the change in temperature
GHG Emissions	EDGAR	Million Tonnes of Carbon Dioxide	Unit of energy
Energy Consumption	EAI	Quadrillion British Thermal Units (BTU)	Unit of energy
GDP	UN	USD	Millions at year value at relative market price

were log transformed before differencing and analyzed for normalization of data as well as interpreting relationships.

The variables were checked for a unit root using ADF tests for stationarity. In this case of testing, the dependent variable is the temperature, and the independent variables are emissions, energy consumption, and GDP. Additionally, if a variable is found to be non-stationary, it was differenced to achieve stationarity.

Cointegration testing checks to see if the variables are moving together over the long run despite having fluctuations in the short term. The test will be applied between each variable and temperature to keep consistency and to examine whether temperature anomalies have long-run relationships with economic indicators. The cointegration model that was used was the Engle and Granger method, to perform pairwise tests between temperature and each economic variable individually (Mikayilov et al., 2018).

Regression analysis was used to assess the short-term correlation between temperature anomalies and economic or energy variables. This test reveals the short-run effects of GDP, emissions, and energy consumption on temperature changes. Ordinary Least Squares (OLS) was used as the linear regression model to explore how economic factors affect temperature anomalies.

As the data was log-transformed and differenced to ensure stationarity, the model is specified as follows:

$$\Delta \log(\text{Temp})_t = \beta_0 + \beta_1 \Delta \log(\text{Emissions})_t + \beta_2 \Delta \log(\text{Energy})_t + \beta_3 \Delta \log(\text{GDP})_t + \varepsilon_t \quad (3.9)$$

This equation models the change in log temperature anomaly at time t as a function of the change in log emissions, energy consumption, and GDP at the same time. The beta coefficients are interpreted as short-run elasticities. The dependent variable is the temperature anomaly, while the independent variables are emissions, GDP, and energy consumption. The model shown above is applied to the China and United States datasets separately to compare how economic changes relate to temperature anomalies in each context.

CHAPTER 4

Results

The aim for this paper was to look at global surface temperature and its development throughout the years and how the use of non-renewable energy sources by mankind has affected global warming. Historical temperature data has been analyzed and the effect renewable energy consumption, non-renewable energy consumption, GHG emissions, GDP and population has on temperature change over time. The results from the analysis will follow the same format as the methodology.

4.1 Global-Level Analysis Results

4.1.1 Unit root testing

Both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root testing was performed on the selected variables. The results are listed in table 4.1. ADF test shows that at level $I(0)$, ln GLST and ln POP are stationary with a significance of 5% and 10% respectively. After first differencing $I(1)$, variables ln GHG, ln REC, ln GDP and ln NREC are stationary with a significance of 5%, 5%, 10% and 1% respectively. For the ADF test, variable ln POP are not stationary at the tested differencing levels.

The PP test concludes that at level $I(0)$, ln POP is stationary with a significance of 1%. At first leveling, PP test shows that all variables are stationary with a significance of at most 5%, except for ln GDP which is non-stationary.

The results for variables ln POP, ln GLST and ln GDP are partially different when comparing the two tests. When combining the all-over result, we conclude that all variables are considered stationary at first differencing $I(1)$. No variables are considered $I(2)$, fitting the requirements for the ARDL model. The unit root testing confirms a long-run stationary relationship within each variable at $I(1)$, rejecting the null-hypothesis for all.

After the unit root testing and differencing the resulting dataset has a total of 25 yearly entries, from 1991 to 2015.

Table 4.1: **Global Analysis: ADF and PP Unit Root Test Results**

Variable	**ADF** $I(0)$	**ADF** $I(1)$	**PP** $I(0)$	**PP** $I(1)$
$\ln$(GLST)	-3.236**	-1.626	-1.768	-9.719***
$\ln$(GHG)	0.556	-3.301**	0.444	-3.091**
$\ln$(REC)	2.702	-3.142**	2.489	-3.494**
$\ln$(POP)	-2.840*	-1.092	-6.867***	-6.355***
$\ln$(GDP)	-0.497	-2.640*	-0.097	-2.464
$\ln$(NREC)	0.350	-3.863***	0.254	-3.755***

Note. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
$I(0)$ = level stationary; $I(1)$ = first difference stationary.

4.1.2 VIF test results

Once stationarity has been confirmed with the unit root testing, multicollinearity was checked. As previously stated, the resulting value should ideally be below 5, at least under 10 to avoid this issue.

Table 4.2 shows the first VIF test of all variables. The results for ln GHG, ln GDP, ln NREC and ln POP are too high and indicate a strong collinearity between the variables. It was then decided to exclude the ln NREC variable, given that it is strongly linked to ln GHG. Based on the literature review and the analysis so far, it was more important to keep the ln GHG.

Table 4.2: **Global Analysis: VIF Test Results for All Independent Variables**

Variable	**VIF score**
$\ln$(GHG)	25.276
$\ln$(REC)	3.441
$\ln$(POP)	13.811
$\ln$(GDP)	25.671
$\ln$(NREC)	20.053

The VIF test was then performed again on the remaining variables. The results (see table 4.3) show that ln GDP and ln POP still have alarmingly high collinearity with the variables. VIF tests were again performed, one where ln POP was dropped and the other where ln GDP was dropped. Both of these tests show agreeable VIF score for all variables.

Table 4.3: **Global Analysis: VIF Test Results for Independent Variables Excluding NREC**

Variable	**VIF score**
$\ln$(GHG)	6.362
$\ln$(REC)	3.436
$\ln$(POP)	13.792
$\ln$(GDP)	25.645

Since both of these variables are considered important for the analysis, it was decided to split the ARDL model into two, where model 1 has the independent variables ln GHG, ln

REC and ln POP (see table 4.4). Model 2 has the independent variables ln GHG, ln REC and ln GDP (see table 4.5).

Table 4.4: **Global Analysis: VIF Test Results for Model 1 (with POP)**

Variable	**VIF score**
$\ln(\text{GHG})$	2.622
$\ln(\text{REC})$	3.426
$\ln(\text{POP})$	2.812

Table 4.5: **Global Analysis: VIF Test Results for Model 2 (with GDP)**

Variable	**VIF score**
$\ln(\text{GHG})$	4.010
$\ln(\text{REC})$	3.309
$\ln(\text{GDP})$	5.228

4.1.3 ARDL Bounds Test

The ARDL models were set up with an appropriate number of lags following the AIC score. The *f*-statistic score was calculated for both models. The results (see table 4.6) show that the models have a score over 6. When comparing it to the bounds table from Pesaran et al. (2001) both models are statistically significant with a threshold of 1%. They exceed the values for both lower and upper bounds, clearly rejecting the null hypothesis. There is a statistically significant long-run relationship between ln GLST and independent variables.

Table 4.6: **Global Analysis: ARDL Bounds Test Results for Model 1 and Model 2**

Model nr.	**Variables**	**F-statistics**	**Significance**	$I(0)$	$I(1)$	**Cointegration**
1	$F(\ln(\text{GHG}), \ln(\text{REC}), \ln(\text{POP}))$	6.07***	10%	2.72	3.77	
			5%	3.23	4.35	
			1%	4.29	5.61	cointegration
2	$F(\ln(\text{GHG}), \ln(\text{REC}), \ln(\text{GDP}))$	7.55***	10%	2.72	3.77	
			5%	3.23	4.35	
			1%	4.29	5.61	cointegration

Note. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
$I(0)$ = lower bounds; $I(1)$ = upper bounds.

Model 1 Results

The results from model 1 (see table 4.7) show statistically significant results for the relationship between the regressors ln GHG, ln REC, ln POP and dependent variable ln GLST. The ln GLST itself has statistically significant results while holding all other factors constant. Showing that for both lag 1 (***) and 2(**) a previous surface temperature increase results in a decrease in temperature for the current period by 0.68 and 0.41 percent respectively.

