The Environment and Macroeconomy

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Declaration

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Abstract

This thesis explores the intricate relationship between the environment and macroeconomic outcomes through three interconnected studies. The first study, *"The Macroeconomic Impact of Global and Country-Specific Climate Risk"*, examines how climate risks influence economic performance at both the global and national levels. It investigates whether climate shocks induce substantial and persistent economic fluctuations. We find that global climate risk is more connected with macroeconomic activity than the country-specific climate risk irrespective of economic status. The second study, *"The Economic Consequences of Green Growth: A Multi-Country Empirical Study"*, evaluates the macroeconomic implications of green growth. While transitioning to environmentally sustainable growth is widely advocated, its particular economic effects—whether in terms of productivity, employment, or investment dynamics—remain a subject of ongoing debate. This chapter provides empirical evidence on the economic trade-offs and benefits of green growth strategies across multiple economies. Our findings suggest that green growth indicators are strongly associated with GDP growth in advanced economies than in emerging economies. The final study,*"R&D Intensity and Global Warming"*, takes a historical perspective on the role of innovation in addressing climate change. This chapter explores whether technological advancements have contributed to climate mitigation and innovation efforts are necessary to address global warming effectively. We observed an inverse relationship between R&D intensity and global warming. This, however, suggests that R&D intensity could positively lead to the reduction in global warming.

List of Acronyms

ARDL	Auto-Regressive Distributed Lag
ASIS	Ancillarity-Sufficiency Interweaving Strategy
CCR	Canonical Cointegration Regression
CRU	Climate Research Unit
CCE-MG	Common Correlated Effect Mean Group
MG-IV(+CCE)	Common Correlation Effects Mean Group Instrumental Variable
CO2	Carbon Dioxide
CD	Cross-sectional Dependency
DFE	Dynamic Fixed Effects
DCCE	Dynamic Common Correlated Effects
DOLS	Dynamic Ordinary Least Square
EKC	Environmental Kuznets Curve
FSV	Factor Stochastic Volatility
FDI	Foreign Direct Investment
FMOLS	Fully Modified Ordinary Least Square
GDP	Gross Domestic Product
GMM	Generalised Method of Moments

IPAT	Integrated Population, Affluence and Technology
IPCC	Intergovernmental Panel on Climate Change
LLDVE	Local Linear Dummy Variable Estimation
MCMC	Markov Chain Monte Carlo
MMQR	Moment Of Method Quantile Regression
MFSV	Multivariate Factor Stochastic Volatility
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Square
PVAR	Panel Autoregressive
PCA	Principal Component Analysis
R&D	Research and Development
SV	Stochastic Volatility
SDGs	Sustainable Development Goals
US	United States
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change
VAR	Vector Autoregressive

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Chapter 1

Introduction

1.1 Motivation

The interaction between the environment and the macroeconomy has become a critical area of research, particularly in light of accelerating climate change, evolving policy landscapes, and the transition to sustainable economic models.[1] Since the period of classical economists, the primary inquiry in economics has been to elucidate the factors contributing to the substantial disparities in living standards among countries and the pronounced fluctuations in global living standards over the long period of time.[2] In recent times, climate change is causing increased volatility in extreme weather events, which is affecting people globally; see Nordhaus and Moffat (2017). Climate risks, as a result of temperature changes, both global and country-specific, pose significant challenges to macroeconomic stability, affecting key indicators such as output growth, inflation and employment.[3] Meanwhile, the shift towards green growth strategies raises questions about their economic consequences, particularly across heterogeneous countries. Additionally, understanding the role of research and development (R&D) in mitigating global warming provides insights into long-term policy measures aimed at reducing environmental damage while fostering economic resilience.

This thesis explores the intricate relationship between the environment and macroeconomic dynamics through three interconnected studies. The first study, *"The Macroeconomic Impact of Global and Country-Specific Climate Risk"*, examines how climate risks influence economic performance at both the global and national levels. Climate change is a key policy concern. It has the potential to damage household welfare and economic activity.[4] In his Nobel Prize Lecture, Nordhaus (2019a) summed up the consensus on climate change: global warming is a threat to humankind and the natural world. The economic implications of cli-

[1] Crist et al. (2017), Nordhaus (2019a), Nordhaus (2019b), and Ruggerio (2021).

[2] Xepapadeas (2005) in the Handbook of Environmental Economics.

[3] For example, Dell et al. (2012), Donadelli et al. (2017) and Kotz et al. (2022).

[4] Giglio et al. (2021). Sheng et al. (2022) also demonstrate that volatility in temperature growth decelerates economic activity roughly five times more than when temperature growth increases by the same amount in the higher uncertainty-based domain of a nonlinear model.

mate change are potentially huge for firms, households and government policy. Stern (2008) summarises that climate risk is global in its nature and impact. The effects may only reveal themselves over the long-term and economic analysis of climate change should have a central role for risk and uncertainty. This chapter seeks to add to the literature on the macroeconomic impact of climate change, focusing upon the nature and impact of global and country specific climate risk over an extended time period. In addition, it investigates whether climate shocks induce persistent economic fluctuations and how macroeconomic policies should respond to such risks.

The second study, *"The Economic Consequences of Green Growth: A Multi-Country Empirical Study"*, examines the macroeconomic implications of green growth policies. While transitioning to environmentally sustainable growth is widely advocated, its economic effects—whether in terms of productivity, employment, or investment dynamics—remain a subject of ongoing debate. Balancing rapid, environmentally friendly development for achieving Sustainable Development Goals (SDGs) is a contentious issue. Green growth promotes natural capital conservation and creates opportunities in employment and trade, which also adds to growth.[5] On the other hand, investment in adaptation and green technology will have an opportunity cost. Adaptation of economic activity and generating green growth has been key to limiting climate change and combating environmental degradation.[6] Whether encouraging green economic activity has a beneficial impact on economic growth more generally is controversial. There is less of a consensus on the exact nature and extent of the potential tension between economic development and environmental protection. One potential way forward is for countries to engage in green growth, which seeks to protect the environmental and also promote growth in general (Bohensky et al., 2011; Griggs et al., 2013; Pretty, 2013; Potts et al., 2016). This chapter provides empirical evidence on the economic growth trade-offs and benefits of green growth strategies across multiple economies.

[5]See Wackernagel and Rees (1997), OECD (2011, 2017), World Bank (2012), Swainson and Mahanty (2018) and Ofori et al. (2023).

[6]See Stern et al. (1996), Tol (2009b) and Nordhaus (2019b).

The final study, *"R&D Intensity and Global Warming"*, takes a historical perspective on the role of innovation in addressing climate change. The assertion that technological advancements will have a positive effect on environmental quality, referred to as the technological effect, is a recurring theme in the extensive literature on the Environmental Kuznet Curve (EKC) hypothesis (see Churchill et al., 2019). Investments in research and development are focused on boosting productivity as well as improving the quality and diversity of products (Fisher-Vanden and Wing, 2008). More R&D investment, for example, is likely to improve environmental quality in situations where effective environmental management systems are in place to ensure proper waste management (Arora and Cason, 1996; Churchill et al., 2019; Huang et al., 2021; Paramati et al., 2021). However, there is uncertainty regarding the effect of technological advancement on global warming emanating from greenhouse gas emissions (Meinshausen et al., 2009; Moss et al., 2010; Arent et al., 2011).

Two significant uncertainties obscure the future requirements of green technology, Fulkerson et al. (1989) argued that the future of energy technology is shaped by increasing energy demand and the pressing issue of the greenhouse gas effect. Although new technology may increase efficiency, increasing output may necessitate the use of additional natural resources, which could result in an increase in carbon emissions. This theory is supported by the fact that R&D has historically produced declining returns (Newell, 2009; Churchill et al., 2019). As our stock of knowledge grows, it becomes increasingly challenging to make new discoveries, leading to a decrease in the amount of research and development conducted over time (Jones, 2009; Newell, 2009; Bloom et al., 2020). However, it is important to note that economic growth still requires an increasing amount of natural resources and may likely cause environmental destruction. This chapter explores whether technological advancements have contributed to climate mitigation and whether sustained innovation efforts are necessary to address global warming effectively. As it assesses the relationship between R&D intensity and share of greenhouse gas emissions contribution to global temperature changes in OECD countries.

Jointly, these three studies provide a comprehensive understanding of the macroeconomic dimensions of environmental challenges. By integrating insights from climate risk analysis, green growth, and technological innovation, this thesis contributes to the broader discourse on sustainable economic development and informs policy discussions on balancing economic growth with environmental sustainability.

1.2 Research Questions

- The first study considers the questions, do the potential future temperature variations impact economic growth, is the impact country-specific or global, and does the conditional volatility matter?
- In the second study, we consider the question: do green growth indicators contribute to economic growth more generally?
- In the final study, we ask: can R&D intensity significantly lead to a reduction in global warming? Is the intensity country-specific or contingent upon global spillovers?

1.3 Chapter Overview and Empirical Strategy

In **chapter 2**, we examine the empirical relationship between economic activity and climate risk. Key time series used in this study are measures of climate risk, macroeconomic activity and carbon emissions. To construct a measure of climate risk, we source temperature data from World Bank Climate Knowledge Portal and we focus upon temperature changes. We use temperature changes as the basis of measuring country-specific and global climate risk. To model macroeconomic activity, we use the growth rate of real GDP. The steady increase in global temperature caused by accumulated carbon dioxide in the atmosphere, which raises atmospheric carbon concentration and eventually changes temperature, is measured using carbon emissions per capita. The data spans from 1901 to 2020 for thirty countries. This research employed a factor stochastic volatility method to measure climate risks in order to assess its impact on macroeconomic activity. Here, we decomposed climate risk into country-specific risks and global spillovers. To examine the relationship between macroeconomic activity, idiosyncratic and global climate risk, this study uses a Bayesian Panel VAR with a hierarchical prior. We consider further robustness and extensions of our approach. These include using dynamic panel methods robust to endogeneity, controlling for temperature levels and alternative identification of shocks. To account for endogeneity and whether our evidence is contingent upon specific empirical methods we generalise our results by using Generalised Methods of Moments estimation (GMM).

In **chapter 3**, we seek to estimate as a growth regression model to examine the importance of green growth indicators for economic activity. This model assumes parameter homogeneity and cross-section independence of stochastic error. Temple (1999) emphasises several econometric challenges for growth regressions. These include parameter heterogeneity, spillovers, and endogeneity. In this chapter, we seek to account for these in what follows. Firstly, we test for country homogeneity and the other parameters. Our homogeneity test is from Pesaran and Yamagata (2008) against the alternate hypothesis that all the slope coefficients are heterogeneous. Secondly, whether the cross-sectional error terms are independent, we can reject the assumption that there is no evidence of cross-sectional dependence. Panel estimators normally assume cross-sectional independence. We formulate a dynamic panel model with heterogeneous coefficients and apply the dynamic common correlated mean group (CCE-MG) estimator. The CCE-MG estimator is capable of capturing unobserved heterogeneity and dynamic relationships, thereby offering enhanced predictive capabilities in comparison to more basic panel data models. The common correlated effects are captured by incorporating cross-section averages to address the influence of common factors. The omission of the common factor from the growth model may result in an omitted variable bias.

The key variable of interest when examining the impact of environmental factors on economic growth is our measure of green growth. We use a measure of optimal green growth from Sarkodie et al. (2023). This indicator measures green growth performance across five broad dimensions: natural asset base, socio-economic opportunities, productivity, quality of life, and policy responses. This data are from 1992 to 2021 for 81 countries. This time period was chosen for the study due to the availability of data for the green growth indicators and total labour force. Other series such as physical capital, human capital, greenhouse gas emissions, urbanisation, foreign direct investment, and green technologies are also used in this study. The data were obtained from the World Bank, OECD, and Penn World Tables.

In **chapter 4**, the data used in this study is panel data of 20 OECD countries from 1870 to 2021 sourced from Jones et al. (2023) and Churchill et al. (2019), extended to include 2015 to 2021 data sourced from the World Bank's World Development Indicators. We use the OECD countries as the case for assessing how Research and Development (R&D) intensity impacts global warming. Central to our analysis is that we seek to explain the impact of R&D on climate change. Our country climate change measure is each country's contribution to global warming via emissions as a ratio. The independent variable is research and development intensity, measured as the ratio of nominal R&D expenditure to nominal GDP sourced from Churchill et al. (2019) and World Development Indicators. Other variables include real GDP per capita, the quadratic function of real GDP per capita, the ratio of broad money to GDP, a common proxy for financial development; total population and the ratio of trade (imports plus exports) to GDP sourced from Churchill et al. (2019) and World Development Indicators—as control variables. These control variables account for the finance, trade, and population-level channels as potential mechanisms to influence R&D and global warming. We further decompose research and development intensity into an idiosyncratic component and a common factor, representative of country-specific and global spillovers of research and development intensity. This allows us to examine their corresponding effects on global warming. We use a multivariate stochastic volatility model and principal component analysis to estimate the country-specific intensity and global R&D spillovers.

To examine our key empirical relationships, we use a variety of estimators. These allow us to examine the robustness of our results. These estimators include: random/fixed effects, fixed effects regression with Driscoll-Kraay standard errors, and two-stage least squares fixed effects instrumental variable methods. The objective, however, is to address potential cross-sectional dependence, and endogeneity while estimating the relationship between R&D intensity and greenhouse gas emissions contribution to global warming. To address non-linearity, heterogeneity, and time-varying effects, we use a polynomial (quadratic) function of research and development intensity, split the sample period into pre-World War II and post-World War II following Churchill et al. (2019) and also based on structural break tests. Further, country groupings into G7 and others are used to throw more light on the heterogeneous effects.

1.4 Overview of Key Findings

Chapter 2 is entitled *"The Macroeconomic Impact of Global and Country-Specific Climate Risk."* This chapter examines the impact of climate risk on macroeconomic activity for thirty countries using over a century of panel time series data. Climate change may have an important global dimension, and there may be an important dimension in the second moment of climate change. Our methods seek to consider this. The key innovation of our chapter is to use a factor stochastic volatility approach to decompose climate change into global and country-specific climate risk and to consider their distinct impacts upon macroeconomic activity. This allows us to differentiate the importance for economic activity of common and idiosyncratic components of climate change. To allow for country heterogeneity, we also differentiate the impact of climate risk upon advanced and emerging economies. While the existing literature has focused on country based climate risk shocks, our results suggest idiosyncratic or country-specific climate risk shocks are relatively unimportant. Global climate risk, on the other hand, has a negative and relatively more important impact on macroeconomic activity.

Evidence from our core results suggests that shocks to country-specific climate risk are relatively less important for macroeconomic activity. While the effect of idiosyncratic risk is generally negative, critical intervals are close to zero indicating less evidence of a substantial impact. Global climate risk is a relatively more important determinant of macroeconomic activity. This is indicated by the larger negative GDP response to a global risk shock after year four. It takes several years for the full effect of a global climate risk shock to feed its way fully into GDP. We examined the exogenous impact therefore of country-specific and the global climate risks on GDP growth from 1950 to 2020 in a separate empirical model. We find stronger evidence that shocks to country-specific climate risk have no effect on GDP growth. We identify an initially negative and important impact of the global risk shock on GDP, with a maximum at year three. This is irrespective of whether we consider advanced or emerging countries. There does seem to be overshooting of GDP after the initial negative shock as additional volatility is induced into GDP by the global climate risk shock, which eventually abates as the response returns to zero. Interestingly, we find that both advanced and emerging countries are adversely impacted by climate risk shocks.

Chapter 3 is entitled *"The Economic Consequences of Green Growth: A Multi-Country Empirical Study."* Using a novel dataset, we examine whether green growth impacts macroeconomic outcomes for a large number of countries. Our green growth measure is a composite index of natural asset base, environmental productivity, environmental-related policy responses, socio-economic outcomes, and quality of life. In testing our central hypothesis, we use empirical methods robust to panel parameter heterogeneity, cross-sectional correlation, and endogeneity. Our empirical results strongly suggest that green growth has a positive impact on GDP growth, especially in an extended model and for advanced economies. Specifically, our country results illustrate that the impact of green growth on GDP growth is considerably heterogeneous. Our evidence indicates that the indicators of green growth are more strongly associated with the growth of gross domestic product (GDP) in advanced countries than emerging economies, as observed across the estimators used for the full sample. Overall, we observed that the lagged term of green growth significantly contributes to economic growth, even in the presence of unfavourable economic and environmental factors. We find strong evidence that indicators of green growth are major contributors to economic growth.