While the model indicates no significant relationship between ln GHG and ln GLST, ln REC does. For variable ln REC, in lag 2 it shows that a 1% increase in renewable energy consumption leads to an increase in surface temperature by 0.35% for the current period, holding other factors constant (**). While for lag 4, it shows a decrease in surface temperature by 0.49% for the current period (**). The overall effect results in a decrease in temperature by 0.14%.

Lastly, ln POP also has an inconsistent statistically significant relationship with ln GLST while holding other factors constant. It indicates that a 1% increase in population for the current time period results in a surface temperature decrease of 91.8% (**). While a 1% increase in population one period ago increases the surface temperature by 91.03% for the current time period (**).

When examining the ln POP results separately, the correlation seems illogical and unreasonably high. Comparing them, the net change in ln GLST is negative 0.15% which is a more plausible result. This inconsistency can imply that the ln POP variable's dynamic might be distorted when its lagged effects are considered independently. Therefore, the overall impact of ln POP on ln GLST should be interpreted rather than the isolated estimates.

Table 4.7: **Global Analysis: ARDL Model 1 Results**

Variable and Lag	coef	std err	z	p>$\lvert z\rvert$	[0.025	0.975]
const	0.003	0.077	0.044	0.966	-0.166	0.172
$\ln$(GLST) lag 1	-0.689	0.173	-3.974	0.002	-1.071	-0.307
$\ln$(GLST) lag 2	-0.414	0.165	-2.517	0.029	-0.777	-0.052
$\ln$(GHG) lag 0	0.176	0.299	0.590	0.567	-0.482	0.835
$\ln$(GHG) lag 1	-0.505	0.287	-1.761	0.106	-1.137	0.126
$\ln$(REC) lag 0	-0.142	0.172	-0.829	0.425	-0.520	0.235
$\ln$(REC) lag 1	0.110	0.176	0.626	0.544	-0.277	0.497
$\ln$(REC) lag 2	0.354	0.149	2.383	0.036	0.027	0.683
$\ln$(REC) lag 3	0.114	0.156	0.736	0.477	-0.229	0.458
$\ln$(REC) lag 4	-0.492	0.170	-2.900	0.014	-0.867	-0.119
$\ln$(POP) lag 0	-91.185	34.917	-2.612	0.024	-168.036	-14.334
$\ln$(POP) lag 1	91.034	34.114	2.669	0.022	15.949	166.120

Model 2 Results

Model 2 again shows statistically significant relationship between the regressors ln GHG, ln REC, ln GDP and dependent variable ln GLST (see table 4.8).

Ln GHG has statistically significant conflicting results for the following periods while holding other factors constant. For the current time period, a 1% increase in ln GHG equals an increase in surface temperature by 0.79% (*). For lag 1, an increase of 1% in ln GHG results in a decrease in surface temperature by 1.66% for the current time period (***). Lastly, for lag 3, a 1% increase in ln GHG suggests a surface temperature increase of 0.54% (*). The overall effect being a decrease of 0.33%,

The statistically significant results for ln REC show a similar relationship with ln GLST as model 1. For lag 2, a 1% increase in ln REC two periods ago equals an increase in surface temperature by 0.55% for current time period while holding other factors constant (***). For lag 3, a 1% increase in ln REC shows a decrease in surface temperature by 0.28% for the current time period (*). Lastly, lag 4 shows that with an increase of 1% in ln REC results in a decrease in temperature by 0.5% for the current time period (***). The overall effect shows a decrease in ln GLST by 0.23%.

Lastly, ln GDP also has statistically significant effect on ln GLST while holding the other factors constant. Lag 0 shows that a 1% increase in ln GDP results in a decrease in surface temperature by 1.22% (***). Contrary to lag 0, lag 1 shows that a 1% increase in ln GDP one period ago increases temperature by 1.63% for the current time period (***). While for lag 3, a 1% increase in ln GDP three periods ago relates to a decrease in temperature by 1.43% for the current period (***). There are inconsistencies with the results for GDP, and the overall effect is a temperature decrease of 1.02%.

Table 4.8: **Global Analysis: ARDL Model 2 Results**

Variable and Lag	**coef**	**std err**	***z***	***p*>$\|z\|$**	**[0.025**	**0.975]**
const	0.064	0.016	3.926	0.004	0.027	0.102
$\ln$(GLST) lag 1	-0.088	0.170	-0.519	0.618	-0.480	0.304
$\ln$(GLST) lag 2	-0.221	0.133	-1.671	0.133	-0.528	0.084
$\ln$(GHG) lag 0	0.798	0.378	2.110	0.068	-0.074	1.670
$\ln$(GHG) lag 1	-1.661	0.481	-3.453	0.009	-2.770	-0.552
$\ln$(GHG) lag 2	0.591	0.339	1.744	0.119	-0.191	1.374
$\ln$(GHG) lag 3	0.546	0.279	1.962	0.085	-0.096	1.189
$\ln$(REC) lag 0	0.293	0.192	1.523	0.166	-0.151	0.737
$\ln$(REC) lag 1	-0.235	0.154	-1.524	0.166	-0.592	0.121
$\ln$(REC) lag 2	0.556	0.138	4.036	0.004	0.238	0.874
$\ln$(REC) lag 3	-0.288	0.149	-1.926	0.090	-0.633	0.057
$\ln$(REC) lag 4	-0.504	0.141	-3.574	0.007	-0.831	-0.179
$\ln$(GDP) lag 0	-1.227	0.305	-4.022	0.004	-1.932	-0.524
$\ln$(GDP) lag 1	1.637	0.443	3.692	0.006	0.614	2.660
$\ln$(GDP) lag 2	-1.438	0.431	-3.335	0.010	-2.434	-0.444

4.2 Panel Data (Country-Level) Analysis Results

Table 4.9: **Panel Analysis: Regression Descriptive Results**

Variable	**Skewness**	**Kurtosis**	**IQR**	**Range**	**Sum of Squares**	**Coefficient of Variation**
Temperatures	-1.25	1.62	14.609	53.361	2.77 × 10^7	0.473
Population	8.94	86.77	1.73 × 10^7	1.44 × 10^9	6.50 × 10^{21}	4.023
GHG Emission	10.16	128.71	82.01	15,943.98	2.93 ×10^{11}	4.302
GDP	10.49	135.01	8.09 × 10^{10}	2.31 × 10^{13}	4.48 × 10^{29}	4.699
Energy consumption	19.23	469.55	0.131	162.08	7.52 × 10^6	6.807
Energy production	16.14	336.11	0.052	126.57	6.42 × 10^6	6.397

GDP, GHG emissions, and energy consumption showed extreme positive skewness from 10 to 19 and excess kurtosis (>100). It means a few countries have extremely high values and the majority clustered at lower values. High range and IQR values for GDP and population indicate extreme outliers and wide disparities across countries. GDP and population had the highest sums of squares. It indicates large variability over time and between countries. The coefficient of variation (CV) compares variability across variables with different scales. High CVs for energy consumption (6.81) and production (6.40) indicate instability. The temperature showed stability as the CV was 0.47. These distributional characteristics support the use of log transformations to reduce skewness, heavy tails and stabilize variance.

4.2.1 Correlation Analysis

To address the extreme skewness and heavy tails observed in the raw data, logarithmic transformations were applied. This improved the distribution for all of the variables. For instance, GHG Emission_log showed a skewness of –0.46 and a kurtosis of 0.075, suggesting a more symmetrical, bell-shaped distribution. The transformations helped reduce the influence of extreme outliers and stabilized variance across observations. The temperature was not log-transformed because it already followed a relatively symmetrical distribution with low skewness (–1.25) and moderate kurtosis (1.62). The values in temperature are bounded and measured in degrees Celsius and contain negative values and therefore applying logarithmic transformation can't be applied (Babb, 2023).

The Spearman correlation matrix reveals greenhouse gas (GHG) emissions are highly correlated with both GDP and population. This means that countries with larger economies or populations tend to emit more greenhouse gases, an expected pattern, where energy activities grow with development.

The figure 4.1, shows strong relationships between GHG Emission_log and GDP_log still show a correlation of 0.88 as an example. The overall trends between variables shows also remained consistent even after applying logarithmic transformations. This shows how Spearman correlation is very robust to skewed datasets and extreme outliers. The relationships shift regarding temperatures. It shows weak to moderate negative correlations with GDP (–0.29), energy consumption (–0.30), and GHG emissions (–0.20). Population is an exception. It has a slight positive correlation with temperature (0.07).

These correlation patterns are important for understanding the broader context of temperature variation and development across countries.

4.2.2 Panel Regression: Fixed and Random Effects

VIF

All five log-transformed predictors have VIF values around 1.00 (see table 4.10). It means virtually no multicollinearity. The intercept shows an inflated VIF of 316, which is common and not of concern (Groß, 2003).

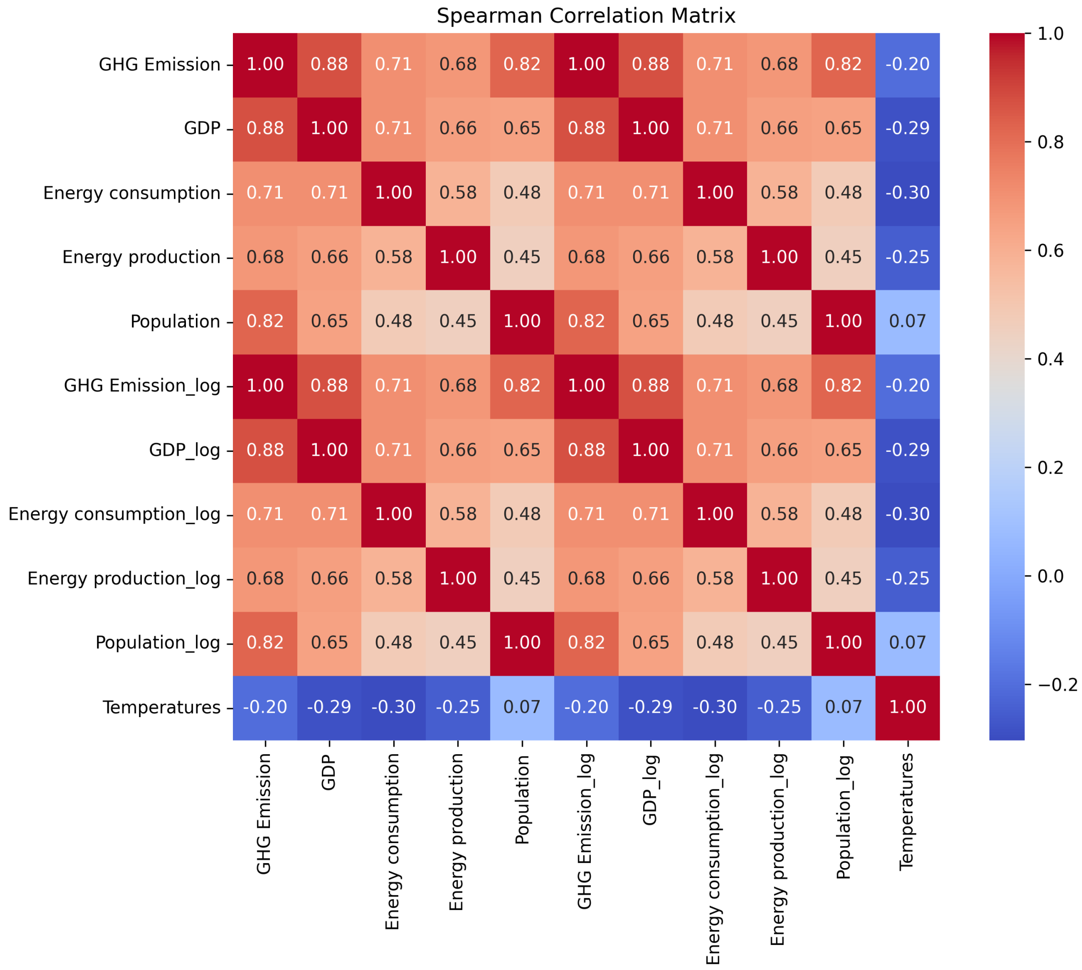


Figure 4.1: Panel Analysis: Spearman Correlation Matrix

Table 4.10: **Panel Analysis: VIF Results**

Variable	**VIF score**
$const$	316.13
$\ln$(GHG)	1.00
$\ln$(GDP)	1.00
$\ln$(EC)	1.00
$\ln$(EP)	1.00
$\ln$(POP)	1.00

Stationarity

Table 4.11 reports the results of the Augmented Dickey-Fuller (ADF) based on 1000 rows. The ADF statistics are highly negative than the critical value. The table has an example of 5% critical value. When the p-values are below the 0.05 threshold, we reject the null hypothesis of a unit root for all series. All variables are stationary.

To account for within country and across country variation over time, both Fixed Effects (FE) and Random Effects (RE) panel regressions were estimated using log transform.

Table 4.12: 85,958 was observed in the fixed effects model. Average temperatures as the dependent variable were analyzed across 128 entities over 34 time periods using a

Table 4.11: **Panel Analysis: Stationarity Results**

Variable	ADF statistics	*p*-value	used lag	Observations	CV (5%)	Stationarity
temperatures	-32.462	< .001	0	999	-2.864	yes
$\ln$(GHG)	-32.770	< .001	0	999	-2.864	yes
$\ln$(GDP)	-18.855	< .001	2	997	-2.864	yes
$\ln$(EC)	-31.296	< .001	0	999	-2.864	yes
$\ln$(EP)	-30.979	< .001	0	999	-2.864	yes
$\ln$(POP)	-32.910	< .001	0	999	-2.864	yes

Table 4.12: **Panel Analysis: Fixed Effects vs. Random Effects**

Model	R^2 within	R^2 between	R^2 overall	*f*-statistics	*p*-value	intercept	Overall fit
FE Model	0.178	-0.058	-0.003	3724.8	< .001	2.965	Slightly better
RE Model	0.178	-0.005	-0.058	3723.4	< .001	5.092	Slightly worse

Fixed Effects (FE) panel data model. The model includes country-specific fixed effects and accounts for the uniqueness a country has that does not differ over time.

The between and overall R-squared values are negative. This means that the model does not capture variance across countries. This is not unusual in FE models. It is focused on within-entity variation, but in RE models, it is different. RE model indicates that temperatures do not exactly correlate with other variables. The high *f*-statistic and *p*-value of < .001 in both models suggest that they are statistically significant. The overall meaning of the variables in total can help explain changes in temperatures.

Table 4.13: **Panel Analysis: FE and RE results**

Variable	Fixed Effects	Random Effects	*p*-value
$\beta_1 \ln$(GDP)	0.333	0.333	< .001
$\beta_2 \ln$(GHG)	-0.426	-0.427	< .001
$\beta_3 \ln$(POP)	0.447	0.448	< .001
$\beta_4 \ln$(EC)	-0.000	-0.000	.790
$\beta_5 \ln$(EP)	0.003	0.003	.005

Table 4.13 shows that a higher GHG emissions is 0.00427℃ decrease in temperatures. This is counterintuitive. Higher GHG emissions lower the average temperatures in this model. It could indicate geographical or time-specific complexities. Positive increase in temperature is GDP, Energy production and Population. Economic activity might contribute to climate effects, urbanization and resource use. If a rise in energy consumption affects the temperature negatively, the *p*-value is 0.7905 and indicates that there is no evidence to support the claim. The F-test for poolability was highly significant 1.70^{05} with a *p*-value < .001 and confirms the presence of unobserved country-specific heterogeneity and impacts the temperature. A Hausman's test was conducted and the results were the same as the FE and RE.

Vector Autoregression (VAR) Model

The Vector Autoregression (VAR) analysis was conducted to explore the dynamic, time-lagged relationships between temperature and GDP, greenhouse gas (GHG) emissions, energy consumption and production, and population. Using a two-lag structure model, these provided insights in how the variables evolve over time and how they affect one another in the short run.