The third key empirical contribution in this thesis is in **Chapter 4**, with the title of *"R&D Intensity and Global Warming."* This chapter examines the relationship between R&D intensity and global warming in the OECD countries. Research and Development is vital for economic growth and mitigating or adapting to the impact of climate change. Investment in R&D may, therefore, lead to technical change that could have positive effects on environmental quality. Against this backdrop, we assess the impact of R&D intensity on global warming for a sample of twenty OECD countries for over one hundred and fifty years of data. Our multiple estimations suggest that R&D intensity is empirically relevant for global warming. Increasing R&D intensity is significantly associated with a reduction in global warming. This relationship is also time invariant in terms of sign of the coefficient. In addition, there are potential global R&D spillovers that are likely to scale up the efforts in reducing global warming. This implies that global R&D spillovers are more important than country-specific intensity. We find that the magnitude of R&D intensity's impact on global warming has been diminishing post-World War II as compared to pre-World War II. The findings are robust to cross-sectional dependence, endogeneity, and structural breaks.

In view of our core results, we find that R&D intensity and global warming are inversely related. Consistently, we find that the coefficient function of R&D intensity is negative and significant for all the estimators and different specifications. The results are consistent with the other findings in terms of the sign of the coefficients. This indicates that, despite addressing structural breaks and the cross-sectional dependence of both R&D intensity and global warming, as well as the other variables, R&D intensity may have the potential to mitigate the effects of global warming. While the formal test finds evidence of one break, the estimator does not suggest that the break is statistically significant. More importantly, there is non-linearity in the relationship between R&D and global warming. We observe a negative coefficient for the quadratic term of R&D, which implies dimisnishing marginal returns. R&D intially is very powerful in reducing a country's contribution to global warming but the effect diminishes with more R&D.

Chapter 2

The Macroeconomic Impact of Global and Country-Specific Climate Risk

2.1 Introduction

Climate change is widely expected to have a significant impact on economic activity for a whole host of countries around the world.[1] In his Nobel Prize Lecture, Nordhaus (2019a) summed up the consensus on climate change: global warming is a threat to humankind and the natural world. The economic implications of climate change are potentially huge for firms, households and government policy. In addition to degradation of both the environment and ecosystem itself, climate change shall damage the economy by impacting primary resources, physical and human capital, R&D and productivity. In response, countries have implemented policies to tackle climate change in an effort to reduce greenhouse gas emissions and abate the adverse economic impact. While a policy consensus has emerged on climate change, some research questions remain.[2] Stern (2008) summarises effectively the challenges for researchers climate economics: climate risk is global in its nature and impact; the effects may only reveal themselves over the long-term; and economic analysis of climate change should have a central role for risk and uncertainty. This chapter seeks to add to the literature on the macroeconomic impact of climate change, focusing upon the nature and impact of global and country specific climate risk over an extended time period.

The United Nation's Intergovernmental Panel on Climate Change (IPCC) noted in its Sixth Assessment Report, in this regard that: our climate has become more volatile through time, with extreme temperature changes impacting an increasing variety of geographic regions (Arias et al., 2021). We observed from an illustrative sample of thirty countries that there has been an increase in both average annual temperature growth and variability. For our sample of thirty countries for over a century of annual data, average annual temperature growth was 0.012°C, with a standard deviation of 0.279°C between 1901 and 1950.

[1] Nordhaus and Moffat (2017) considered several existing analyses on the macroeconomic implications of climate change using a systematic research synthesis. They found that the damage to income ranged from over 2 per cent to over 8 per cent, depending upon whether there was 3°C or 6°C warming. See also Weitzman (2007), Tol (2009a), Burke et al. (2015), Donadelli et al. (2017), Alessandri and Mumtaz (2021), Kotz et al. (2021), Kahn et al. (2021), Pindyck (2021), Donadelli et al. (2022), and Kotz et al. (2022).

[2] See Weitzman (2007), Stern (2008) and Pindyck (2021).

From 1950 to 2020 average annual temperature growth rose to 0.015°C, with the standard deviation increasing to 0.292°C. This increase in climate variability is important, not least since Alessandri and Mumtaz (2021), Kotz et al. (2021) and Donadelli et al. (2022) present evidence that climate risk in the form of temperature variability can have a detrimental impact upon macroeconomic outcomes. This is based upon both empirical and theoretical research, using either realized temperature volatility or *ex ante* stochastic volatility measures of climate risk.[3]

There are several channels by which climate risk may impact the economy. Investments which are irreversible, and have an option value of waiting, may be delayed by firms due to uncertainty (Dixit and Pindyck, 1994; Bloom, 2009). This may result in decreased expenditures on new business capital and R&D. Berestycki et al. (2022) document that climate policy uncertainty is linked to substantial declines in investment in capital-intensive industries, notably in pollution-intensive sectors subject to climate policy changes. Extensive research has emphasised the urgency of incorporating the physical aspect of climate threats into economic impact studies.[4] These studies demonstrate that climate risks have a negative impact, not only upon labour productivity and capital quality, but also upon R&D expenditures, thereby lowering economic growth. In other words, climate risks can directly influence both economic production and consumption.

Our chapter makes four contributions to the literature on the economic impact of global warming. Firstly, we illustrate climate interconnectedness from one country to the next for our large sample of countries using generalised temperature spillover indices from Diebold and Yilmaz (2012), which is order invariant. Our evidence suggests that temperature changes have experienced spillovers from one country to the next, indicating the interconnectedness of these countries. In essence, connectedness motivates the notion that there are common

[3] See Cascaldi-Garcia et al. (2023) for an extensive discussion of empirical measures of uncertainty and risk.

[4] See for example Donadelli et al. (2017), Donadelli et al. (2021), Kotz et al. (2021), Pindyck (2021), Donadelli et al. (2022), Kotz et al. (2022), and Sheng et al. (2022).

factors in temperature changes. Given this global interconnectedness, it is critical to model common factors of climate when assessing its impact on macroeconomic activity.

Our second contribution is to consider the impact of climate variability upon real GDP growth by differentiating between the impact of global climate risk and country specific climate risk using a factor model. Global climate risk may matter more than idiosyncratic climate risk for economic activity, since climate change is a global phenomenon, as suggested by Stern (2008). Factor models are widely used in empirical macro research: see Kose et al. (2003), Foerster et al. (2011) and Fernández et al. (2018).[5] Related to, but different from our factor approach, Alessandri and Mumtaz (2021) use univariate stochastic volatility associated with temperature to examine the long-term impact of climate change uncertainty on economic growth.[6] However, the potentially distinct impact of global and country specific climate uncertainties upon GDP growth have not been considered by the literature as far as we are aware. In light of this, the purpose of this present work is to extend Alessandri and Mumtaz (2021) by employing factor stochastic volatility, which is multivariate, as opposed to stochastic volatility which is univariate, to decompose climate uncertainties. Our factor stochastic volatility approach to modeling climate change more fully accounts for the global nature of climate risk.

The third contribution of our chapter is to consider the impact of climate change over the very long term. This also chimes with Stern (2008) who emphasizes that climate change can be long term in its nature or impact. We therefore consider around 120 years of data when examining the impact of global and country specific climate risk on GDP. This contrasts with existing studies which typically consider a more recent sample period. And while climate change has become more acute in recent years, climate risk has potentially impacted outcomes for an extended period. We also assess whether our results are sensitive to the sample period chosen and whether the effects of climate change have become more acute in

[5] Ang et al. (2009) and Herskovic et al. (2016) investigated a common factor in idiosyncratic volatility in quantitative asset pricing, as well as high idiosyncratic volatility and low returns.

[6] We also differentiate our measure of climate uncertainty from Gavriilidis (2021) and Sheng et al. (2022).

recent years. Fourthly, our work distinguishes the effects of climate risk upon advanced and emerging economies because the effects of climate change may depend upon country characteristics. Despite the possibility of cummulative temperature increases above pre-industrial levels ranging from 1.5°C to 4.5°C, certain regions may be heterogeneously impacted by global warming (see Houghton, 1996; O'Brien and Leichenko, 2000). We consider whether the climate risk experienced by emerging economies is country-specific or mainly the result of global spillovers. Both advanced and emerging economies are major contributors of greenhouse gas emissions which could substantially affect their economies due to climate risk. Both groups of countries may be heterogeneously impacted by climate risk and be more or less able to abate the impact of climate variability.

To preview our result, we established that overall climate risk is substantial and relevant for macroeconomic activity, consistent with the earlier literature such as: Dell et al. (2012), Donadelli et al. (2017), Alessandri and Mumtaz (2021), Donadelli et al. (2021), Kotz et al. (2021), Donadelli et al. (2022), Kotz et al. (2022), Sheng et al. (2022), among otherss. Separating climate risk into global and country-specific elements we make our key contributions. Country specific climate risk shocks have a relatively less important impact on GDP fluctuations. By comparison, global climate risk has a negative and relatively more important impact on GDP, and induces more volatility of macroeconomic activity. Our results indicate that both advanced and emerging economies are impacted to a greater extent by common, rather than the idiosyncratic climate risk, which emphasizes the global dimension of climate change. In addition, we find evidence of strong interconnectedness of temperature changes among the countries in our sample. Most importantly, both temperature changes and GDP growth depict positive spillover effects from one country to another. Our econometric method's ability to capture cross-sectional heterogeneity and spillovers renders our findings robust and substantial.

The rest of the study is divided as follows: the second section briefly discusses the existing literature, the third describes the empirical model and method used in the empirical analysis;

the fourth section reports our empirical results; and the fifth section concludes the study.

2.2 Literature Review

Uncertainty is increasingly important for empirical research in several economic applications, see Cascaldi-Garcia et al. (2023). In an early study, Bernanke (1983) argues that an increase in uncertainty damages the economy's total demand through a conventional channel tied to the real option theory. Bloom (2009) suggests that uncertainty influences decision-making because it increases the option value of waiting. In other words, corporations and, in the case of durable products, consumers are more cautious when confronted with uncertainty due to the significant costs associated with making poor investment decisions. Consequently, investments, hirings, and expenditures are postponed until periods of lesser uncertainty. Due to the misallocation of resources across businesses, uncertainty is also anticipated to have a negative influence on the supply-side productivity of the economy (Bloom et al., 2018). According to Bloom et al. (2018), it is argued that in periods of normal economic conditions, less efficient companies tend to experience a decrease in size, while more productive firms tend to grow, thereby contributing to the overall maintenance of high aggregate productivity. In situations characterised by elevated levels of uncertainty, businesses tend to impose restrictions on their expansion and contraction activities. This, in turn, hampers a substantial portion of the productivity-enhancing reallocation process, ultimately resulting in a decline in the evaluated aggregate total factor productivity. The main question of this study pertains to whether there existss a correlation between a heightened likelihood of encountering greater temperature variations in the future, specifically an increase in the conditional volatility of yearly temperatures, and its potential impact on economic growth.

As already mentioned climate change is a key policy concern. It has the potential to damage household welfare and economic activity (Giglio et al., 2021).[7] Two lines of research

[7] Sheng et al. (2022) show that temperature growth volatility slows economic activity about five times more than a comparable rise in temperature, under high uncertainty in a nonlinear model.

underpin our study. The first line examines the economic implications of climate change. They substantially argued on the negative relationship between income and global warming. To assess the relationship between climate and economic activity researchers use various methods, including the general equilibrium model, and the integrated assessment model in its reduced form.[8] The second line of research examines the macroeconomic implications of increases in risk and uncertainty associated with climate change. The literature establishes the critical role of macroeconomic volatility on investment, consumption, and output.[9] By examining the relationship between climate risk, notably climate change uncertainty, and macroeconomic activity, this study aims to bring new and diverse evidence to inform policy direction and academic discussion.

It should be noted that several chapters examine the empirical relationship between economic development and weather conditions. For instance, Dell et al. (2012) seek to determine the economic effects of climate change in an empirical context. They accomplish this by tracing the temporal evolution of countries' average temperatures and output growth. According to Dell et al. (2012), rising temperatures have a greater negative impact on economic growth in developing nations than in industrialised nations. Similar to Dell et al. (2012), Brenner and Lee (2014) used a panel of nations to determine if changes in temperature and precipitation levels are associated with slowed economic growth.[10] They demonstrate that rising temperatures have a detrimental effect on economic growth in warm, developed nations, whereas increased precipitation has a beneficial effect on growth, particularly in developed nations with low average precipitation. Meanwhile, Zhao et al. (2018) contend that the impacts of annual temperature on productivity can also vary widely among countries. Using global sub-

[8] These studies investigated the link between climate change as in temperature, rainfall and precipitation growth on aggregate production and consumption and in general economic productivity or economic growth (Hassler et al., 2016; Stern, 2016; Nordhaus and Moffat, 2017; Alessandri and Mumtaz, 2021; Kotz et al., 2021, 2022).

[9] While Ciccarelli and Marotta (2021), Kahn et al. (2021), Kim et al. (2021), and Sheng et al. (2022) examined climate risk and uncertainty impact of economic activities in diverse ways.

[10] Brenner and Lee (2014) anticipate a substantial increase in the global average temperature in the coming decades. They analyse historical temperature and precipitation variations to determine whether changes in temperature and precipitation are connected with economic growth declines.

national short panel data, they review the link between temperature and economic growth and demonstrate that climate-related negative consequences can differ at the regional level. Donadelli et al. (2017) demonstrate empirically that a temperature shock has a substantial, negative, and statistically significant effect on total factor productivity, production, and labour productivity. In contrast, they demonstrate that quicker adaptation to climate shocks is associated with lower welfare costs. In line with that, welfare benefits increase dramatically when the rate of adaptation improves over time. According to Kotz et al. (2022), a rise in the number of rainy days and excessive daily rainfall, as well as a nonlinear reaction to the total annual and averaged monthly variations in rainfall, slows economic growth rates. In addition, both daily rainfall and total annual rainfall are most detrimental to high-income countries and industries, such as services and manufacturing, supporting previous research that emphasised the benefits of greater annual rainfall for low-income, agriculturally-based economies.

Apparently, numerous studies have identified connections between overall changes in temperature and economic growth either in short or long-term, but data on the relationship between within-year temperature variability and macroeconomic variables is scant (Donadelli et al., 2022); few studies have suggested that the relationship between climate uncertainty and economic outcomes is significant and very important (Burke et al., 2015; Pindyck, 2021). Other studies are of the view that climate change risks as a result of uncertainty leads to output losses and surges in prices. Essentially, the negative effect of climate risks or uncertainties emanate from demand-side and supply-side shocks (Batten, 2018; Batten et al., 2020; Ciccarelli and Marotta, 2021; Kiley, 2021). Further, Kotz et al. (2022) postulate that climate change exacerbates growth such that variability of rainfall responds to economic growth non-linearly. It is demonstrated by Sheng et al. (2022) that climate risks have a detrimental impact on economic activity to a similar extent regardless of whether the risks are caused by changes in temperature growth or volatility. However, when temperature growth increases by a similar magnitude in the higher uncertainty-based regime in a nonlinear context, the volatility of temperature growth contracts economic activity roughly five times more than when temperature growth decreases by a similar amount. Donadelli et al. (2021) explore labour productivity, patent obsolescence, and capital quality in their analysis of the negative R&D expenditure effect of rising temperatures. According to them, temperature shocks are damaging to economic growth due to a decline in investment on research and development. It has been found by, Donadelli et al. (2022) that richer economies are more susceptible to the negative economic consequences of temperature fluctuation shocks. Kotz et al. (2021) argue that day-to-day temperature variability is influenced by seasonal differences and income, resulting in the greatest risks in low-income regions and low-latitudes.

In contrast, there is research which suggests that the economic effects of climate change are negligible. Pretis et al. (2018) find that, beyond global nonlinear temperature effects, monthly temperature and precipitation variability has no impact on economic growth under 1.5°C or 2°C warming. They also document that temperature variations have almost no effect on growth in economies with a yearly average temperature, but temperature variations appear to have significant consequences in countries with extremely high or low average yearly temperature temperatures.

The topic of climate spillovers have received limited attention in the existing body of research. The existence of this gap becomes apparent when examining multiple facets of climate interactions. Prominent instances encompass investigations that delve into the direct impacts of climate change, as exemplified in the scholarly contribution of Schleypen et al. (2022). Moreover, the examination of spillover effects of regional temperatures, as illustrated by Cashin et al. (2017), underscores the insufficient consideration given to this complex phenomenon.

Furthermore, scholarly research has increasingly focused on investigating intricate aspects of climate spillovers. For instance, Zhao et al. (2023) have delved into the systemic risk that emerges from the interconnection between coal-supported electricity generation and weather patterns. The research conducted by Khalfaoui et al. (2022) and Su et al. (2022) demonstrates the growing acknowledgement of the interdependencies between climate policy spillovers and their impacts on energy systems. These studies shed light on the interconnected nature of climate-related dynamics, both within and between sectors and regions.