Table 4.14: **Panel Analysis: VAR Model Results**

Dependent Variable	Predictor Variable	Coefficient β	SE	*t*-statistics	*p*-value	Interpretation
Temperature	const	14.308	4.033	3.548	< .001	Constant
	$\ln(EP)$ L1	0.623	0.314	1.983	.047	Positive**
$\ln$(GHG)	const (Intercept)	13.308	1.581	8.416	< .001	Significant
	$\ln(EC)$ L1	0.234	0.121	1.927	.054	Positive*
$\ln$(GDP)	const	22.270	1.549	14.369	< .001	Constant
	$\ln(GDP)$ L1	0.079	0.031	2.510	.012	Positive**
	$\ln(EP)$ L1	-0.278	0.120	-2.301	.021	Negative**
$\ln$(EC)	const	1.722	0.413	4.168	0.000	Constant
	$\ln(Temp)$ L1	-0.006	0.003	-1.995	.046	Negative**
	$\ln(GHG)$ L1	-0.024	0.008	-2.879	.004	Negative***
$\ln$(EP)	$\ln(GDP)$ L2	0.018	0.008	2.217	.027	Positive**
$\ln(POP)$	const	16.332	1.204	13.56	< .001	Constant
	$\ln(EC)$ L2	-0.184	0.092	-1.988	0.047	Negative**
	$\ln(EP)$ L2	0.188	0.094	2.004	.045	Positive**

Note. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results in table 4.14 indicate that Energy production at lag 1 has a statistically significant and positive effect on Temperatures, *p* = 0.047. It reveals that the constant term in GHG reflects a strong baseline level of GHG emissions. For GDP, energy consumption, energy production and population shows that the constant is highly significant, meaning, that they all have a strong baseline.

Energy consumption log at lag 1 shows a positive, marginally significant effect. GDP (*p* = 0.012) and Energy production (*p* = 0.021) are statistically significant predictors of current GDP. Temperatures (*p* = 0.046) and GHG emissions (*p* = 0.004) at lag 1 are statistically significant predictors of energy consumption. The results reveal that GDP at lag 2 has a positive and statistically significant effect on Energy production (*p* = 0.027). Both Energy consumption and Energy production at lag 2 are statistically significant predictors of population (*p* = 0.047 and *p* = 0.045, respectively).

4.3 Case Studies Results

The Augmented Dickey-Fuller (ADF) test was first used to assess unit roots in each variable. The results indicated that most variables were non-stationary but achieved stationarity after first differencing for China and after second differencing for some U.S. variables. This step was to prevent any spurious relationships. For China, the ADF test confirmed that all variables became stationary after first differencing. Specifically, log-transformed GDP had a test statistic of -4.8219 (p< .001), emissions -3.6032 (p = .005), energy -2.9641 (p = .038), and temperature anomaly -5.3834 (p< .001). In the U.S. dataset, GDP ($I(0)$) was stationary at level with a test statistic of -4.2889 (p< .001), whereas emissions and energy required second differencing, with test statistics of -9.3403 and -4.2298 (both p< .001). The temperature anomaly series was also stationary at level (test statistic = -3.5302, p = .007).

Table 4.15: **Case Studies: ADF Unit Root Test Results**

	China		**USA**		
Variable	**ADF** $I(0)$	**ADF** $I(1)$	**ADF** $I(0)$	**ADF** $I(1)$	**ADF** $I(2)$
$\ln$(GDP)	1.2050	-4.8219***	-4.289***	-	-
$\ln$(EC)	-0.9471	-2.9641**	-2.5608	-0.7205	-4.2298***
$\ln$(GHG)	-1.0273	-3.6032***	-1.5596	-1.9708	-9.2403***
$\ln$(TA)	-0.6882	-5.3834***	-3.5302***	-	-

Note. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
$I(0)$ = level; $I(1)$ = 1st differencing;$I(2)$ = 2nd differencing .

Based on the ADF findings, the China dataset was integrated of the order one $I(1)$, whilst the data set included variables of zero $I(0)$ and two $I(2)$. Engle-Granger Cointegration testing was applied only to the China dataset, whilst the United States had 2 stationary data set leading it to be unqualified for testing. No cointegration was found between temperature and emissions (p = .100), GDP (p = .173), or energy consumption (p = .099), indicating no evidence of a long run relationship.

Table 4.16: **Case Studies: Engle-Granger Cointegration Results**

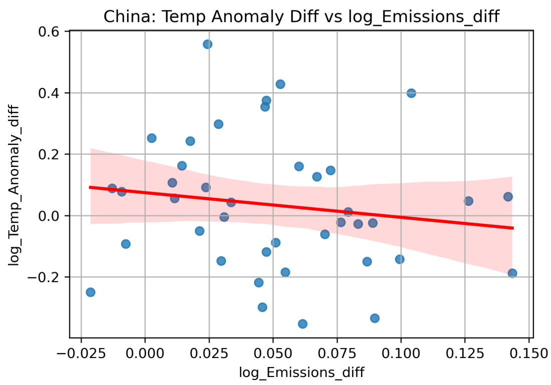
Variables	***p*-value**	**Cointegrated**
$\ln$(TA) $+ \ln$(GHG)	.100	Not Cointegrated
$\ln$(TA) $+ \ln$(GDP)	.173	Not Cointegrated
$\ln$(TA) $+ \ln$(EC)	.099	Not Cointegrated

Short term fluctuations were assessed using Ordinary Least Squares (OLS) regression with temperature anomaly as the dependent variable and emissions, energy consumption, and GDP as independent variables. Scatter plot followed the same suit.

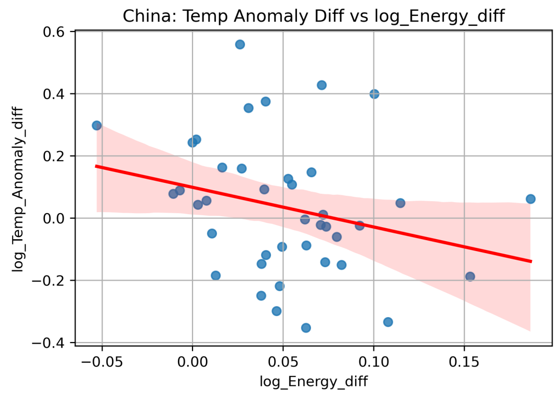
Table 4.17: **Case Studies: OLS results**

	China			**USA**		
Variable	**Coefficient** β	**SE**	***p*-value**	**Coefficient** β	**SE**	***p*-value**
$\ln$(GHG)	1.6796	1.502	.271	-2.8852	3.479	.413
$\ln$(EC)	-1.9928	1.321	.140	5.0315	4.230	.242
$\ln$(GDP)	-0.6156	0.400	.132	0.5719	0.124	< .001

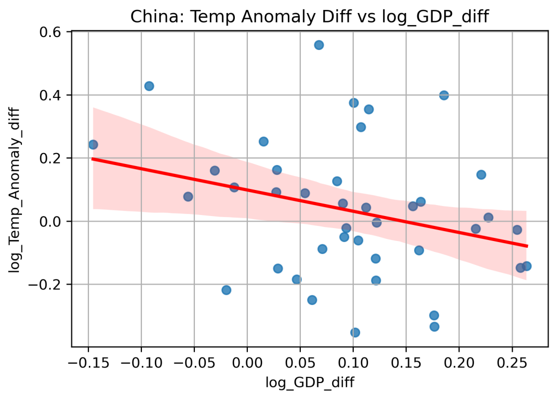
For China, the OLS model yielded an R^2 of 0.141, showing a weak implication. None of the variables showed statistical significance at 5% level; emissions β = 1.6796 (SE = 1.502, p = .271), energy consumption β = 1.9928 (SE = 1.321, p = .140), and GDP β = -0.6156, (SE = 0.400, p = .132). The high standard errors in emissions and energy suggests a degree of uncertainty in the coefficients. The scatter plots (see figures 4.2) showed a negative trend overall with emissions showing the weakest. Emissions show a weak slope and a wide spread of data points, particularly around the x-axis. Similarly, the energy and GDP showed a slightly steeper negative trend, notably the energy consumption plots were more packed at the center of the x axis with vertical spread.



(a) Temp diff vs. ln(GHG) difference



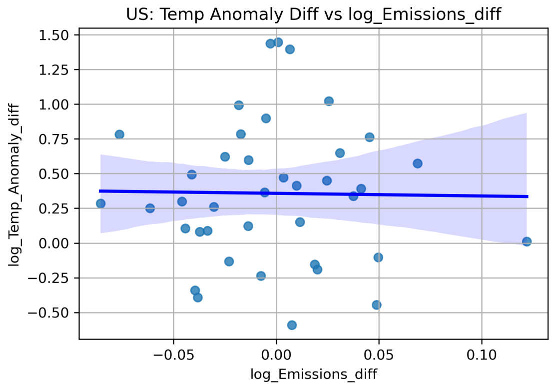
(b) Temp diff vs. ln(Energy) difference



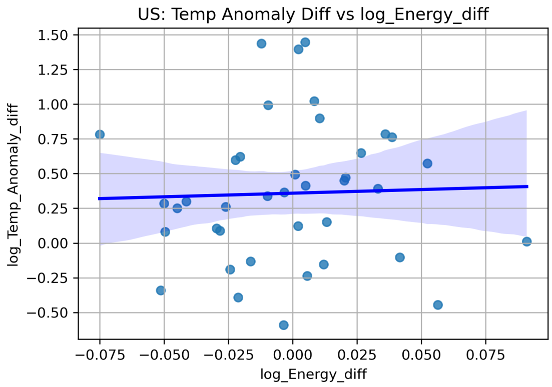
(c) Temp diff vs. ln(GDP) difference

Figure 4.2: Case Studies: China Variables Scatter Plots

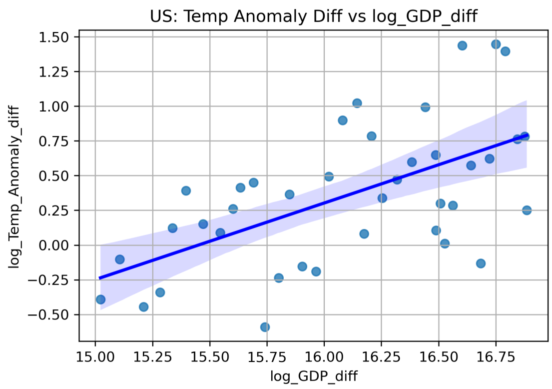
Adjacently, United States OLS resulted an R^2 of 0.383. Notable statistical significance is from GDP (β = 0.5719, *p* < .001), whilst emissions (β = -2.8852, *p* = -9.949) and energy consumption (β = 5.0315, *p* = -3.556) were not. The high standard errors of these variables may also indicate uncertainty for its coefficients, making it difficult to draw firm conclusions. The scatter plots (see figures 4.3) for United States showed a limited linear trend in both emissions and energy consumption. Both displayed a nearly flat regressions line with a wide spread of vertical data points near the center of the x-axis, indicating a weak or no association with temperature anomalies. In contrast, GDP shows a clear positive trend with its plots clustered to an upwards slope line of best fit, making it consistent with the regression coefficient.



(a) Temp diff vs. ln(GHG) difference



(b) Temp diff vs. ln(Energy) difference



(c) Temp diff vs. ln(GDP) difference

Figure 4.3: Case Studies: USA Variables Scatter Plots

CHAPTER 5

Discussion

5.1 Global and Country Analysis

The panel regression study shows in Table 4.13 results that there is a statistically significant positive association between GDP, population, energy production and temperature. The within R-squared in FE and RE models are almost identical with the value of 0.1783. It indicates that 17.8% of the combined variables, such as GDP, emissions, energy production, energy emission and production, contribute to the variation in temperatures within countries over time.

As time goes on economic and demographic expansion within countries is linked to rising average temperatures. These developments are expected to reflect rising energy demand, changes in land use, and increased human activity in both urban and rural areas. Urbanization and economic development may result in increased emissions from construction, transportation, and industry, which contributes to global warming (Stephenson et al., 2010).

5.1.1 GDP

Within a country, the FE-model shows that GDP may affect an increase in temperature over time. Due to infrastructure growth, urbanization and the intensification use of energy. According to the ADF, $\ln(\text{GDP})$ is stationary. Statistical properties do not change much over time. In the long run, GDP moves together with temperature. According to the VAR results show that a higher GDP in the past affects a positive current GDP. A higher energy production in the past is associated with a negative effect on GDP. It shows that an increase in energy production may not show immediate economic growth. Other variables, including temperatures, GHG emissions, energy consumption, and population, were not statistically significant predictors of GDP.

From the ARDL model 2, the GDP results are conflicting, showing both positive and negative impacts on the surface temperature. As stated in the literature review, the relationship between GDP and emissions (especially CO_2) has an inconclusive relationship. Some research shows no link between GDP and emissions, while other research supports the Kuznets curve theory (Bilgili et al., 2016; Panayotou, 1993; Zhang & Zhang, 2018). The theory means there is an inverted u-shaped relationship between the two factors. Given that over time, the use of renewable energy will become more financially beneficial, creating a negative relationship between GDP and emissions in the long run.

The results for Model 2 support that claim and takes one step further in the analysis compared to for example Panayotou (1993), and Zhang and Zhang (2018), and relates GDPs relationship with the global surface temperature, as a result of the change in emissions impacting climate change. This shows that the wealthier the globe becomes in total, it will first decrease temperature, then increase before again decreasing. The initial decrease might display the delayed effects of an increase in GDP, where the increase can possibly be linked to higher energy consumption, industrial output and emissions associated with increased economic activity and initial industrialization. Lastly, the decrease could be linked to the increased economic growth of renewable energy.

While the small sample size used for the model makes it hard for the results to be treated as definitive evidence, the model however highlights a potential non-linear relationship between GDP and temperature change during the observed time period.

5.1.2 Energy consumption and energy production

Both the energy consumption and production series are clearly stationary (ADF –31, $p <$ 0.01), so it's valid to include them in our regressions without differencing. Their VIFs are around 1.00, indicating virtually no overlap with the other predictors. This means our coefficient estimates and their statistical tests for these energy variables are trustworthy.

The FE-analysis shows that energy production has a positive effect on temperatures. However, energy production does not. The RE-analysis result is almost the same as FE. The VAR results show that higher temperatures in the past and higher past GHG emissions are associated with a decrease in current energy consumption. A spike in energy use or production one or two years ago doesn't produce any immediate change in average temperature. It highlights how slowly the temperature responds to energy production and energy consumption on an annual basis.

Both Model 1 and Model 2 from the ARDL analysis show similar results for the impact renewable energy consumption has on GLST. The net change in surface temperature from Model 1 and Model 2 are negative 0.14% and 0.23% respectively. These models show at lag 2, renewable energy consumption actually increases temperature before the curve changes to a negative impact. Considering that the models are based on data collected from 1991-2015, the initial positive relationship could be an indication of the initial renewable energy industrialization. In more recent years the initiative for renewable energy is rapidly increasing as the effects of climate change are worsening, causing urgency in the development of renewable energy production in order to mitigate GHG emissions. The increase in temperature from lag 2 could be a result of this, showing that the renewable energy industry is being increasing its development in order to be able to shift away from non-renewable energy sources. The later decrease in temperature for lag 3 and 4 in Model 2 and lag 4 in model 1 shows the eventually negative relationship renewable energy has on temperature change long term. Once the initialization of production is set, the net effect is as wanted and helps mitigate GHGs positive effect on GLST. This result helps further strengthen the findings of Kinyar and Bothongo (2024) and Bilgili et al. (2016), not only does renewable energy consumption decrease emissions, but it acts as a countereffect on GLST.