Significantly, there has been increased attention on indirect climate spillovers, as evidenced by research conducted by Zhang et al. (2023). This study has provided valuable insights into the complex mechanisms through which climate change can spread across interconnected systems, thereby emphasising the necessity for a more holistic comprehension of the extensive consequences associated with climate spillovers.

Given ongoing investigations, it is apparent that climate spillovers are a multifaceted and interconnected phenomenon that warrants increased scholarly focus. The scholarly literature emphasises the significance of not only mitigating the immediate impacts of climate change but also recognising the complex web of repercussions that can span across geographical, sectoral, and policy domains, ultimately influencing the global socioeconomic framework. The available data on climate change and macroeconomic activity indicate that an increase in annual average temperature has an effect on macroeconomic growth. However, a number of fundamental elements of the economy are affected by deviations in daily temperature from seasonal expectations that are not adequately reflected in annual averages.

2.3 Empirical Methods

2.3.1 Data

Key time series used in this study are measures of climate risk, macroeconomic activity and carbon emissions. We use temperature changes as the basis of measuring country-specific and global climate risk. To model macroeconomic activity, we use the growth rate of real GDP. The steady increase in global temperature caused by accumulated carbon dioxide in the atmosphere, which raises atmospheric carbon concentration and eventually changes temperature, is measured using carbon emissions per capita. Moreover, we use carbon emission per capita since this is also important for the relationship between climate risk and macroeconomic activity. The data spans from 1901 to 2020 for thirty countries.[11]

Climate Data

To construct a measure of climate risk, we source temperature data from World Bank Climate Knowledge Portal and we focus upon temperature changes. Temperature is derived from the Climate Research Unit (CRU) observed dataset. The CRU gridded time series are a widely used climate dataset that covers all land domains of the world except Antarctica on a 0.5° latitude by 0.5° longitude grid. It is calculated by obtaining climate anomalies from large networks of weather stations' observations within a country. However, a key innovation in this chapter is that climate risk is measured by a factor stochastic volatility model of average temperature changes. The primary practical and computational benefit of the factor stochastic volatility (FSV) model lies in its parsimony. This model effectively represents the variances and covariances of a vector of time-series by employing a low-dimensional stochastic volatility (SV) structure that is determined by common factors. It is a frequently observed phenomenon that the quantity of common factors among extensive sets of time-series vectors tends to be significantly smaller, typically by one or two orders of magnitude. This occurrence has a notable impact on the accuracy of estimation and computational processes.[12] Unlike the FSV which uses a multivariate process, previous studies modelled climate risk by a standard normal factor model in which both the idiosyncratic time series variances and common factors variances are combined as a univariate stochastic volatility process.[13]

[11] Countries include both advanced and emerging economies. These are Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Italy, Japan, Netherlands, Portugal, Sweden, United States, Norway, Argentina, Bolivia, Brazil, Chile, Colombia, Cuba, Indonesia, India, Sri Lanka, Mexico, Peru, Uruguay, and Venezuela. Further details on our data set can be found in Table 2A-3 in the appendix.

[12] By contrast, it is linked to a significant computation complexity when the number of dimensions of The data are moderate to large, see Kastner et al. (2014). Pitt and Shephard (1999) believe that using models to accurately measure VAR is a worthwhile topic.

[13] Huber et al. (2018), Alessandri and Mumtaz (2021) and Sheng et al. (2022) used a Bayesian stochastic volatility model to evaluate the long term impact of climate change on economic growth. They follow a univariate stochastic volatility process, in contrast to our factor approach.

Macroeconomic Activity

Macroeconomic activity in our study is measured by the real GDP growth rate and real GDP per capita. However, the majority of the results use real GDP growth. The only time growth in real GDP per capita is used instead is in robustness checks. The real GDP growth rate is calculated by authors using real GDP per capita and population data from the Maddison Project and the World Bank's World Development Indicators. Dell et al. (2012) document two possible outcome of temperature impact on economic activity; that is, (*i*) level of output through agricultural yields, and (*ii*) productivity growth through investment and institutional effectiveness. In addition, the authors suggest that warmer temperatures may slow growth in developing and underdeveloped countries rather than temporarily lowering output. These growth effects would imply huge repercussions of global warming because even minor growth effects have large consequences over time.[14] According to Burke et al. (2015), the global climate and economic activity are intertwined. It is essential to note that hotter climates reduce output by reducing investment, lowering worker productivity, worsening health outcomes, and lowering agricultural and industrial output—thereby, thwarting overall macroeconomic activity (Moore and Diaz, 2015; Carleton and Hsiang, 2016). Some recent studies have emphasised the importance of understanding the impact of climate uncertainty on macroeconomic growth (Kiley, 2021; Kotz et al., 2021; Donadelli et al., 2022; Kotz et al., 2022). According to Dell et al. (2012), transient weather shocks that capture levels and growth effects have an impact on the growth rate during the shock's initial phase. This effect eventually goes the other way when weather returns to its steady state. As an illustration, a temperature shock may result in lower agricultural output, but after the temperature returns to normal, agricultural production recovers. By contrast, the growth effect manifests during the weather shock and cannot be reversed: a country's failure to innovate during one era pushes it further behind the curve over the long term.

Climate change potentially impacts the demand and supply side of an economy: from the

[14]See also Lucas (1988) on why the determinants of long run economic growth can be staggering.

supply side, it disrupts output by adversely affecting prices and hampering future growth through extreme weather conditions and natural disasters—and perhaps affect physical capital as a demand side effects (Ciccarelli and Marotta, 2021). Arguably, the aforementioned effects from both demand and supply sides relative to climate change have been identified as simple, taking into account the short-term and long-term effects. Thus, shifts in consumption, income, exports, investment, and infrastructure are closely linked to climate awareness and migration (Batten et al., 2020).

Carbon Emissions

Carbon dioxide emissions are caused by the combustion of fossil fuels, deforestation, agriculture, and industrial activities such as the production of cement. They include carbon dioxide emitted during the combustion of solid, liquid, and gas fuels, as well as gas flaring. Productivity and economic growth have a direct influence on individual well-being. Since at least the industrial revolution, global economic growth has been driven by energy from fossil fuel, which contributes to greenhouse gas emissions. Carbon emissions cause global warming on the long run affecting atmospheric carbon concentration, which alters temperatures and induces climate change (Pindyck, 2021).

2.3.2 Modelling Climate Risk

Common variation in the unpredictable component of a large variety of economic variables, is frequently referred to as time-varying macroeconomic uncertainty (Jurado et al., 2015; Mumtaz and Theodoridis, 2017; Beckmann et al., 2019). Commonly used uncertainty measures do not capture the long-lasting bursts of activity that seem to correlate with real economic activity (Jurado et al., 2015). Nonetheless, Jurado et al. (2015) state that there is no objective measure of uncertainty when it comes to assessing macroeconomic activity and uncertainty. To this end, the Jurado and coauthors develop novel metrics of uncertainty and connect them to macroeconomic activity. The objective is to generate reasonable econometric estimates of uncertainty that are decoupled from the structure of specific theoretical models, as well as from reliance on any single or limited number of measurable economic indicators. Other measures of climate change policy uncertainty and overall economic policy uncertainty have emerged, with these indices being built against the backdrop of newschapters using specific keywords, see Baker et al. (2016), among others.[15]

We construct our climate risk measures by using the multivariate factor stochastic volatility (MFSV) model proposed by Kastner and Frühwirth-Schnatter (2014).[16] The following steps are used to construct our country-specific and global climate risk measures:

- **Step 1**: We compute the changes in average annual temperature for 30 countries from 1901 to 2020. This is done by simple differencing: $\Delta\mathbb{T}_{it} = \mathbb{T}_{it} - \mathbb{T}_{it-1}$, where $\mathbb{T}_{it}$ represents the average annual temperature for the country i at time t.

- **Step 2**: Subsequently, we follow Kastner and Frühwirth-Schnatter (2014) to model our climate risk measures as:

$$\mathbb{Z}_{it} = \Lambda_i f_t + \Sigma_{it}, \quad \Sigma_{it} \sim \mathcal{N}(0, \mathrm{H}_{it}) \tag{2.1}$$

  $\mathbb{Z}_{it}$ denotes log changes in annual temperature for our sample of 30 countries. We replace $\mathbb{T}_{it}$ with $\mathbb{Z}_{it}$ to differentiate the univariate and multivariate modelling of our climate risk measures. f_t represents the common latent factor, which denotes the contribution of the common global factor of a country i's temperature changes. Λ_i is the factor loading for country i. Σ_{it} denotes the idiosyncratic volatilities, the country-specific climate risks. In our PVAR model, we denote the global climate risk measure, $\Lambda_i f_t$ as $\sigma^{\mathbb{T}}_{Ft}$, and the country-specific climate risk measure, Σ_{it}, as $\sigma^{\mathbb{T}}_{it}$.

- **Step 3**: We estimate the MFSV model by selecting one factor ($r = 1$) since we are

[15] Gavriilidis (2021) develops an index for climate policy uncertainty to measure the volatility of climate change policy and its related implications for the US. Our work is focused upon developing a more broad-based, multi-country measure of climate uncertainty.

[16] The theoretical foundation of this model is extensively outlined in the Appendix 6.3.

interested in a single global climate risk factor and implement the MCMC approach with 5000 draws.

2.3.3 Panel VAR

To examine the relationship between macroeconomic activity, idiosyncratic and global climate risk, this study uses a Bayesian Panel VAR with a hierarchical prior. This Bayesian Panel VAR method was created by Jarociński (2010). It provides a richer approach because it treats all parameters as random variables and incorporates them into the estimation process. The hierarchical structure of our panel VAR model, which allows for the possibility of heterogeneous responses to climate risk shocks across the selected countries, is one of the model's key components. To capture the endogenous relationship between climate risk and macroeconomic activity, we define $\boldsymbol{X}_{it} = [\sigma^{\mathbb{T}}_{it},\ \sigma^{\mathbb{T}}_{Ft},\ y_{it}]'$ with country-specific climate risk ($\sigma^{\mathbb{T}}_{it}$), global climate risk ($\sigma^{\mathbb{T}}_{Ft}$) and y_{it} denotes the growth rate of real GDP. Both climate risk measures are obtained from the factor stochastic volatility model in equation (2A-2) using annual temperature changes. In accordance with Jarociński (2010), we assume a panel model as follows:

$$\boldsymbol{X}_{it} = \sum_{l=1}^{L} \boldsymbol{B}'_{il}\boldsymbol{X}_{it-l} + \boldsymbol{b}'_i\boldsymbol{w}_t + \boldsymbol{\Gamma}'_i\boldsymbol{z}_{it} + \boldsymbol{u}_{it} \tag{2.2}$$

where $\boldsymbol{w}_t$ is a vector of common exogenous variable and $\boldsymbol{X}_{it}$ is a n vector of endogenous variables. The subscrpits $i = 1, ..., N$ represents countries, $t = 1, ..., T$ represents time periods, and $l = 1, ..., L$ represents the lags. In terms of the $\boldsymbol{X}_{it-1}$ and $\boldsymbol{w}_t$ coefficients, we define an exchangeable prior. The prior is non-informative for the $\boldsymbol{z}_{it}$ coefficients, which may contain country-specific constant terms. The vector $\boldsymbol{u}_{it}$ contains $\mathcal{N}(0, \boldsymbol{\Sigma}_i)$ VAR innovations which are iid. The variables to which the exchangeable prior applies are collected in a vector called $\boldsymbol{x}_{it} = [\boldsymbol{X}'_{it-1}...\boldsymbol{X}'_{it-l}, \boldsymbol{w}'_t]'$. In terms of data matrices, the model for country i can be obtained by vertically stacking $\boldsymbol{X}'_{it}, \boldsymbol{x}'_{it}$ and $\boldsymbol{w}'_t$ for all t:

$$\boldsymbol{X}_i = \mathbb{X}_i\boldsymbol{B}_i + \boldsymbol{Z}_i\boldsymbol{\Gamma}_i + \boldsymbol{U}_i \tag{2.3}$$

$\boldsymbol{X}_i$ and $\boldsymbol{U}_i$ are $T \times n$. Where $\mathbb{X}_i$ is $T \times K$, $\boldsymbol{Z}_i$ are $T \times M$, $\boldsymbol{B}_i$ are $K \times n$ and $\boldsymbol{\Gamma}_i$ are $M \times n$. $\boldsymbol{B}_i$ $= [\boldsymbol{B}'_{i1}, ..., \boldsymbol{B}'_{iL}, \boldsymbol{b}'_i]'$ relates the coefficients matrix of $\boldsymbol{B}_i$ to the coefficients of equation (2.2). Therefore, we can formulate $\boldsymbol{x}_i = \text{vec}\boldsymbol{X}_i$, $\boldsymbol{\beta}_i = \text{vec}\mathbf{B}_i$, $\boldsymbol{\gamma}_i = \text{vec}\boldsymbol{\Gamma}_i$.

The data-generating statistical model is assumed to be as follows, in which the probability for country i has the form

$$p(\boldsymbol{x}_i|\boldsymbol{\beta}_i, \boldsymbol{\gamma}_i, \boldsymbol{\Sigma}_i) = N((\boldsymbol{I}_n \otimes \mathbb{X}_i)\boldsymbol{\beta}_i + (\boldsymbol{I}_n \otimes \boldsymbol{Z}_i)\boldsymbol{\gamma}_i, \boldsymbol{\Sigma}_i \otimes \boldsymbol{I}_T)) \tag{2.4}$$

Country coefficients on the variables in $\mathbb{X}_i$ are assumed to be normally distributed with a mean of $\overline{\boldsymbol{\beta}}$ and a variance of $\boldsymbol{\Lambda}_i$ which may vary by country:

$$p(\boldsymbol{\beta}_i|\overline{\boldsymbol{\beta}}, \boldsymbol{\Lambda}_i) = N(\overline{\boldsymbol{\beta}}, \boldsymbol{\Lambda}_i) \tag{2.5}$$

The prior for $\boldsymbol{\Lambda}_i$ and $\overline{\boldsymbol{\beta}}$ is uniform on the real line and non-informative:

$$p(\overline{\boldsymbol{\beta}}) \propto p(\boldsymbol{\gamma}_i) \propto 1 \tag{2.6}$$

Subsequently, the standard diffuse prior is also applied to the error's variances:

$$p(\boldsymbol{\Sigma}_i) \propto |\boldsymbol{\Sigma}_i|^{-\frac{1}{2}(n+1)} \tag{2.7}$$

The equations (2.4) to (2.7) define the dynamic models of variables in $\boldsymbol{X}_i$ and exogenous controls in $\boldsymbol{W}$ as particular instances of the unknown underlying model defined by $\overline{\boldsymbol{\beta}}$.

Mumtaz and Sunder-Plassmann (2021) implemented the hierarchical VAR prior to threshold and regime switching, demonstrating its robustness given that it permits cross-sectional heterogeneity. In such circumstances, regularisation is required because the majority of macroeconomic data contain time series with few observations. The Bayesian literature provides several methods for achieving parsimony within the PVAR framework to address this issue. One body of research applies shrinkage priors to various regions of the parameter space, see Koop and Korobilis (2016) and Koop and Korobilis (2019). This method theoretically treats the PVAR as a large VAR with asymmetric shrinkage with respect to the coefficients in $\boldsymbol{\Lambda}_i$, $\boldsymbol{B}_i$, and the free elements of $\boldsymbol{\Sigma}_i$. Canova and Ciccarelli (2004), Canova and Ciccarelli (2009) and Jarociński (2010) make use of the observation that domestic macroeconomic dynamics are relatively similar across countries, implying that the matrices $\mathbf{\Lambda}_i$ are comparable. However, interdependencies, whether dynamic or static, are typically disregarded when data from multiple countries are combined by averaging $\mathbf{\Lambda}_i$.

The functional form of the prior, which is standard and motivated by computational ease, consists of a normal, uniform, inverted gamma density combined with a degenerated inverted Wishart density for $\mathbf{\Sigma}_i$, making the prior conditionally conjugate. The Bayes theorem is used to calculate the posterior density of the model's parameters, which is a normalised product of the likelihood and the prior (Jarociński, 2010). Due to the prior's conditional conjugacy, all conditional posterior densities can be conveniently and numerically analysed using the Gibbs sampler because they are all normal, inverted gamma, or inverted Wishart (Gelman et al., 1995).