5.1.3 Greenhouse Gas Emissions

GHG emissions were negatively associated with temperature in several models from the panel regression study. This is a very unusual result; however, this likely reflects a geographic factor where countries with high emissions are often located in cooler climates. While these countries are major contributors to global emissions, their average across country temperatures remain relatively low due to their climate zones. This underscores the importance of considering spatial context and the global, not local, nature of emissions and climate feedback. The VAR results shows that higher energy consumption in the past is associated with an increase in GHG emissions. GDP and Population at lag 1 also exhibit some effects on GHG emissions.

From the ARDL models the results from the relationship between GHG and GLST are conflicting. While model 1 shows no statistically significant link, model 2 does. The results of model 2 imply a statistically significant relationship where it initially at lag 1 decreases GLST and at lag 3 it increases the surface temperature. The net change in temperature results in a decrease of 0,33%. This is contradictory to what previous studies have shown of the relationship between emissions and temperature. Since the effect GHG has on temperature starts as an increase and later change to a decrease it is possible that GHG has a long-term positive influence on GLST and that the effect takes several lags before the results are evident as increase in temperature. One of the limitations of the ARDL models developed is that they only cover a timespan of 25 years, and if the impact of change in emissions takes longer than that to become visible, then this can be a flaw of the models. Some studies have also shown that an increase of GHG in the atmosphere can initially show decades long delays in temperature increase because of the ocean's ability to absorb heat (*Carbon Dioxide and Climate*, 1979; Meehl et al., 2011; Oh et al., 2024). This can also be a reason why the panel regression study did not show the positive impact GHG emissions have on surface temperature.

5.1.4 Population

From the panel regression study the role of population is particularly interesting. While correlations between population and temperature were weak in the bivariate sense, population showed a strong positive effect in the fixed-effects models. Changes in population over time, especially in urbanizing regions, do have a measurable impact on temperature. In the VAR results, both energy consumption and energy production are statistically significant predictors of population. Higher energy production two periods ago is associated with an increase in population. Density in population reflects the expansion of energy and transport infrastructure. Population growth appears to be a stronger driver of temperature than emissions alone.

The ARDL model 1 does not match these findings. As previously mentioned, the findings on ln POP are conflicting and seemingly illogical. The net change in temperature is negative 0.15% for a 1% increase in population. Given the inconsistency of the population results in the ARDL model, the results of the panel regression study are more plausible and reflect the findings of the literature review.

5.1.5 Land Surface Temperature

The global land surface temperature shows a statistically significant result in the ARDL model 1, indicating that an increase in temperature for both one and two time periods ago results in a temperature decrease in current time period. This result is supported by the VAR model from the panel regression study, where previous temperatures are strongly linked to the current temperature. These outputs can be a visualization of how the earth's global system works in regulating its own temperature, where oceans act as a temperature buffer and absorb heat (*Carbon Dioxide and Climate*, 1979; Hansen et al., 2023; Meehl et al., 2011; Oh et al., 2024).

5.2 Case Studies

This segment of this study was to evaluate the short and long relationships between temperature changes with economic and environmental factors, GDP, energy consumption, and CO_2 emissions, in China and the United States. Two of the world's most influential economies and environmental impact (Mehmood et al., 2024; Yu et al., 2022).

No cointegration in China's variables suggest that temperature anomalies do not move unison with GDP, energy usage, or emissions in the long run. This aligns with the findings of Mehmood et al. (2024) using BARDL model. It could imply that China has decoupled economic growth from environmental degradation from energy policies or emissions reduction, or the possibility of a delay from the time scale of the dataset. Alternatively, shifting from services from the heavy industry such as manufacturing could weaken the relationship between emissions and temperature, at a possible cost of GDP (Mehmood et al., 2024). In the short run, the regression model for China revealed no statistically significant predictors and overall had limited explanatory power, with consistent with the findings by Zhang and Zhang (2018). This suggests that the changes in economic out, energy usage, or emissions are not the main derivatives that causes temperature changes in China. The high uncertainty of standard errors could mean that the data set maybe volatile from other external factors such as regional climate or certain policies

By contrast, the United States yielded stronger results, in particular with GDP with higher significance with temperature anomalies. The results support the observation Mikayilov et al. (2018), who found strong coupling between GDP and emissions in developed countries. It suggests that there is a short-term relationship in economic activity and environmental factors in the US context. This could be attributed to GDP having a higher relationship with energy consumption and emissions, acting as a proxy for environmental burden. While GHG and EC did not exhibit significant coefficients, the wide spread of plots may reflect on different economic sectors that may inflict environmental pressure as indicated in studies like Zou (2018).

The differences between the two countries highlight how economic factors, energy systems, and policy can shape the nature between climate and economic interactions. The US model suggests a tight short-term coupling between economic growth and environmental outcomes; Chinas pattern appears to be more complex and potentially influences by external factors. It is of note to acknowledge that there are several limitations in this analysis. The models that were presented assume linearity and do not account for lagged effects. Additionally, the exclusion of variables such as renewable, population density, imports/exports and other fuel types may assist in giving a preferable explanatory power. The time series is relatively short for detecting climate trends, and data quality may vary between countries. Furthermore, whilst GDP showed predictive power in the US case, the results highlight the importance of incorporating lag structures, and non-linear dynamics, or additional country variables to offer a more comprehensive understanding of climate activity (Kompas et al., 2018).

5.3 Limitations

Greenhouse gas emissions affect the entire planet, not just the regions where they originate. According to panel analysis missions may not correlate strongly with temperature at the national level, even though they are a primary driver of global warming. This distinction underscores the need to interpret emissions data in light of regional climate characteristics and consider the global feedback mechanisms of climate change. As such, GHG emissions should be viewed as a global predictor of warming, rather than a reliable indicator of local temperature trends.

Because of the nature of the data collected and merged, the intersection of the datasets covers a variation of time periods. The dataset used for the ARDL models covers 25 years, with yearly entries starting from 1991 to 2015. For the Panel analysis, the data covers from 1980 to 2013. Furthermore, the case study of China and United States was observed from 1980 to 2020. Given the sample size, the results of all conducted analysis should only be used as indications of relationships between the regressors and the global land surface temperature, further analysis should be done that covers a larger timespan and that includes the most recent years. However, the developed models have been shown to support previous research in the fields

The methods of measuring temperature have evolved over time and are informed by the dataset used. Weather stations were moved in the 1940s and electric thermometers were implemented in the 1980s and show cooler temperatures compared to mercury thermometers used in previous years (Kaggle & zgrcemta, 2022). These uncertainties in temperature measurements did not impact our developed models since the intersect datasets used started from the 1980s earliest.

Lastly it is important to restate that the globe is a complex ecosystem and the number of factors contributing to it is extensive. As mentioned, following the scope of this report, only land surface temperature, GDP (both PPP and per capita), GHG emissions, population, energy consumption and production were looked at. The topic of climate change is vast and has enormous amounts of research. In order to keep the report at an appropriate length, it limited literature and sub-topics that we could explore, and our focus remained on what was relevant according to our scope.

CHAPTER 6

Conclusion

The growing concern about climate change and its effects on ecosystems, economies, and life itself has driven the need to understand what is affected by further examining the earth's surface temperatures in relation to these variables. There is a relationship between global surface temperature and key socioeconomic and environmental indicators such as greenhouse gas (GHG) emissions, energy production and consumption, GDP and population. Through advanced models like Autoregressive Distributed Lag (ARDL), cointegration tests, unit root test and panel regression, we were able to get both short- and long-term dynamics between these variables. This is shedding some light on the complexity of climate change and its drivers.

Key findings include the existence of long-term cointegration among variables. This means that surface temperatures, GHG emissions, energy consumption and production, GDP and population levels are linked, and overtime have long term interactions. In our study, greenhouse gas emissions did not clearly show a connection with rising temperatures. In the panel regression models, countries with greater GHG emissions often experienced lower average temperatures. Seeing that a number of these countries are in colder areas, the findings are influenced by the climate. The data we have only spanned over a time frame that may not be long enough. The complete impact might not be entirely visible. Oceans can soak up heat, as other studies show, and they can delay the warming effect for decades. The reason we did not see a strong link between emissions and temperature may be explained by our models. Despite our results, most studies show that GHG emissions and non-renewable energy consumption are main factors of global temperature increase. Greenhouse gas emissions, particularly of carbon dioxide CO_2, are the main long-term predictors regarding the rise in global surface temperatures. This stresses how fossil fuel dependence affects overall global warming.