The estimation procedure employs Gelman et al. (1995)'s hierarchical linear model modified by Jarociński (2010). The concept of similarity is formalised as a Gaussian prior for each country's coefficients that is centred on the countries' common mean—an exchangeable prior. This method offers two distinct benefits: (*i*) we can estimate the cross-country average impulse response to climate risk shocks by averaging the coefficients. In light of this, there is a greater likelihood of estimation precision when information from a panel is utilised as opposed to business cycle dynamics from a single time series. (*ii*) Since our model allows for heterogeneous effects of climate risk shocks across the panel, the exchangeable prior, or hierarchical prior, implies that the posterior estimates of country-specific impulse responses incorporate panel data. It is essential to note that the precision of estimates for individual countries could potentially be enhanced (Mumtaz and Sunder-Plassmann, 2021). Above all, it treats all parameters as random variables and incorporates them into the estimation process, this method is more flexible (also see Jarociński (2010) for details).

Identification Strategy

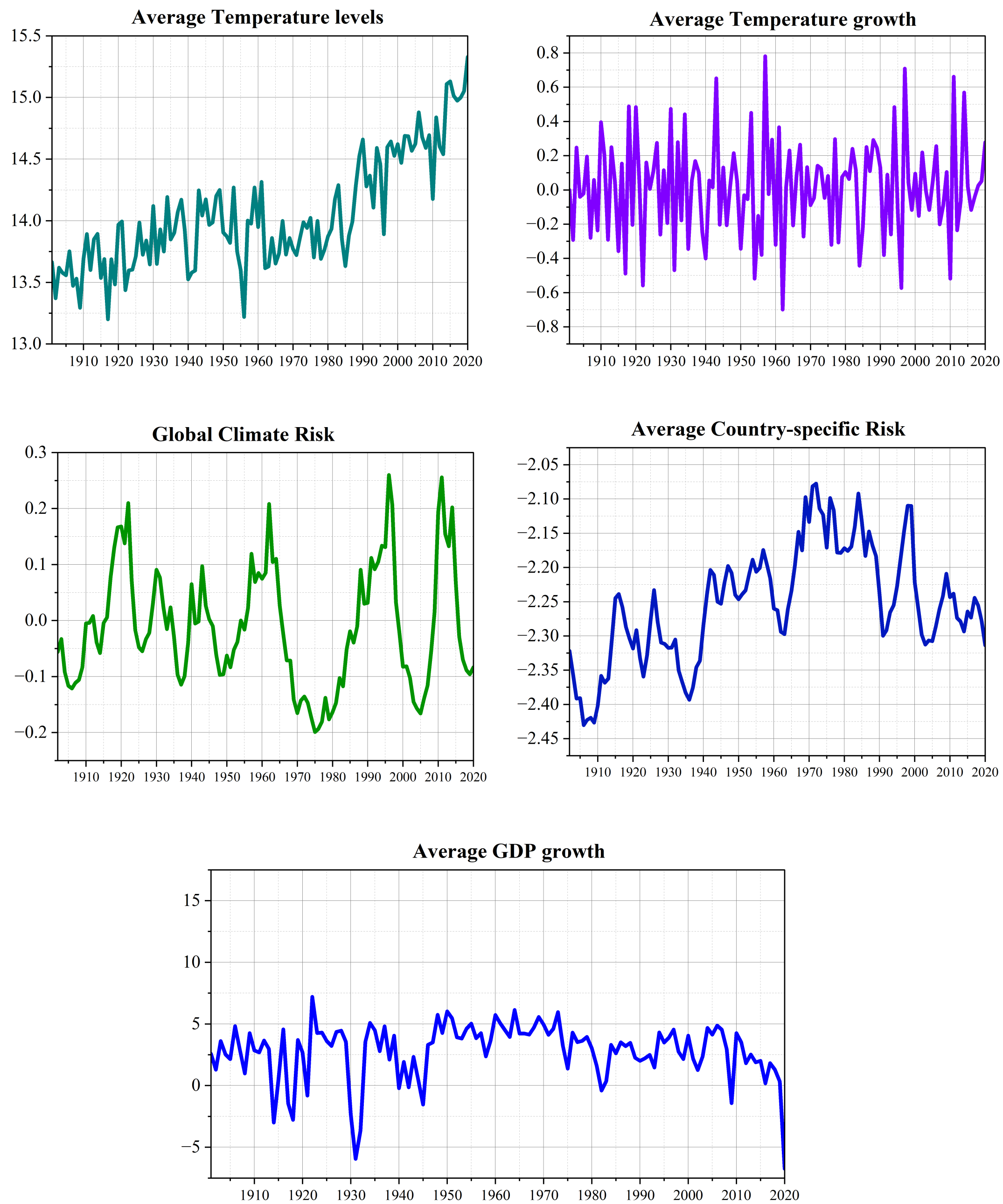
In this section we set out the identification scheme we use to operationalise our empirical model. We utilise impulse response functions based upon the estimated parameters of our PVAR model to consider the impact of climate risk shocks on economic activity. We are therefore focused upon the effect of a climate risk shock upon GDP. Climate risk can have a contemporaneous impact upon economic activity in our model and this is consistent with weather shocks impacting the economy within year. Our model also allows there to be a more nuanced and data driven interaction and feedback between climate and GDP in the medium to long run. Our panel VAR model therefore allows for a two-way interaction between climate and macroeconomic activity: in theory, temperature can influence GDP growth and respond endogenously to GDP growth. Against this backdrop, we use a recursive identification strategy. Our Cholesky factorization of shocks implies macroeconomic activity has no immediate impact on climate change. In computing the orthogonalized impulse response shocks, we typically order climate variables first in bivariate VARs, whether they be temperature growth or uncertainty. We order economic activity last, except when we also include $CO2$ in our model.

2.4 Empirical Results

2.4.1 Descriptive Statistics

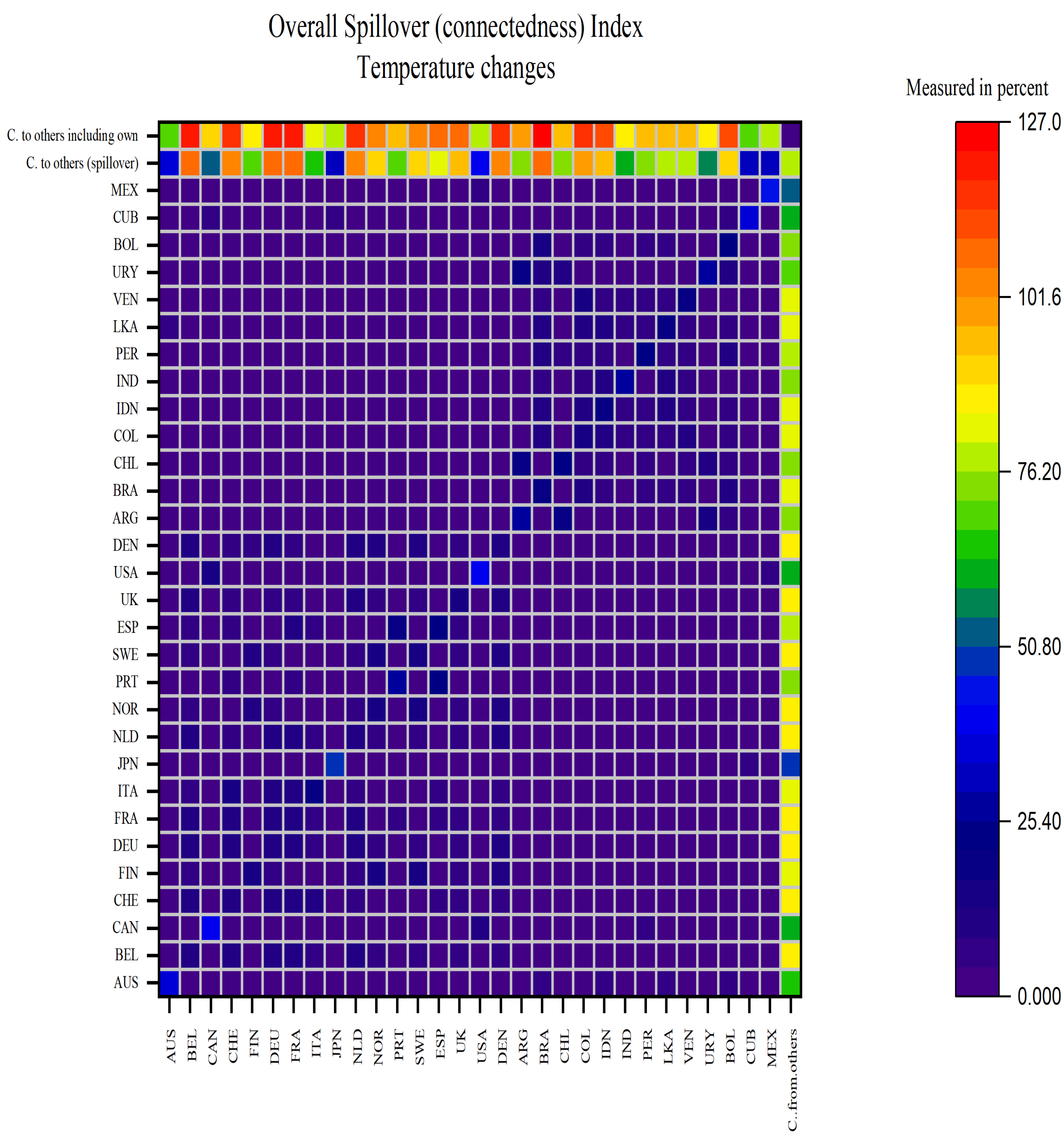
Graphical evidence of the key variables of interest is provided in Figure 2.1: which depicts climate risk, temperature changes, temperature levels, and GDP growth rate from 1901 to 2020. It is clear that temperature levels have risen dramatically on average for the countries we sample since the beginning of the last century, and especially over the last sixty years. For our sample of countries, average temperatures have risen by nearly 2°C over the full sample period. The increase in temperatures is for both advanced and emerging economies. Advanced economies have increased by around 2°C, while emerging economies have increased

Figure **2.1:** Climate risk, temperature and GDP



Notes: This figure presents average time of series of country temperature levels, temperature growth and GDP growth rates for the period 1901 to 2020. Unweighted averages of all 30 sampled countries. Temperature levels and temperature growth are measured in Degree Celsius and GDP growth are in percentages.

Figure **2.2:** Generalised spillover index: temperature changes



Notes: The Generalized Directional Spillover heatmap represents the estimated contribution to the forecast error variance of country i from innovations to country j for temperature using Diebold and Yilmaz (2012). The off-diagonal column sums represent contributions to Others, while the row sums represent contributions from Others; when these are totaled across countries, we get the Spillover Index numerator. The figure indicates that there are considerable temperature linkages from one country to another in our sample, and that therefore climate is international or global in nature. C denotes contribution either from others, to others or to others including own.

1°C. Temperature growth has been highly variable over the entire sample period, although with more pronounced and frequent spikes later in the second half of the sample period. Despite some recessions, GDP growth in both advanced and emerging economies has been consistent. The results from Diebold and Yilmaz (2012) applied to our temperature data are provided in Figure 2.2. The key message from this figure is that temperatures in one country are linked to temperatures in other countries. This can be gleaned from the sizable spillover percentages in Figure 2.2, which are at least 29% and frequently considerably more. We use this preliminary evidence to justify our focus in This chapter on the macroeconomic impact of global temperature.

Descriptive statistics are presented in Table 2.1. In addition to mean, standard deviation, maximum and minimum statistics, we include Pearson correlations. Economic growth has generally be positive over the entire sample period. It is important to note that the correlation between country-specific climate risk ($\sigma_{it}^{\mathbb{T}}$) and GDP growth (y_{it}) is negative and significant, for the entire sample, 1901 to 2020. We find that temperature growth ($\mathbb{T}_{it}$) is positively correlated with GDP growth (y_{it}) but crucially this is not a statistically significant relationship. In contrast, there is a negative correlation between the country-specific climate risk ($\sigma_{it}^{\mathbb{T}}$) and GDP growth (y_{it}) in Table 2.1. Similarly, a negative correlation is observed between univariate climate risk ($\mathrm{H}_{it}^{\mathbb{T}}$) and GDP growth ($y_{it}$). The correlation between country-specific climate risk ($\sigma_{it}^{\mathbb{T}}$) and GDP growth (y_{it}), as well as univariate climate risk ($\mathrm{H}_{it}^{\mathbb{T}}$), is statistically significant at the 5% level. In terms of carbon emissions ($\mathrm{CO2}_{it}$), it is clear that there has been an increase of 0.85 metric tonnes per capita on average per year between 1901 and 2020, with a standard deviation of 1.46 metric tonnes per capita.

The study revealed that there was a discernible pattern of temperature fluctuations, indicating a mean rise of 0.5°C over the period spanning from 1901 to 2020. Similarly, Alessandri and Mumtaz (2021) find that the volatility in temperature for different economic regions ranges from 0.1°C to 0.5°C. What seems to be surprising is the trend in country-specific and global temperature volatility for our sample. Our evidence suggests that the

Table **2.1:** Descriptive statistics and correlation matrices

Statistics	y_{it}	$\mathbb{T}_{it}$	$\sigma^{\mathbb{T}}_{it}$	$CO2_{it}$	$H^{\mathbb{T}}_{it}$	$\sigma^{\mathbb{T}}_{Ft}$
Mean	2.793	0.014	-2.234	0.827	0.541	-0.012
SD	2.317	0.287	0.221	0.647	0.284	0.106
Min	-6.740	-0.699	-2.430	-0.334	0.000	-0.199
Max	7.194	0.781	0.000	1.619	1.363	0.260

Correlations	y_{it}	$\mathbb{T}_{it}$	$\sigma^{\mathbb{T}}_{it}$	$CO2_{it}$	$H^{\mathbb{T}}_{it}$	$\sigma^{\mathbb{T}}_{Ft}$
y_{it}	1					
$\mathbb{T}_{it}$	0.007	1				
$\sigma^{\mathbb{T}}_{it}$	0.007	-0.003	1			
$CO2_{it}$	0.015	0.011	0.074***	1		
$H^{\mathbb{T}}_{it}$	-0.038**	0.005	0.324***	0.477***	1	
$\sigma^{\mathbb{T}}_{Ft}$	-0.044**	0.011	-0.007	-0.034**	-0.033**	1

Notes: This table presents descriptive statistics of the data used in the study. Descriptive statistics are mean, standard deviation (SD), minimum, maximum and Pearson correlations. This is for temperature changes in °C ($\mathbb{T}_{it}$), idiosyncratic country specific climate risk ($\sigma^{\mathbb{T}}_{it}$), global climate risk ($\sigma^{\mathbb{T}}_{Ft}$), country carbon emissions ($CO2_{it}$), and country annual real GDP growth (y_{it}). And also univariate climate risk ($H^{\mathbb{T}}_{it}$). Global and idiosyncratic climate risk are from equation (2A-4). Data period 1901 to 2020 for 30 countries. Asterisk ***, **, * denote 1%, 5% and 10% significance levels, respectively.

idiosyncratic (country-specific) and global (common) factor have time variation in volatility. This substantiates the benefit of our approach. There could be heterogeneity. However we have sought to accommodate that by splitting our sample of countries into advanced economies and emerging countries, based upon a demarcation from the World Bank.[17] We also argue that the Alessandri and Mumtaz (2021)'s approach used in estimating temperature volatility differs from ours. Since we decomposed the univariate climate risk into country-specific and global climate risks, our approach uses latent factors that make Σ_t appear sparser in order to overcome the dimensionality curse.

We have temperature change as our underlying measure of climate. Temperature changes more likely to have constant mean than temperature levels. Formally we test for whether the panel time series are non-stationary using panel unit root tests. In particular we use Levin et al. (2002) (LLC) and Im et al. (2003) (IPS) Panel Unit Root tests. Both LLC and IPS

[17] https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html

have a null hypothesis of panel unit root. These methods applied to temperature changes confirm they are I(0) stationary. The results in Table 3A-6 reject the null hypothesis for the panel time series temperature change ($\mathbb{T}_{it}$) that the data have a unit root, since the test statistic is much less than the critical value at the 1% statistical level. Panel unit root tests are employed to test whether the underlying temperature change data has panels containing a unit root. However, our finding suggests that there is no evidence of a unit root.