The results also show a positive relationship between GDP and surface temperature, suggesting economic growth is associated with increased environmental impact. Economic development is often viewed as a clear sign of progress; however, this research underscores the clear need for understanding economic growth's connection to environmental degradation. Nations could maintain a certain level of economic growth while reducing their carbon footprint via greener economic policies and more efficient technologies.

Furthermore, the study revealed that population growth relates to surface temperature changes. An increasing population leads to higher energy demand, more resource extraction and greater emissions. Population growth and managing its environmental impact is and will be a challenge in the future. The results emphasize the importance of addressing energy consumption and population dynamics in climate policy.

The study also brings to light large heterogeneity across countries because of economic growth, population size and energy usage exert an influence upon surface temperature. Developed countries, that happen to have high GDP, emit a greater quantity of GHGs and consume more energy. In contrast, developing countries do contribute a smaller amount to overall global emissions, but may undergo disproportionately harsh effects from climate change with restricted infrastructure, economic resources and countries adaptability. Industrialized nations bear main accountability for past emissions, however, developing nations regularly show the greatest susceptibility to climate change repercussions. This stresses that global entities must collaborate to address climate change. International agreements must perpetually continue to promote equitable climate justice. They should ensure financial as well as technical support reaches developing countries so these nations can transition to low-carbon economies in addition to building resilience to climate impacts, as demonstrated in the Paris Agreement.

It is important to acknowledge about several limitations in this research. Random effects (RE) models incorporate within-country and between-country variations; however, omitted time-invariant variables may still particularly bias this approach. RE models, while attempting to capture both dimensions, may not account fully for characteristics unique to each country. Fixed effects models do focus exclusively on within-country variation as they control for time-invariant unobserved heterogeneity yet overlook cross-country comparisons. On the other hand, depending just on either model shows problems. One must take into account all of the trade-offs. Additionally, that temperature measurement methods changed along with the fact data availability differed throughout the time periods may affect any consistency within the dataset.

6.1 Recommendations

Based upon the findings, policymakers should stress the reduction of GHG emissions via an adaptation toward renewable energy. For policymakers to have access to information that is accurate and timely, governments should invest in the betterment of climate data collection and monitoring systems. Subsequently, we need to collaborate more strongly on an international scale to tackle climate change. Policymakers should work to develop clean energy; work to standardize efficient energy; make the public aware of environmental challenges and then act equitably regarding climate.

6.2 Future research

The study also highlights the importance of superior data. The findings stress the necessity to invest in data collections and monitoring systems that both policymakers and researchers can use.

Future research could include additional dimensions such as mortality rates, biodiversity loss, ocean temperatures (both surface and deep levels), or regional climate zones, like desert, tundra and rainforest, to get a more comprehensive picture of climate dynamics.

With a more recent dataset one could also more closely investigate the impact renewable energy has today in contrast to what the ARDL model results showed for 2015. This could be compelling because of the rise of the renewable energy sector and industry, and how well it actually is able to mitigate climate change.

6.3 Final remarks

Climate science progression is driven by more advanced observational technologies together with the evolution of climate modeling. These tools let researchers simulate more environmental variables and incorporate more detailed data, as well as generating projections with improved accuracy. Global collaborators must also continue to progress to allow researchers to make empirical progress and effectively guide responses for the continuing climate crisis.

Implementing policies remains a persistent challenge due to clashing priorities and varying circumstances. Research findings must be prioritized to policymakers and businesses, allowing the public to effectively take climate change as a present reality and not a future possibility.

In order to meaningfully mitigate the climate crisis, severe and drastic changes must be made. This includes political will, society transformation, and deep commitment to intergenerational equity. The need for urgent, science-based and inclusive climate action becomes not only a recommendation, but a responsibility.

References

Administration, U. E. I. (2024). Total energy data. Retrieved January 2, 2025, from https : / / www . eia . gov / international / data / world / total - energy / more - total - energy - data ? pd = 44 & p = 004000000000000000000000000000000000000000000000000f00o & u = 0 & f = A & v = mapbubble & a= - &i = none & vo = value & t = C & g = 00000000000000000000000000000000000000000001 & l = 249 - ruvvvvvfvtvnvv1vrvvvvfvvvvvvfvvvou20evvvvvvvvvvnvvvs0008 & s = 315532800000 & e = 1672531200000

Akhmat, G., Zaman, K., Shukui, T., & Sajjad, F. (2014). Does energy consumption contribute to climate change? evidence from major regions of the world. *Renewable and Sustainable Energy Reviews*, *36*, 123–134. https://doi.org/10.1016/j.rser.2014.04.044

Babb, D. (2023). *Transforming data | METEO 810: Weather and climate data sets*. Retrieved April 13, 2025, from https://www.e-education.psu.edu/meteo810/content/l5_p5.html

Bilgili, F., Koçak, E., & Bulut, Ü. (2016). The dynamic impact of renewable energy consumption on CO2 emissions: A revisited environmental kuznets curve approach. *Renewable and Sustainable Energy Reviews*, *54*, 838–845. https://doi.org/10.1016/j.rser.2015.10.080

Byrne, M. P., Hegerl, G. C., Scheff, J., Adam, O., Berg, A., Biasutti, M., Bordoni, S., Dai, A., Geen, R., Henry, M., Hill, S. A., Hohenegger, C., Humphrey, V., Joshi, M., Konings, A. G., Laguë, M. M., Lambert, F. H., Lehner, F., Mankin, J. S., . . . Zhang, Y. (2024). Theory and the future of land-climate science [Publisher: Nature Publishing Group]. *Nature Geoscience*, *17*(11), 1079–1086. https://doi.org/10.1038/s41561-024-01553-8

Callendar, G. S. (1938). The artificial production of carbon dioxide and its influence on temperature [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/qj.49706427503]. *Quarterly Journal of the Royal Meteorological Society*, *64*(275), 223–240. https://doi.org/10.1002/qj.49706427503

Calov, R., & Ganopolski, A. (2005). Multistability and hysteresis in the climate-cryosphere system under orbital forcing [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2005GL024518]. *Geophysical Research Letters*, *32*(21). https://doi.org/10.1029/2005GL024518

Carbon dioxide and climate: A scientific assessment. (1979, March 13). National Academies Press. https://doi.org/10.17226/12181

Dell, M., & Jones, B. (2009, January). *TEMPERATURE AND INCOME: RECONCILING NEW CROSS-SECTIONAL AND PANEL ESTIMATES*. Retrieved April 25, 2025, from https://www.nber.org/system/files/working_papers/w14680/w14680.pdf

Dogan, E., Tzeremes, P., & Altinoz, B. (2020). Revisiting the nexus among carbon emissions, energy consumption and total factor productivity in african countries: New evidence from nonparametric quantile causality approach. *Heliyon*, *6*(3), e03566. https://doi.org/10.1016/j.heliyon.2020.e03566

Earth, B. (2018). Climate change: Earth surface temperature data. Retrieved January 2, 2025, from https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data

Faghmous, J. H., & Kumar, V. (2014). A big data guide to understanding climate change: The case for theory-guided data science. *Big Data*, *2*(3), 155–163. https://doi.org/10.1089/big.2014.0026

Fankhauser, S., & S.J. Tol, R. (2005). On climate change and economic growth. *Resource and Energy Economics*, *27*(1), 1–17. https://doi.org/10.1016/j.reseneeco.2004.03.003

Foote, E. (1856). ART. XXXI.–circumstances affecting the heat of the sun's rays; - ProQuest. *American Journal of Science and Arts*, *22*(66). Retrieved April 13, 2025, from https://www.proquest.com/openview/c37d950c9a629a7aeea63e4120fc72ae/1?cbl=42401&pq-origsite=gscholar

for Environmental Information, N. C. (2025, January 2). Climate at a glance: National time series 110 (TAVG). Retrieved January 2, 2025, from https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/national/time-series/110/tavg/12/0/1970-2020

for Global Atmospheric Research) Community, E. (D. (2024). EDGAR_2024_ghg. https://doi.org/10.2760/4002897