2.4.2 Climate Risk as Univariate Stochastic Volatility

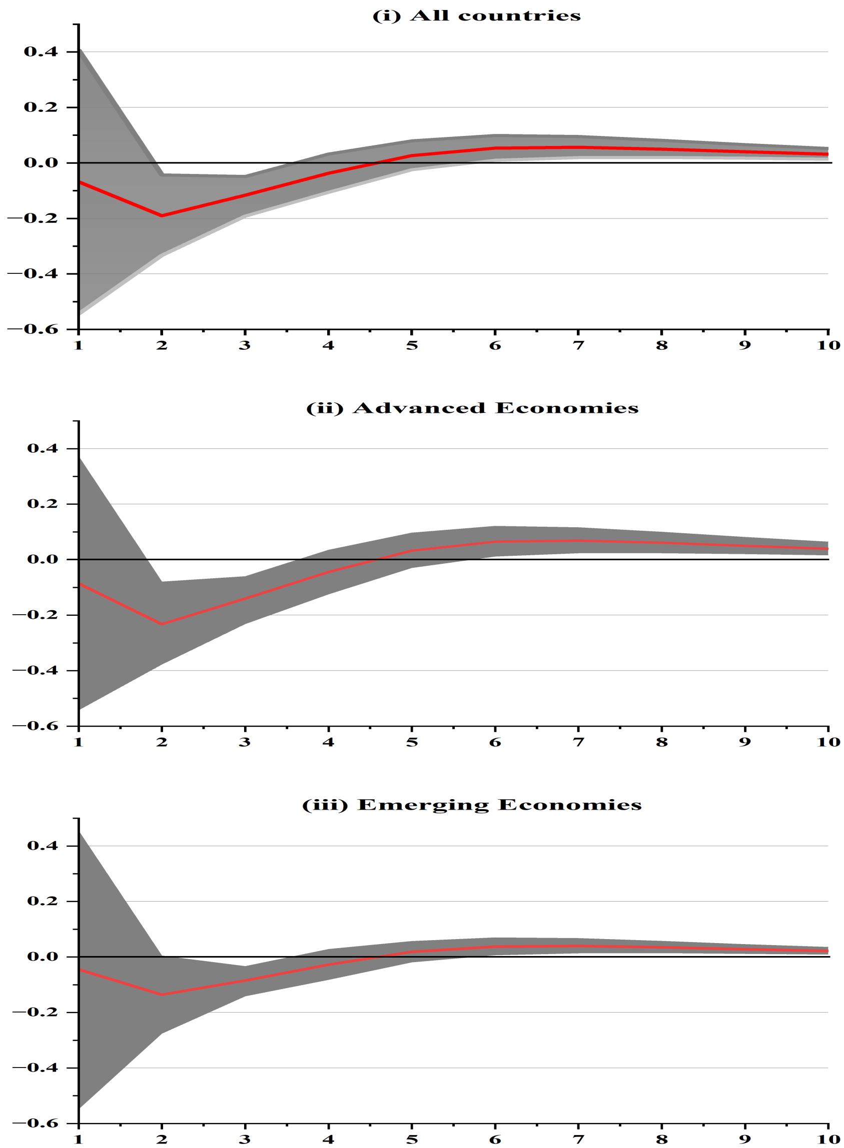
In this section, we present baseline empirical results of the relationship between climate risk and macroeconomic activity.[18] To set the scene, we begin by considering the impact of univariate country climate risk upon GDP growth using standard impulse response analysis. Climate risk based upon univariate stochastic volatility of temperature changes conflates both idiosyncratic and global climate risk. The impact upon GDP of a univariate climate variability shock are presented in Figure 2.3. We present three panels of impulse response functions based upon the estimated Panel VAR with univariate climate variability ($\mathrm{H}^{\mathbb{T}}_{it}$) and GDP growth ($y_{it}$).[19] We plot 10 year response horizons to these climate variability shocks for all 30 countries in our sample. This shall allow us to benchmark the effect of climate variability on macroeconomic activity in general. We see from Figure 2.3 that climate risk has an important and negative effect upon GDP. This is because the median posterior response in the top panel of Figure 2.3 of economic activity to a univariate climate risk shock for all countries is below zero and the response critical interval does not contain the zero axis.

We also present evidence that for both advanced and emerging economies, in the lower panels, climate variability also has a negative effect upon economic activity. After year six, there is a relatively small yet positive effect of univariate climate risk upon growth for all nations. Consistent with our findings, Donadelli et al. (2017) present evidence that univariate

[18]Further information on the parameters associated with model estimation are reported in Table 2A-5 in the Appendix.

[19]See Chapter 2 - Appendix A for the methodology underpinning $\mathrm{H}^{\mathbb{T}}_{it}$.

Figure **2.3:** Impact of univariate climate variability on GDP



Notes: This figure presents evidence of the impact of univariate climate variability on macroeconomic activity. A measure of risk based upon univariate stochastic volatility comprises idiosyncratic and global climate risk. Specifically the top panel is the impulse response function from a shock to temperature change (univariate stochastic) volatility ($\mathrm{H}^{\mathbb{T}}_{it}$) upon GDP growth ($y_{it}$) for all countries. Our sample of 30 advanced and emerging economies is between 1901 and 2020. We use a bivariate Panel VAR, PVAR($\mathrm{H}^{\mathbb{T}}_{it}$, y_{it}) to produce the impulse responses in this figure. The evidence suggests there is a negative impact from two years to four years. The shock is a one standard deviation increase in risk. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

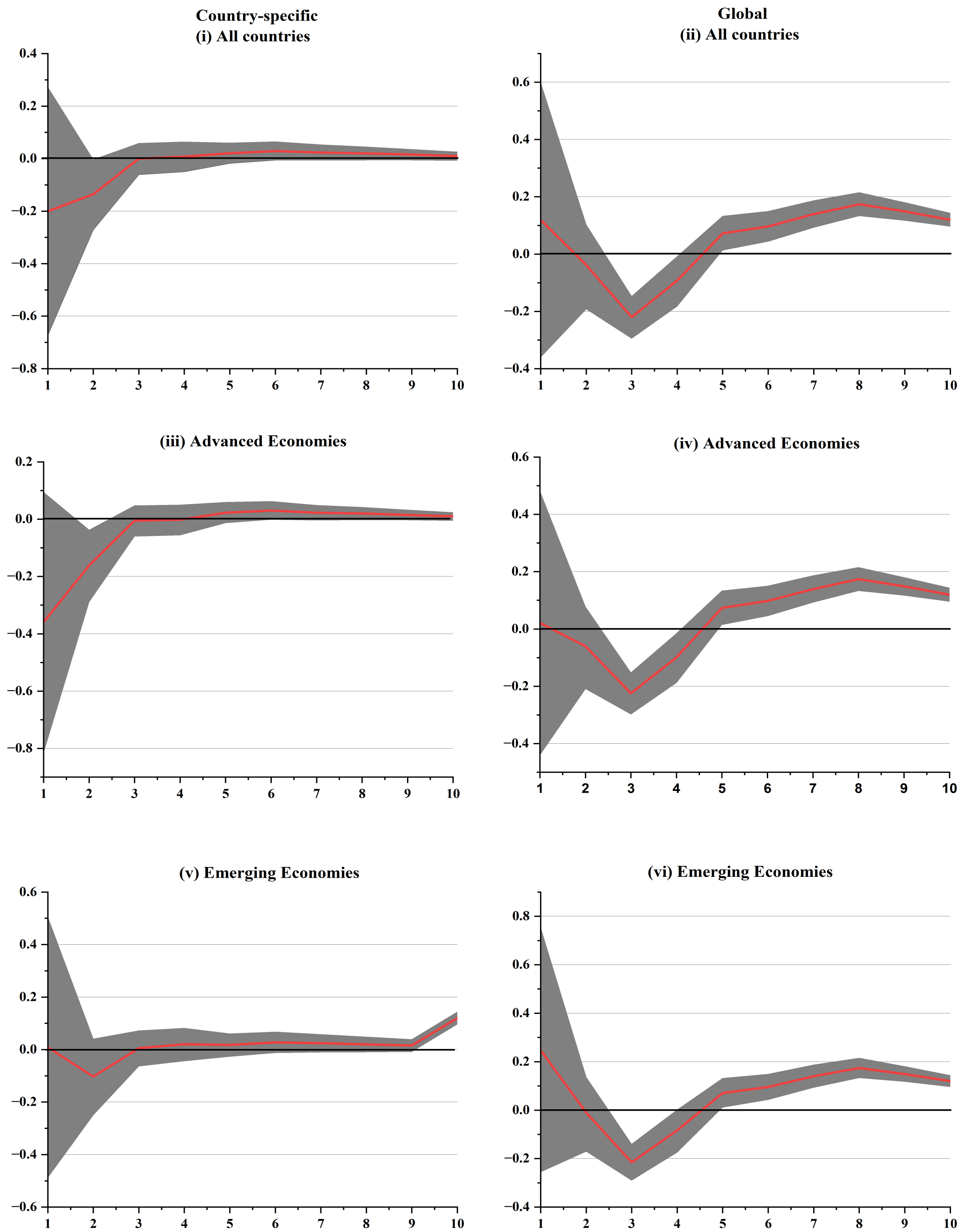
temperature variability has a negative relationship with real economic activities. That is, an increase in temperature variability is more likely to reduce overall economic activity through for example, lower labour productivity. Meanwhile, Kotz et al. (2021) document that due to seasonal differences and income levels, low-income countries are more susceptible to greater climate risks. In a separate study, Kotz et al. (2022) confirmed that advanced countries are also not spared of the economic impact of climate risk. Burke et al. (2015) confirmed in their study that temperature uncertainty has a negative impact on overall output and increases prices as a result of both supply-side and demand-side shocks. Donadelli et al. (2022) and Sheng et al. (2022) acknowledge that the impact of climate risks on macroeconomic activity is significant and negative.

2.4.3 Climate Risk and Factor Stochastic Volatility

Having considered the impact of univariate climate risk on GDP, we now look to our main results, which differentiate global and idiosyncratic climate risk. Figure 2.4 presents the core results of the impact of global and idiosyncratic climate risk on macroeconomic activity. We initially focus in Figure 2.4 on the impact of country specific risk ($\sigma_{it}^{\mathbb{T}}$) in panel (i) and global climate risk ($\sigma_{Ft}^{\mathbb{T}}$) in panel (ii), delineated by the factor stochastic volatility model for the full sample period. Evidence from the core results suggests that shocks to country-specific climate risk are relatively less important for macroeconomic activity. While the effect of idiosyncratic risk is generally negative, critical intervals are closer to zero indicating less evidence of a substantial impact. Global climate risk is a relatively more important determinant of macroeconomic activity. This is indicated by the larger negative GDP response to a global risk shock after year three. It takes several years for the full effect of a global climate risk shock to feed the way through GDP.

In the past few years, the cross-sectional and distributional ramifications of climate change have been debated. It has been argued that rising temperatures may only or largely affect impoverished countries that are heavily dependent on agriculture and have low capacity for

Figure **2.4:** Global and country specific climate risk impact upon GDP



Notes: This figure presents evidence of the impact of global and country specific climate risk on macroeconomic activity. Specifically the left column is the impulse response function from a shock to idiosyncratic country climate risk ($\sigma^{\mathbb{T}}_{it}$) upon GDP growth (y_{it}). The right column of panels are global climate risk ($\sigma^{\mathbb{T}}_{Ft}$) upon GDP growth (y_{it}). Our sample of 30 advanced and emerging economies between 1901 and 2020. We use a trivariate Panel VAR, PVAR($\sigma^{\mathbb{T}}_{it}$, $\sigma^{\mathbb{T}}_{Ft}$, y_{it}). The evidence suggests the impact on macroeconomic activity of a country specific climate risk shock is more rapid, negative and short-lived. The shock is a one standard deviation increase in risk. Global climate risk, on the other hand, is an important determinant of macroeconomic activity. A global climate risk shock could either impede or promote macroeconomic activity. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

response to climate change (Burke et al., 2015; Feng and Kao, 2021; Kiley, 2021; Kotz et al., 2022). In line with this argument, we split our sample into advanced and emerging countries to investigate the impact of climate risk on these distinct country groupings. The outcome for advanced and emerging economies depicted in Figure 2.4 as Panel (iii), (iv), (v) and (vi). The Figure 2.4 emphasizes that both advanced and emerging economies are more susceptible to global risk shocks, than to idiosyncratic climate shocks. This is a surprising result, since typically poorer countries are considered to be more likely to be effected by climate change. But our results would indicate that this distinction within our modeling context may have been over emphasized.

2.4.4 Robustness/Extension

Climate Risk Impact on GDP Per Capita

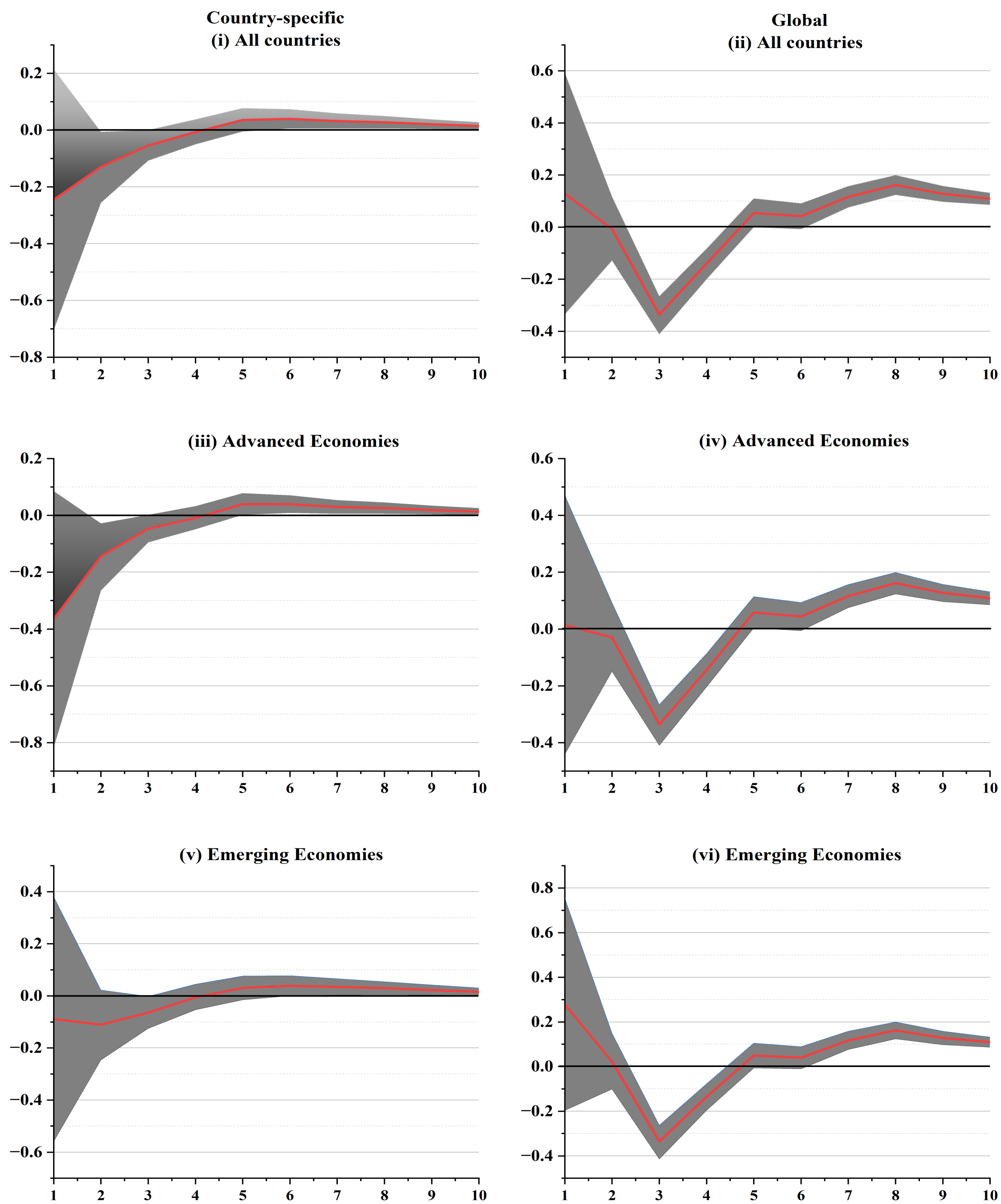
From a development standpoint, GDP per capita growth may be more interesting to capture macroeconomic activity, since it also has implications for average living standards. To understand the dynamics of shocks to country-specific climate risk, and the global climate risk from a development perspective, in the spirit of Dell et al. (2012) and Donadelli et al. (2017), we substitute GDP growth with GDP per capita growth in our baseline model. According to the findings in Figure 2.4, global climate risk is important for macroeconomic activity. The short run impact is rapid, sizable and negative. This findings is an indication of the robustness of our baseline model with GDP growth (as shown in Figure 2.5).

Climate Risk, Carbon Emissions and GDP Growth

Pindyck (2021) emphasises the importance of carbon emissions as the largest contributor to greenhouse gas emissions, which cause global warming in the long run by affecting atmospheric carbon concentration and influencing temperature through climate change. We examined aggregate outcomes directly in our baseline model, ignoring a priori assumptions about which mechanisms to include and how they might interact, operate, and combine.

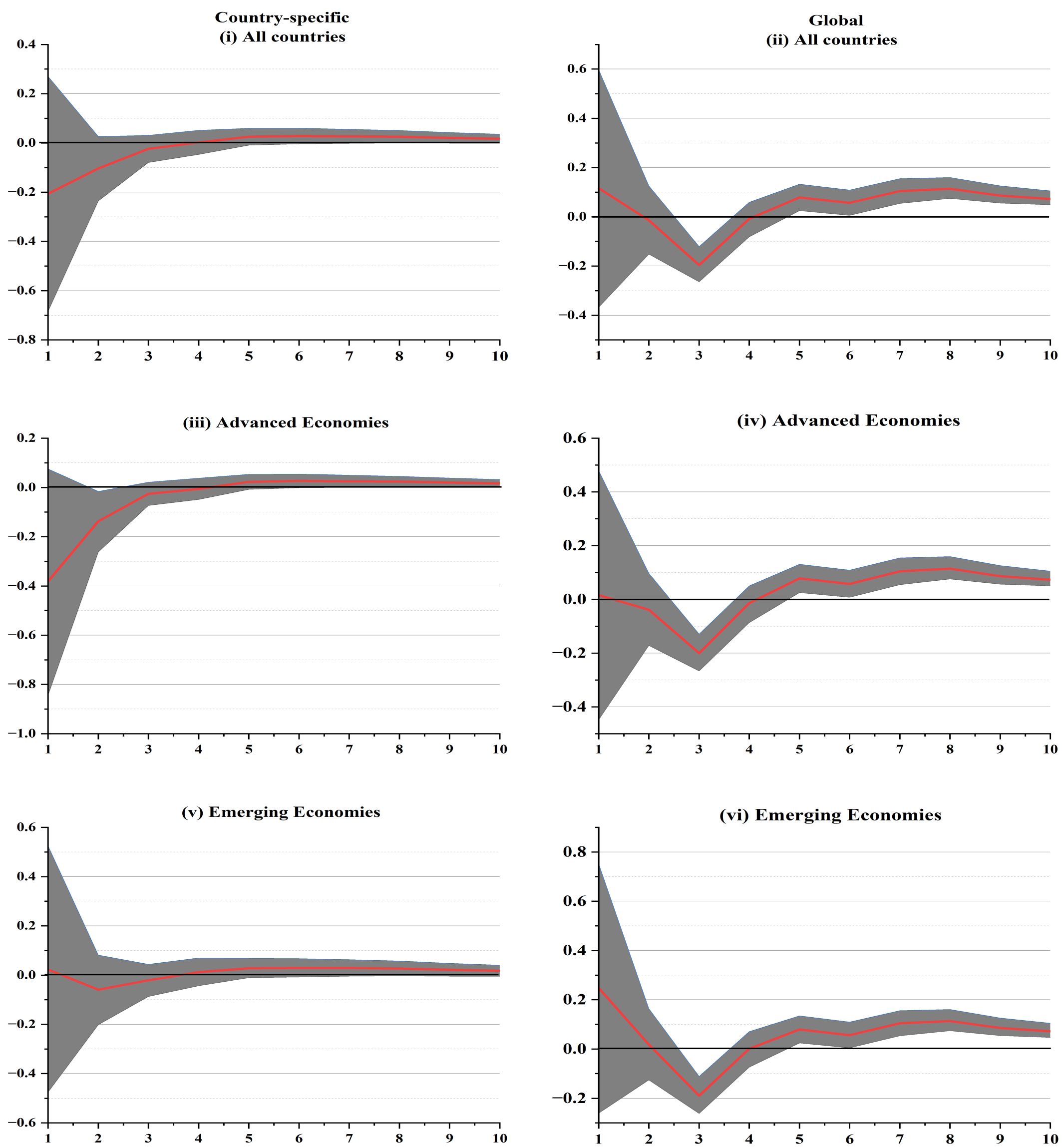
Figure **2.5:** Robustness/extension

Impact of Country-specific and Global Climate Risk on GDP per capita



Notes: This figure presents evidence of the impact of climate risk on macroeconomic activity. Our sample of 30 advanced and emerging economies between 1901 and 2020. We use a trivariate Panel VAR, PVAR($\sigma^{\mathbb{T}}_{it}$, $\sigma^{\mathbb{T}}_{Ft}$, ypc_{it}) for panel (i) and (ii). The evidence suggests the impact on GDP per capita of a climate risk shock is more rapid, negative and pronounced. Meanwhile, country specific shocks impact on GDP growth is not important. The shock is a one standard deviation increase in risk. Global climate risk, on the other hand, is an important determinant of macroeconomic activity. A global climate risk shock could impede and later promote macroeconomic activity. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

Figure **2.6:** Robustness/extension
Intervening Role of Carbon emissions



Notes: This figure presents evidence of the impact of climate risk on macroeconomic activity, taking into account the role of carbon emissions. Panel (iii) and (iv) use a four-variable Panel VAR, PVAR($\sigma^{\mathbb{T}}_{it}$, $\sigma^{\mathbb{T}}_{Ft}$, y_{it}, $\mathrm{CO2}_{it}$). The evidence suggests the impact on GDP of a climate risk shock is more rapid, negative and pronounced. Meanwhile, country specific shocks impact on GDP growth is relatively less important. The shock is a one standard deviation increase in risk. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

Furthermore, we used temperature fluctuations with the intention of isolating their effects from time-invariant country characteristics.

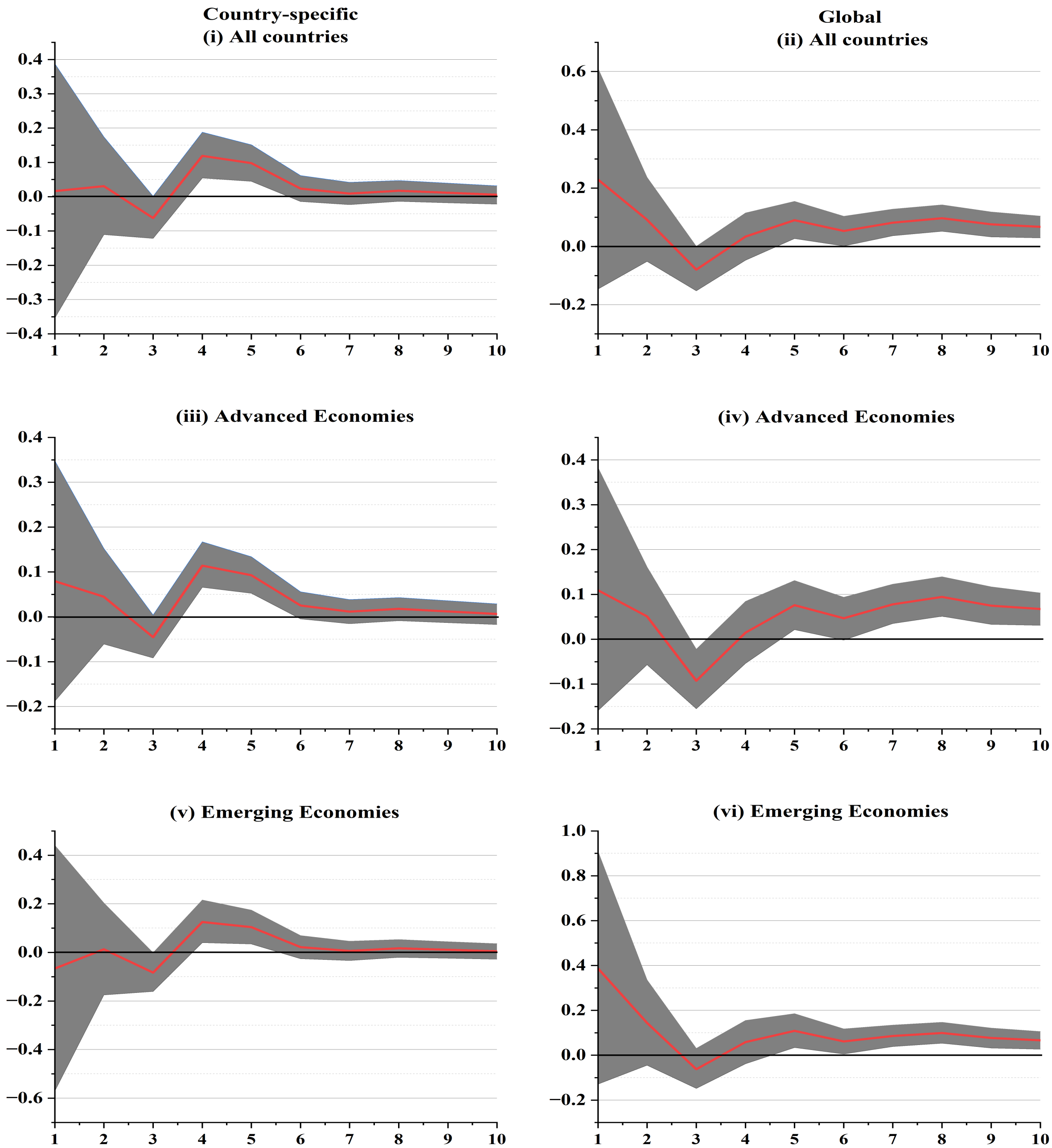
We expand our baseline model to include carbon emissions in order to better understand the mechanism or transmission channel between climate risk and macroeconomic activity, i.e., country-specific climate risk, global climate risk, and GDP growth. We discovered that the results of our baseline model do not differ from the results of the extended model with carbon emissions. Our findings suggest that country-specific climate risk are unimportant for macroeconomic activity, despite a negative impact in the two years following the shock. Global climate risk, on the other hand, is an important determinant of macroeconomic activity. In the initial phase of a global climate risk shock, macroeconomic activity may be hindered; however, macroeconomic activity is subsequently boosted, as shown in Figure 2.6.

It may be the case that climate change is a recent phenomenon and its impact is different in recent decades. We examined the exogenous impact therefore of country-specific and the global climate risks on GDP growth from 1950 to 2020 in a separate empirical model. To comprehend how climate risk has contributed to the overall macroeconomic activities of selected countries, we tend to focus on the post-war period. This sample is comparable to those from Alessandri and Mumtaz (2021) and Donadelli et al. (2022). Figure 2.7 illustrates the outcome for the post 1950 sample. We find stronger evidence that shocks to global climate risk have an initially negative impact on GDP, albeit for advanced economies at year 3 after the global risk shock. There is less evidence of an initially negative impact for emerging countries. There does seem to be overshooting of GDP after the fourth year as additional volatility is induced into GDP by the global climate risk shock, especially for idiosyncratic shocks.

Further Robustness

In this subsection we consider further robustness and extensions of our approach. These include using dynamic panel methods robust to endogeneity, controlling for temperature levels

Figure **2.7:** Country-specific and Global Climate risk/carbon emissions impact on GDP: post 1950



Notes: This figure presents evidence of the impact of climate risk on macroeconomic activity accounting for the transmission channel of carbon emissions. Specifically the left panel is the impulse response function from a shock to country climate risk ($\sigma_{it}^{\mathbb{T}}$) upon GDP growth (y_{it}). The right column of panels are country-specific climate risk ($\sigma_{it}^{\mathbb{T}}$) upon carbon emissions ($\mathrm{CO2}_{it}$). Our sample of 30 advanced and emerging economies between 1950 and 2020. We use a four-variable Panel VAR, PVAR($\sigma_{it}^{\mathbb{T}}$, $\sigma_{Ft}^{\mathbb{T}}$, y_{it}, $\mathrm{CO2}_{it}$). The evidence suggests that idiosyncratic climate shocks do not have a strong impact on GDP after 1950, although it is negative. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

Table **2.2:** Dynamic panel system GMM and robust estimations

	GMM M1	GMM M2	GMM M3	ROBUST M1	ROBUST M2	ROBUST M3
y_{it-1}	-0.02***	-0.02***	-0.02***	-0.02	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.05)	(0.05)	(0.04)
$\sigma^{\mathbb{T}}_{it}$	0.06***	0.06***	—	0.06	0.06	—
	(0.01)	(0.01)	—	(0.09)	(0.08)	—
$\sigma^{\mathbb{T}}_{Ft}$	-37.99***	—	-39.89***	-37.99**	—	-39.894**
	(1.64)	—	(1.35)	(16.84)	—	(15.50)
Constant	2.73***	3.16***	2.45***	2.73***	3.16***	2.45***
	(0.07)	(0.02)	(0.08)	(0.49)	(0.25)	(0.53)
Wald Chi^2	1107.82***	253.11***	888.81***	10.10**	1.89	9.05**
Instruments	436	436	435	436	436	435
AR(2)						
Z-stats.	0.13	0.18	0.15	0.09	0.14	0.12
P-value	0.89	0.86	0.88	0.92	0.89	0.91
Sargan Test						
Chi^2	118.33	118.41	118.44	—	—	—
P-value	1.00	1.00	1.00	—	—	—
Obs.	3480	3480	3480	3480	3480	3480

Notes: This table presents dynamic panel data estimation with the two-step system generalised method of moment (GMM) (Blundell and Bond (1998)) and Windmeijer (2005) Robust (ROBUST) standard errors techniques. Idiosyncratic climate risk ($\sigma^{\mathbb{T}}_{it}$), global climate risk ($\sigma^{\mathbb{T}}_{Ft}$), and country annual real GDP growth (y_{it}). Data period 1901 to 2020 for 30 countries. Asterisk ***, ** and * denote 1%, 5% and 10% significance levels, respectively. Standard errors are in parentheses. M1 represent the model [y_{it} = F(y_{it-1}, $\sigma^{\mathbb{T}}_{Ft}$, $\sigma^{\mathbb{T}}_{it}$)], M2 represent the model [y_{it} = F(y_{it-1}, $\sigma^{\mathbb{T}}_{it}$)], and M3 represent the model [y_{it} = F(y_{it-1},$\sigma^{\mathbb{T}}_{Ft}$)]. The Z-statistics for the AR(2) model represents the Sargan test for over-identifying restrictions. H0: The over-identifying restrictions are valid. Wald Chi^2 assess the validity of the instruments employed in the estimation. The null hypothesis for the Wald chi-squared test is that the instruments are valid, meaning they are uncorrelated with the error term and meet the necessary assumptions.

and alternative identification of shocks. To account for endogeneity and whether our evidence is contingent upon specific empirical methods we can generalise our results by using Generalised Methods of Moments (GMM) estimation from Blundell and Bond (1998), Blundell et al. (2001), Blundell and Bond (2000) and Windmeijer (2005). Also whilst Bai and Ng (2006, 2008b) and Bai and Ng (2008a) show in linear models that the factor estimates can be treated as known if $\sqrt{T}/N \to 0$, as in our case, there may be a question whether generated regressors drive our results. We go with the grain of Pagan (1984) and use GMM to circumnavigate this potential issue to obtain consistent estimates of the relationship between climate risk and macroeconomic activity. We find evidence of a stronger and more deleterious impact upon macroeconomic activity from the global climate risk factor, relative to idiosyncratic results, using dynamic panel systems GMM, including with robust standard errors. These results are provided in Tables 2.2 and 2B-1 in the Appendix 6.3. Finally, we re-ordered the variables in a benchmark VAR with GDP, idiosyncratic and global climate risk to examine whether benchmark results from impulse responses were order invariant. We found evidence that our impulse responses were not sensitive to the ordering of the variables in the VAR.[20]

2.5 Conclusion

In this chapter, we examined the impact of climate risk on macroeconomic activity for thirty countries using over a century of panel time series data. Climate change may have an important global dimension, and there may be an important dimension in the second moment of climate change. Our methods sought to consider this. The key innovation of our chapter was to use a factor stochastic volatility approach to decompose climate change into global and country-specific climate risk and to consider their distinct impacts upon macroeconomic activity. This allows us to differentiate the importance for economic activity of common and idiosyncratic components of climate change.

To allow for country heterogeneity, we also differentiated the impact of climate risk upon advanced and emerging economies. While the existing literature has focused on country based climate risk shocks, our results suggest idiosyncratic or country-specific climate risk shocks are relatively unimportant. Global climate risk, on the other hand, has a negative and relatively more important impact on macroeconomic activity. Since the impact of global climate risk on macroeconomic activity is empirically identified as negative. It is important

[20]In additional analysis, we considered a comparison of the full sample and subsamples. While we did not formally test for structural breaks, we found evidence that the global risk factor consistently had a negative and important (i.e., statistically significant) impact on GDP, relative to the idiosyncratic. Hence, this analysis is based upon the entire sample of results which benefits from the full time span of the extended dataset and the power of the panel.

to investigate how the transition to green economic activities is more likely to lead to positive gains in macroeconomic activity. Therefore, in the next chapter we investigate the economic consequences of green growth in a multi-country empirical study.