Groß, J. (2003, June). *Variance inflation factors*. Retrieved April 20, 2025, from https://journal.r-project.org/articles/RN-2003-004/RN-2003-004.pdf

Guzman, J. M., Martine, G., McGranahan, G., Schensul, D., & Tacoli, C. (2009, June). *Population dynamics and climate change*. https://www.researchgate.net/publication/262178194_Population_Dynamics_and_Climate_Change

Hansen, J. E., Sato, M., Simons, L., Nazarenko, L. S., Sangha, I., Kharecha, P., Zachos, J. C., von Schuckmann, K., Loeb, N. G., Osman, M. B., Jin, Q., Tselioudis, G., Jeong, E., Lacis, A., Ruedy, R., Russell, G., Cao, J., & Li, J. (2023). Global warming in the pipeline. *Oxford Open Climate Change*, *3*(1), kgad008. https://doi.org/10.1093/oxfclm/kgad008

Intergovernmental Panel On Climate Change (Ipcc). (2023, July 6). *Climate change 2021 – the physical science basis: Working group i contribution to the sixth assessment report of the intergovernmental panel on climate change* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781009157896

Kaggle & zgrcemta. (2022). World GDP (GDP, GDP per capita, and annual growths) [Data sourced from the World Bank: https://data.worldbank.org/]. Retrieved January 2, 2025, from https://www.kaggle.com/datasets/zgrcemta/world-gdpgdp-gdp-per-capita-and-annual-growths

Kalvig, S. (2007). *Himmel og hav om klimaendringer i norge og verden*.

Kinyar, A., & Bothongo, K. (2024). The impact of renewable energy, eco-innovation, and GDP growth on CO2 emissions: Pathways to the UK's net zero target. *Journal of Environmental Management*, *368*, 122226. https://doi.org/10.1016/j.jenvman.2024.122226

Kompas, T., Pham, V. H., & Che, T. N. (2018). The effects of climate change on GDP by country and the global economic gains from complying with the paris climate accord. *Earth's Future*, *6*(8), 1153–1173. https://doi.org/10.1029/2018EF000922

Kossin, J. P., Olander, T. L., & Knapp, K. R. (2013). Trend analysis with a new global record of tropical cyclone intensity [Section: Journal of Climate]. https://doi.org/10.1175/JCLI-D-13-00262.1

Kuznets, S. (1985). Economic growth and income inequality [Num Pages: 13]. In *The gap between rich and poor*. Routledge.

Mandal, G., An, S.-I., Park, J.-H., Yun, K.-S., Liu, C., & Paik, S. (2025). Northern hemisphere sea ice variability in a transient CGCM simulation of the past 2.6 ma [Publisher: Nature Publishing Group]. *Nature Communications*, *16*(1), 39. https://doi.org/10.1038/s41467-024-55327-2

Meehl, G. A., Arblaster, J. M., Fasullo, J. T., Hu, A., & Trenberth, K. E. (2011). Model-based evidence of deep-ocean heat uptake during surface-temperature hiatus periods [Publisher: Nature Publishing Group]. *Nature Climate Change*, *1*(7), 360–364. https://doi.org/10.1038/nclimate1229

Mehmood, K., Tauseef Hassan, S., Qiu, X., & Ali, S. (2024). Comparative analysis of CO2 emissions and economic performance in the united states and china: Navigating sustainable development in the climate change era. *Geoscience Frontiers*, *15*(5), 101843. https://doi.org/10.1016/j.gsf.2024.101843

Mikayilov, J. I., Hasanov, F. J., & Galeotti, M. (2018). Decoupling of CO2 emissions and GDP: A time-varying cointegration approach. *Ecological Indicators*, *95*, 615–628. https://doi.org/10.1016/j.ecolind.2018.07.051

Newell, R., Raimi, D., & Aldana, G. (2019, July). *GlobalEnergyOutlook2019.pdf*. Retrieved April 16, 2025, from https://www.econ2.jhu.edu/courses/101/GlobalEnergyOutlook2019.pdf

Oh, J.-H., Kug, J.-S., An, S.-I., Jin, F.-F., McPhaden, M. J., & Shin, J. (2024). Emergent climate change patterns originating from deep ocean warming in climate mitigation scenarios [Publisher: Nature Publishing Group]. *Nature Climate Change*, *14*(3), 260–266. https://doi.org/10.1038/s41558-024-01928-0

on Climate Change, I. P. (2018). *Global warming of 1.5 ℃: An IPCC special report on the impacts of global warming of 1.5 ℃ above pre-industrial levels and related global greenhouse gas emission pathways.* IPCC. Retrieved April 27, 2025, from https://www.ipcc.ch/sr15/

on Trade {and} Development (UNCTAD), U. N. C. (n.d.). Gross domestic product (GDP) - total. Retrieved January 2, 2025, from https://unctadstat.unctad.org/datacentre/dataviewer/US.GDPTotal

Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development [Number: 992927783402676 Publisher: International Labour Organization]. *ILO Working Papers*. Retrieved April 12, 2025, from https://ideas.repec.org//p/ilo/ilowps/992927783402676.html

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jae.616]. *Journal of Applied Econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

Roser, M., Ritchie, H., Rodés-Guirao, L., Mathieu, E., Gerber, M., Ortiz-Ospina, E., & Hasell, J. (2023). Population growth. https://ourworldindata.org/population-growth#explore-data-on-population-growth

Stephenson, J., Newman, K., & Mayhew, S. (2010). Population dynamics and climate change: What are the links? *Journal of Public Health*, *32*(2), 150–156. https://doi.org/10.1093/pubmed/fdq038

Torres-Reyna, R. (2007, January 12). *Panel data analysis fixed and random effects using stata*. Retrieved April 15, 2025, from https://www.princeton.edu/~otorres/Panel101.pdf

UN. (1992). *United nations conference on environment and development, rio de janeiro, brazil, 3-14 june 1992* [United nations] [Publisher: United Nations]. Retrieved April 27, 2025, from https://www.un.org/en/conferences/environment/rio1992

UN. (2022). Global humanitarian overview 2023 [Publisher: United Nations]. Retrieved April 27, 2025, from https://www.un-ilibrary.org/content/books/9789210024136/read

UNFCC. (2025). *What is the kyoto protocol? | UNFCCC*. Retrieved April 27, 2025, from https://unfccc.int/kyoto_protocol

Xie, A., Zhu, J., Qin, X., Wang, S., Xu, B., & Wang, Y. (2023). Surface warming from altitudinal and latitudinal amplification over antarctica since the international geophysical year [Publisher: Nature Publishing Group]. *Scientific Reports*, *13*(1), 9536. https://doi.org/10.1038/s41598-023-35521-w

Yu, J., Tang, Y. M., Chau, K. Y., Nazar, R., Ali, S., & Iqbal, W. (2022). Role of solar-based renewable energy in mitigating CO2 emissions: Evidence from quantile-on-quantile estimation. *Renewable Energy*, *182*, 216–226. https://doi.org/10.1016/j.renene.2021.10.002

Zhang, Y., & Zhang, S. (2018). The impacts of GDP, trade structure, exchange rate and FDI inflows on china's carbon emissions. *Energy Policy*, *120*, 347–353. https://doi.org/10.1016/j.enpol.2018.05.056

Zivot, E., & Wang, J. (2006). Vector autoregressive models for multivariate time series. In *Modeling financial time series with s-PLUS®* (pp. 385–429). Springer. https://doi.org/10.1007/978-0-387-32348-0_11

Zou, X. (2018). VECM model analysis of carbon emissions, GDP, and international crude oil prices. *Discrete Dynamics in Nature and Society*, *2018*, 1–11. https://doi.org/10.1155/2018/5350308

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