Chapter 3

The Economic Consequences of Green Growth: A Multi-Country Empirical Study

3.1 Introduction

Policymakers in many countries are increasingly promoting green growth, since it provides environmental services and protects natural resources. This is highlighted by the multi-country Paris Agreement of 2015, which committed signatories to a legally binding international treaty on climate change. Adaptation of economic activity and generating green growth is key to limiting climate change and combating environmental degradation.[1] Whether encouraging green economic activity has a beneficial impact on economic growth more generally is controversial. Green growth potentially boosts economic activity through investment and innovation in production.[2] Green growth promotes natural capital conservation and creates opportunities in employment and trade, which also adds to growth.[3] On the other hand, investment in adaptation and green technology will have an opportunity cost. How to balance environmentally friendly development to achieve Sustainable Development Goals (SDGs) is a matter of debate. Our research revisits the link between green growth and economic growth more generally.

This chapter makes three important practical contributions to the literature on green growth. Firstly, we use a recently developed measure of green growth from Sarkodie et al. (2023) to assess the important of whether going for green growth is beneficial for economic activity in general. This novel measure of green growth has several advantages. It is comprehensive and consistent in its country coverage. It is also broad in coverage and exploits information along five environmental dimensions. These include environmental policy responses, environmental productivity, socio-economic opportunities, the natural asset base, and quality of life. In more detail, the green growth index is comprised of approximately 152 environmental and growth-induced indicators sourced from the OECD database. We seek to build upon existing research on green growth and sustainable development. Prior

[1]See Stern et al. (1996), Tol (2009b) and Nordhaus (2019b).

[2]Bohensky et al. (2011), Griggs et al. (2013), Pretty (2013), Potts et al. (2016).

[3]See Wackernagel and Rees (1997), OECD (2011, 2017), World Bank (2012), Swainson and Mahanty (2018) and Ofori et al. (2023).

research focused on a more narrow measure of green growth (Zhao et al., 2022b; Zhou et al., 2022). Lin and Zhu (2019b) developed a comprehensive index of the green economy and utilised a method that uses non-radial direction distance function to assess the growth of the green economy. Nevertheless, these indices may miss relevant dimensions of green growth, such as environmental policy responses and productivity. It can be argued that a worthwhile green growth index ought to fully capture a diverse range of environmental factors (Liu et al., 2015, 2018; Swain and Ranganathan, 2021). In addition, a green growth index should evolve with changes in environmental, economic, and social dynamics (Capasso et al., 2019). We contend that the transition from brown to green growth requires deliberate, diverse measures informed by economic resources, political decisions, socio-economic capacities, and environmental results. Intuitively, we describe green growth as a sustainable economic development strategy that is independent of adverse environmental impacts, while promoting eco-technological efficiency, alleviating poverty, and enhancing social inclusion. The green growth index developed by Sarkodie et al. (2023) encompasses these critical parameters. In contrast to the conventional approaches for creating indices, they utilise an innovative summary index strategy employing a generalised least squares attributed-standardized-weighted index that accounts for strongly correlated variables and missing data.

Our chapter's second contribution is to employ recent developments in panel econometrics, empirical methods little used in the green growth literature. In doing so we account for cross-country heterogeneity, cross-country spillovers and potential endogeneity. We utilise panel econometric estimators that are robust to cross-sectional dependence and dynamic linkages.[4] Spillovers and common shocks are accounted for in particular by the Dynamic Common Correlated Effects (DCCE) estimators initiated by Pesaran (2006). This approach is robust to common shocks like global crises and pandemics, potentially offering insights into the effects of our green growth measure on economic activity.[5]

[4] See Pesaran (2006), Chudik et al. (2013) Chudik and Pesaran (2015) and Ditzen (2022).

[5] Illustrative examples of research using the Dynamic Common Correlated Effects estimator include Eberhardt and Teal (2011), Pesaran and Tosetti (2011), Vos and Everaert (2021) and Ditzen (2022).

Our third contribution is related to our theoretical framework, built upon a three-input Cobb-Douglas production function, which is sufficiently flexible for a range of measures typically considered to be important for the economy-environment nexus. Our goal is to understand the conditions or mechanisms by which green growth indicators may impact economic growth from an empirical standpoint.[6] There remains a notable gap in understanding the relationship between green growth indicators and GDP growth, as well as the effectiveness of these indicators in reducing environmental degradation and improving economic and social circumstances; see Adedoyin et al. (2020), Awan et al. (2021), Wang et al. (2023a) and Wang et al. (2023b).

We now provide a summary of key results. Our empirical study finds that green growth significantly contributes to driving economic growth. The relationship between green growth and GDP growth is conditioned upon physical capital investment, urbanisation, human capital, and green technologies. Our evidence indicates that the indicator of green growth are more strongly associated with the growth of gross domestic product (GDP) in only advanced economies. This study is in five sections: section one introduces the context of green indicators and GDP growth; section two briefly discussess thees the existing literature on the subject matter; section three highlights the empirical methods used; section four discusses the empirical results; and section five concludes the study.

3.2 Literature Review

The debate on the relationship between development and the environment has recently intensified. A consensus has emerged that environmental pollution and climate change have the potential to severely harm the environment and sustainable development; see Crist et al. (2017) and Ruggerio (2021). There is less of a consensus on the exact nature and extent of the potential tension between economic development and environmental protection. One po-

[6] Similarly, Omri and Belaïd (2021) employed a Cobb-Douglas production function to examine the impact of renewable energy on socio-economic well-being, taking account of environmental factors.

tential policy approach is for countries to engage in green growth, which seeks to protect the environmental and also promote growth in general (Bohensky et al., 2011; Griggs et al., 2013; Pretty, 2013; Potts et al., 2016). Despite green growth policies being beneficial, quantifying their statistical impact on jobs and socio-economic opportunities remains challenging (see, for example Hammer et al., 2011; Shao et al., 2020). Slower innovation prompts increased government investment in research and development (Allen, 2011; Anderson et al., 2014; OECD, 2017). However, funding for environmental and energy-related goals has remained stagnant, accompanied by a shift towards renewable sources (De Coninck and Bäckstrand, 2011). To effectively align with environmental objectives, there is a need for long-term incentives due to the global deceleration in environmental technology innovation (Acemoglu et al., 2012; O'Neill et al., 2017; Naylor et al., 2021).

Grossman and Krueger (1991) argues that the rate of technological advancement determines how much of an impact economic growth has on environmental quality. Technological advancements spur the creation of environmentally friendly production methods, which increase clean productivity; see also Schmalensee (2012) and Hao et al. (2023). Because natural capital, which includes the environment, is an input to the production function, environmental conservation could lead to increased use of natural capital and, therefore, increased income; see Hinterberger et al. (1997), Wackernagel and Rees (1997) and Hallegatte et al. (2012). Market failures, such as external costs and poorly defined property rights, are prevalent in the utilisation of environmental resources; addressing these failures can increase the effective supply of natural capital and thus output. It can also increase the welfare of people directly through improvements in air and water quality, which may not be captured by standard GDP statistics but is nonetheless an important goal of economic policy (Jaffe et al., 2005; Hallegatte et al., 2012). Without necessarily slowing the processes down, green growth involves making growth processes more resource-efficient, cleaner, and more resilient; see Hallegatte et al. (2012), Schmalensee (2012), Hickel and Kallis (2020), and Hao et al. (2023). Green innovation is a crucial strategy for promoting harmony between humans and the natural world, focusing on six pursuits: products, processes, market orientation, ecological considerations, material flow reduction, and motivating factors and enhanced business standards. It is expected to be a key factor in future economic growth, utilizing green technologies to conserve energy, prevent pollution, recycle waste, and create environmentally friendly products (Chen et al., 2006; Luo et al., 2022).[7]

From a different perspective, Hickel and Kallis (2020) argue that complete decoupling from carbon emissions is extremely unlikely to be achieved at a rate fast enough to keep global warming from exceeding 1.5°C or 2°C, even under positive policy conditions. Moreover, there is no direct evidence that unconditional decoupling from resource use can be achieved on a global scale against the backdrop of continued economic growth. Jaffe et al. (2005) stressed that in the event of inadequate or ineffective environmental policies, it is highly probable that investments in the creation and adoption of new environmentally friendly technologies will be significantly less than what would be deemed socially acceptable. Information issues and beneficial knowledge, as well as adoption spillovers, have the potential to further erode innovation's incentives. Meanwhile, Du et al. (2021) emphasised that environmental regulation will substantially encourage the development of green technologies and the improvement of industrial structures when economic development levels are typically high. Consequently, environmental regulation can contribute to the greening of the economy in two ways: the development of new environmentally friendly technologies and the improvement of industrial structures. Capasso et al. (2019) in an earlier study document that green growth necessitates expertise in managing intricate scenarios, steering technological advancements towards more environmentally friendly technologies, evaluating imperfections in the market, structural systems, and transformative systems, and prioritising green growth procedures across various levels.

The extant literature presents empirical evidence that substantiates the idea that green

[7] Schiederig et al. (2012) explored the literature on green innovation and innovation management. The authors propose that the terms environmental, ecological, and green innovation are all being used interchangeably.

growth policy can stimulate economic growth.[8] Nevertheless, it is crucial to acknowledge that the relationship between green growth and GDP growth is complex and can differ based on various factors, including the specific measures chosen to assess green growth, the country's level of economic growth, and the policy framework in place (Omri and Belaïd, 2021). In their study, Omri and Belaïd (2021) discovered that green growth exerts a favourable and substantial influence on the growth of gross domestic product (GDP). The study additionally discovered that the impact of green growth on GDP growth is more pronounced in nations with elevated levels of economic development. Other studies have also discovered a positive and significant relationship between green growth and economic growth.[9] However, these studies indicate that countries with more stringent environmental regulations, greater technological innovation, and a higher level of environmental awareness tend to experience a more pronounced effect.

Empirical studies in this field use a variety of econometric methods. In particular, Adedoyin et al. (2020) applied the fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS), and canonical cointegration regression (CCR) in a time series study of the United States for the period 1981 to 2017. Omri and Belaïd (2021) utilised the system GMM to understand the role of renewable energy consumption as a mechanism in driving environmental impact on socio-economic welfare with a sample of 31 transition and developing economies. Wang et al. (2023a) studied how green policy with respect to China's city pilot policy affects labour productivity and overall growth by using the difference-in-difference (D-I-D) method for samples spanning 2006 and 2016. Wang et al. (2023b) also used the moment of method quantile regression (MMQR) method to assess the long-run relationship between green finances, taxes, and carbon emissions for OECD countries from 1990 to 2020.

[8] see Adedoyin et al. (2020), Awan et al. (2021), Omri and Belaïd (2021), Wang et al. (2023a) and Wang et al. (2023b).

[9] see also Adedoyin et al. (2020), Awan et al. (2021), Zhou et al. (2022), Wang et al. (2023a), and Wang et al. (2023b).

The existing studies diverge in relation to the use of indicators to represent green growth. For instance, Zhou et al. (2022) investigates the influence of financial technology (fintech) and environmentally-friendly finance (green finance) on the promotion of sustainable economic growth in China's regional economy. The approach involved compiling an extensive green economic growth index by utilising China's provincial panel data spanning 2011 to 2018. Zhou et al. (2022) used twelve indicators to construct the green growth index. The findings indicate that the utilisation of fintech and the implementation of green finance have a substantial positive impact on the advancement of environmentally sustainable economic growth. It is worth noting that this effect varies across different regions. Stronger impact was observed for the eastern part of China than the central and western part of China. Fintech innovation primarily drives sustainable economic growth by facilitating green credit and investment, thereby enhancing the maturity of green finance. Meanwhile, Lin and Zhu (2019b) examined the link between government expenditure and environmentally sustainable economic growth in 282 cities at the prefecture level, spanning the years 2005 to 2016. The study develops a green economic growth index by employing a non-radial direction distance function with six variables. It then assesses the impact of fiscal education and R&D spending on green economic growth. The study reveals that the green economic growth index experiences fluctuations as a result of local government politics. Additionally, investment in research and development (R&D) and education contributes to the promotion of green economic growth by fostering technological advancements and enhancing human capital.

The green growth indicators are crucial for monitoring and evaluating the current state of the green growth model. Due to varying interpretations of the concept of green growth, researchers employ diverse approaches to develop green growth indices. Nevertheless, these indices fail to accurately depict the actuality of the situation. To effectively study the influence of green growth indicators on GDP growth, it is necessary to employ a more intricate measure to fully grasp this phenomenon and perhaps reduce the dimensionality of the index.

3.3 Modelling Strategy

3.3.1 Theoretical Motivation

We motivate our empirical model using a Cobb-Douglas production function with three inputs; see Mankiw et al. (1992), Durlauf et al. (2005), Hassler and Krusell (2018) and De Visscher et al. (2020). In our model, economic activity (Y_{it}) for country i at time t is determined by the following inputs: labour, L_{it}, physical capital, K_{it}, and other determinants of economic activity, X_{it}. In general terms, this three input production function can be written in the basic functional form as follows:

$$Y_{it} = f(L_{it}, K_{it}, X_{it}) \tag{3.1}$$

The Cobb-Douglas production function gives a specific functional form of economic activity. Taking account of (constant) total factor productivity (A_{0i}) for country i and a stochastic error term ($e^{\epsilon_{it}}$), economic activity becomes:

$$Y_{it} = A_{0i} L_{it}^{\alpha_{1i}} K_{it}^{\alpha_{2i}} X_{it}^{\alpha_{3i}} e^{\epsilon_{it}} \tag{3.2}$$

This relationship includes heterogeneous country elasticities, α_{1i}, α_{2i} and α_{3i}. Each country may combine inputs; labour, capital and other factors to produce outputs in different ways. To re-express this production function as a heterogeneous growth equation with three inputs, we take the log first difference of both sides of equation (3.2) parameters, and we have:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta l_{it} + \alpha_{2i}\Delta k_{it} + \alpha_{3i}\Delta x_{it} + \varepsilon_{it} \tag{3.3}$$

In this equation, the growth rate of GDP (Δy_{it}) is the function of growth rate of labour (Δl_{it}), growth of capital (Δk_{it}), and the growth rate of other potential environmental determinants of economic growth (Δx_{it}). Here ε_{it} is a stationary stochastic error term which comprises measurement error, time-varying total factor productivity, and potentially common cross-country factors beyond those accounted for by the fixed effects α_{0i}. Such a common factor model, more formally could be written as follows:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta l_{it} + \alpha_{2i}\Delta k_{it} + \alpha_{3i}\Delta x_{it} + \gamma_i F_t + u_{it} \tag{3.4}$$

Equation (3.4) accounts for common factors F_t such that in equation (3.3) $\varepsilon_{it} = \gamma_i F_t + u_{it}$. These common factors include global environmental factors, which impact different countries heterogeneously through factor loading γ_i.

When empirically modeling environmental determinants of economic activity, we take two approaches. Our first approach is more parsimonious and focuses on a single summary statistic of environmental activity. Our single measure is our green growth indicator (Δg_{it}) from Sarkodie et al. (2023), which we use to replace Δx_{it} in equation (3.4). This broad-based country-specific indicator of environmental activity potentially spans the full gambit of relevant environmental activity. Consequently, our central empirical model of the relationship between green growth and economic growth, which accounts for cross-country heterogeneity and spillovers, becomes:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta l_{it} + \alpha_{2i}\Delta k_{it} + \alpha_{3i}\Delta g_{it} + \gamma_i F_t + u_{it} \tag{3.5}$$

Secondly, we estimate an extended empirical approach, with key environmental drivers highlighted by the environmental literature. Doing so will give us a better sense of whether our parsimonious model is robust to alternative measures of environmental activity. Thus, our extended approach includes being guided by, for example, the environmental model known as the Integrated Population, Affluence and Technology (IPAT) approach from York et al. (2003) and Wei (2011). In this model, urbanisation impacts economic growth, transforms rural populations, and causes infrastructural strains, inequality, and environmental concerns (Sit and Yang, 1997; Li et al., 2019). In addition, industrialisation increases energy consumption, income levels and foreign direct investment, while increasing emissions of CO2 and other greenhouse gases; see Sadorsky (2013), Aller et al. (2021), Singhania and Saini (2021), and Fang et al. (2022). Consequently, greenhouse gas emissions are typically considered to cause global warming, which leads to climate change (Ivanovski and Churchill, 2020). Climate change adaptation requires a shift towards green growth, influenced by economic resources, socio-economic abilities, political decisions, and environmental concerns; see Brown (2000), Pretty (2013), Ofori et al. (2023), Sarkodie et al. (2023), among many others. Our extended environmental growth regression therefore includes population, technology, emissions and FDI. Thus, the determinants of economic growth overall in the more general specification becomes:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta l_{it} + \alpha_{2i}\Delta k_{it} + \alpha_{3i}\Delta g_{it} + \alpha_{4i}\Delta p_{it} + \alpha_{5i}\Delta \tau_{it} + \alpha_{6i}\Delta e_{it} + \alpha_{7i}\Delta fdi_{it} + u_{it} \quad (3.6)$$

Here, the country-specific growth rate of the urban population is denoted by Δp_{it}. The growth rate of environmentally friendly technologies is $\Delta \tau_{it}$. Greenhouse gas emissions are Δe_{it}. Finally, the growth rate of foreign direct investment is Δfdi_{it}. Also in equation (3.6), heterogeneous country specific parameters are α_{1i} to α_{7i}.

To account for the dynamic nature of economies and the crucial role of knowledge and skills in driving economic productivity, we substitute labour (Δl_{it}) with human capital (Δhc_{it}). This substitution incorporates human capital into a Cobb-Douglas production function as well as extended environmental regression (Becker et al., 1990; Romer, 1990; Lööf and Heshmati, 2002; Mehra et al., 2014). The model is adjusted to match the features of contemporary economies and offers a more comprehensive framework for examining economic growth and development. Typically measures of labour input does not take into consideration variations in worker quality or skill levels; see Hanushek and Kimko (2000), Krusell et al. (2000) and Katiraee et al. (2021). The labour input variable with a measure of human capital enables a more sophisticated evaluation of the workforce, considering factors such as experience, expertise, and specialisation; see also Teixeira and Queirós (2016).

3.3.2 Econometric Methods

This section sets out the econometric methods used in this chapter. We seek to estimate equation (3.3) as a growth regression to examine the importance of green growth indicators for economic activity. This model assumes parameter homogeneity and cross-section independence of stochastic error. Temple (1999) emphasizes several econometric challenges for growth regressions. These include parameter heterogeneity, spillovers, and endogeneity. We seek to account for these in what follows. Firstly, we test for country homogeneity in the

α_{0i}, α_{1i} to α_{3i} parameters in equation (3.3). Our homogeneity test is from Pesaran and Yamagata (2008) against the alternate hypothesis that all the slope coefficients are heterogeneous. Secondly, whether the cross-sectional error terms ε_{it} in equation (3.3) are independent, i.e., $cor(\varepsilon_{it}, \varepsilon_{jt} \neq 0), \forall i \neq j$, we can reject the assumption that there is no evidence of cross-sectional dependence. Panel estimators normally assume cross-sectional independence.

Panel Cross Sectional Dependency Test

If cross-sectional errors are not independent, and when cross-sectional unit interdependence is ignored, the error term in a regression exhibits cross-sectional dependence. The correlation between units violates the fundamental OLS assumption that the error term is independent and identically distributed (see Chudik and Pesaran, 2013, 2015). Cross-sectional dependence in the error term can lead to omitted variable bias or endogeneity, resulting in estimation inconsistencies; see also Pesaran (2015). Cross-sectional dependence can be calculated using the correlation between units. For example, unit i and unit j errors can be correlated. If the correlation is high, cross-sectional dependence is evident. The test for cross-sectional dependence identifies panel variables or residuals with weak cross-sectional dependence. We conducted this important test using the cross-sectional dependency (CD) from Pesaran (2015, 2021).

According to Ditzen (2021), the magnitude of common factors can be quantified by a constant ranging from 0 to 1, known as the exponent of cross-sectional dependence. Chudik et al. (2011) categorise CD into four types based on its limiting behaviour: strong ($\alpha = 1$), semi-strong ($0.5 \leq \alpha < 1$), weak ($\alpha = 0$), and semi-weak ($0 < \alpha < 0.5$) cross-sectional dependency. Semi-weak cross-sectional dependence can be defined as follows: even when the number of cross-sectional units increases indefinitely, the combined impact of the common factors remains constant. Owing to strong cross-sectional dependence, the cumulative impact of the common factors intensifies as the number of cross-sectional units increases.

Panel Slope Heterogeneity

We also seek to account for parameter heterogeneity in our empirical modelling. Pesaran and Yamagata (2008) proposed the test for slope heterogeneity, which standardises Swamey's test for slope homogeneity under the assumption that all slope coefficients across cross-sectional units are identical. However, if the homogeneous assumption is present in the proposed model, the test for slope heterogeneity appears to be reliable but may produce inefficient estimates. In contrast, if the proposed model contains slope heterogeneity, the homogeneous assumption may also result in biased and inconsistent estimates. In this context, the test for slope heterogeneity performs plausible and implicit estimates for the two hypotheses and compares them to determine the best option. Given that the unrestricted model relies on a cross-sectional unit-specific OLS regression model, i.e., the model under the alternative assumption, and the restricted model relies on a weighted fixed effects method, which supports the homogeneous slopes. The test is predicated on the disparity between the two models. Large values of the test statistic indicate an inconsistency between estimations of fixed effects and estimates of unit-specific effects; thus, the null hypothesis of slope homogeneity can be rejected.

Common Correlated Effects

Following Chudik et al. (2013) and Ditzen (2021), we formulate the dynamic panel model with heterogeneous coefficients below:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta y_{it-1} + \alpha_{2i}\Delta z_{it} + \sum_{l=0}^{p_T} \gamma_{il}^{'} F_{t-l} + \epsilon_{it} \tag{3.7}$$

where α_{0i} represents country-specific fixed effects, α_{1i} and α_{2i} are the country-specific parameter coefficients to be estimated, and $\Delta z_{it} = (\Delta l_{it}, \Delta k_{it}, \Delta g_{it}, \Delta p_{it}, \Delta \tau_{it}, \Delta e_{it}, \Delta fdi_{it})$ is growth rates in labour, physical capital, green growth, urbanisation, green technologies, greenhouse gas emissions, and foreign direct investment, whereas Δy_{it} is GDP growth. $\sum_{l=0}^{p_T} \gamma_{il}^{'} F_{t-l}$ are the common correlated effects captured by incorporating cross-section averages to address the influence of common factors.

The omission of the common factor from equation (3.7) results in an omitted variable bias, which in turn causes ordinary least squares estimation to become inconsistent, see Everaert and De Groote (2016). Pesaran (2006) and Chudik and Pesaran (2015) have put forth a proposed estimator that aims to consistently estimate equation (3.7) by employing cross-sectional averages as an approximation for the common factors. The cross-sectional averages are augmented with a lagged floor of $\sqrt[l]{T}$ in a dynamic model. The model is written as:

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i}\Delta y_{it-1} + \alpha_{2i}\Delta z_{it} + \sum_{l=0}^{p_T} \gamma_{il}' \overline{\mathcal{Z}}_{t-l} + \epsilon_{it} \tag{3.8}$$

Where $\sum_{l=0}^{p_T} \gamma_{il}' \overline{\mathcal{Z}}_{t-l}$ estimates $\sum_{l=0}^{p_T} \gamma_{il}' F_{t-l}$ in equation (3.7). The variables $\overline{\mathcal{Z}}_{t-l}$ represent the cross-sectional averages of both the dependent and independent variables. The estimated coefficients of the cross-sectional averages, denoted as γ_{il}', are commonly regarded as nuisance parameters. The model can be fitted using either a mean-group estimator, as proposed by Pesaran and Smith (1995), Pesaran (2006), and Chudik and Pesaran (2019), or a pooled estimator, as suggested by Pesaran (2006) and Juodis et al. (2021). The estimator in question is commonly referred to as the common-correlated effects mean-group (CCE-MG) estimator.

The CCE-MG estimator is capable of capturing unobserved heterogeneity and dynamic relationships, thereby offering enhanced predictive capabilities in comparison to more basic panel data models; see Churchill et al. (2018). These estimators integrate data from both cross-sectional and time-series dimensions, thereby enhancing the precision and reliability of parameter estimates. This approach proves to be particularly beneficial when working with small sample sizes (Eberhardt and Teal, 2011). The (dynamic) common correlated effect (D-CCE) estimators offer a unique approach that incorporates elements from both approaches. D-CCE models are designed to represent time-varying common factors and individual-specific effects in a dynamic panel data context; see Chudik et al. (2013) and Ditzen (2021). They provide a flexible framework for modelling cross-sectional dependence that changes over time (Chudik and Pesaran, 2015). Therefore, they are likely to provide valid and reliable estimations over the static and dynamic fixed effects estimators.[10]

We assume that investments in physical capital and economic growth are endogenous. This suggests that countries with a high GDP per capita have the ability to save a greater amount of money and consequently amass a larger amount of capital. This results in a situation where investments in physical capital and the level of GDP have a reversed causality. For further information, refer to the works of Temple (1999) and Durlauf and Aghion (2005). As proposed by Temple (1999), it is possible to use the lags of the endogenous variable as an instrument. To prevent a decrease in the degree of freedom resulting from including additional variables in the model, we use the lags of GDP growth and physical capital as instruments. Given this, we use the common correlated effect mean group instrumental variable estimator proposed by Ditzen (2018).[11]

3.3.3 Data

This section sets out the data used in our study. The key variable of interest when examining the impact of environmental factors on economic growth is our measure of green growth. We use a measure of optimal green growth from Sarkodie et al. (2023). This indicator measures green growth performance across five broad dimensions: resource use, natural asset base, socio-economic opportunities, productivity, quality of life, and policy responses. This series has the advantage that it separates economic growth from resource consumption by considering environmental externalities, encouraging sustainable practices in energy, agriculture, and industry, and promoting social inclusion. The series is a composite index of environmental determinants of economic growth with over 152 variables. This data are from 1992 to 2021 for 81 countries. This time period was chosen for the study due to the availability of data

[10] Tweedie (2001) argues that fixed effects estimator does not permit heterogeneity and may effectively estimator parameter coefficients when the homogeneity assumption holds.

[11] Throughout the common correlated effect mean group instrumental variable estimations, we instrument physical capital as an endogenous variable with one-year and two-year lags and the one-year lag of economic growth as exogenous variables following Temple (1999) and Ditzen (2018) given as $\Delta k_{it} = \Delta k_{it-1}$, Δk_{it-2}, Δy_{it-1}.

for the green growth indicators and total labour force. Other series such as physical capital, human capital, greenhouse gas emissions, urbanisation, foreign direct investment, and green technologies are also used in this study. The data were obtained from the World Bank, OECD, and Penn World Tables. Table 3A-1 in the Appendix describes the series and their measurement units.

The Cobb-Douglas production function and extended environmental model both motivate our choice of empirical determinants of economic growth, in the spirit of Mankiw et al. (1992), Durlauf et al. (2005), Hassler and Krusell (2018) and De Visscher et al. (2020). The Cobb-Douglas production function incorporates three inputs, namely physical capital, labour, and the green growth index. We additionally expand our proposed model by incorporating additional environmental indicators, e.g., the IPAT alongside the Cobb-Douglas production function model; see equation (3.6). Considering the environmental and macroeconomic factors underpinning the basic Cobb-Douglas production function model and the IPAT extended model, we incorporate variables such as urbanisation, greenhouse gas emissions, green technologies, and foreign direct investment into a unified model. Subsequently, we replace labour with a human capital index. Given that, labour does not take into consideration variations in worker quality or skill levels; see Hanushek and Kimko (2000), Krusell et al. (2000) and Katiraee et al. (2021). Human capital enables a more sophisticated evaluation of the workforce, considering factors such as experience, expertise, and specialisation; see also Teixeira and Queirós (2016).

We present the correlations between green growth and GDP growth for our full sample, the advanced economies and emerging economies, in Table 3A-2 in the Appendix. The evidence suggests that overall green growth has a positive but insignificant correlation with GDP growth, and perhaps this is also evident in emerging economies. However, we find a positive and significant correlation in advanced economies. While there may not always be an insignificant correlation between green growth indicators and GDP growth, specific circumstances can result in such a correlation; see, for example, Schaltegger and Synnestvedt

(2002), Van den Bergh (2011), Fritz and Koch (2016) among otherss. The factors that lead to this situation are transition costs (Gurney et al., 2009; McCann, 2013), policy adjustments (Schaltegger and Synnestvedt, 2002), resource reallocation (IPCC, 2014), consumer behaviour (Mercure et al., 2016), and global economic factors (Fritz and Koch, 2016). The implementation costs of transitioning may impede the rate of economic growth, while modifications in policies may have an impact on the efficiency and production levels of industries (Gurney et al., 2009; McCann, 2013). The process of reallocating resources may initially result in a decrease in production for conventional industries (IPCC, 2014), while consumer behaviour can impact revenues (Mercure et al., 2016). Global economic conditions can also have an impact on both indicators (Fritz and Koch, 2016).

3.3.4 Green Determinants of Economic Growth

Urbanisation has a significant influence on economic growth. Urbanisation is also referred to as the transformation of rural populations into urban people or the urbanisation of rural areas which gives rise to infrastructural strains, inequality, and environmental concerns (Sit and Yang, 1997; Li et al., 2019). The industrialisation that results from urbanisation has an effect on energy consumption (Sadorsky, 2013; Fang et al., 2022). Urbanisation influences energy demand by increasing the demand for housing, transport, and other publicly provided utilities; see Güneralp and Seto (2008). Urbanisation increases traffic due to industrial activity, puts pressure on the agricultural sector to produce more food for both rural and urban populations (Epstein and Jezeph, 2001; WHO, 2016), boosts commercialisation (McMichael, 2000; Song and Knaap, 2004), modifies the urban structure (Güneralp and Seto, 2008; Blonigen and Cristea, 2015), stimulates financial development, which encourages investment activities and industrialisation (Douglas et al., 2002; Güneralp and Seto, 2008), increases the demand for production materials, and stimulates the movement of labour from the countryside to the city as they contribute to urbanisation and influence energy demand (Rephann and Isserman, 1994; Douglas et al., 2002; Kamal-Chaoui and Robert, 2009).

With respect to environmental quality determinants, Ivanovski and Churchill (2020) present evidence that the convergence path away from greenhouse gas emissions depends critically on income per capita, international trade, and urbanisation in Australia from 1990 to 2017. Aller et al. (2021) also show that a number of important factors influence CO2 emissions, including GDP per capita, fossil fuel consumption, urbanisation, industrialisation, democratisation, trade effects, and political polarisation. Notably, income level influences these determinants, and foreign direct investment is also responsible for environmental degradation (Wagner and Timmins, 2009; Singhania and Saini, 2021). Moore et al. (2022) emphasised that the potential costs and effectiveness of mitigation technologies play a crucial role in understanding the disparities in emissions trajectories and, consequently, their impacts on global warming, which eventually causes climate change.

Climate change adaptation and mitigation necessitate a vital shift towards green growth (Sarkodie et al., 2023). Sarkodie et al. (2023) suggest that the transition from brown to green growth requires a range of strategic actions that are influenced by economic resources, socio-economic abilities, political decisions, and environmental issues, referred to as green growth indicators. Green growth indicators are crucial for achieving sustainable development by harmonising the growth of an economy with the optimal objective of conserving the environment; see Brown (2000), Griggs et al. (2013), Pretty (2013). Given that green growth indicators help to assess progress, monitor the environmental consequences, and prioritise long-term sustainability (van Vuuren et al., 2015; Díaz et al., 2019; Delabre et al., 2021; Pörtner et al., 2023). Moreover, green growth entails providing guidance for policy decisions (World Bank, 2012), fostering inclusive development (Wackernagel and Rees, 1997; Swainson and Mahanty, 2018), ensuring resource efficiency (Potts et al., 2016), promoting global cooperation (Ofori et al., 2023), and enhancing resilience to climate change (Stern et al., 1996; Hallegatte et al., 2012; Schmalensee, 2012; Hickel and Kallis, 2020; Hao et al., 2023). In addition, green growth indicators facilitate assessment of a nation's climate-related vulnerabilities; see also Füssel (2010), Formetta and Feyen (2019), and Sarkodie et al. (2023).

Table **3.1:** Descriptive statistics

	Mean	SD	Max.	Min.	Obs.
Δy_{it}	3.19	4.59	42.78	-45.66	2,430
Δl_{it}	1.71	2.13	19.64	-11.49	2,430
Δk_{it}	3.67	2.77	18.80	-3.44	2,430
Δg_{it}	0.55	0.14	1.00	0.00	2,430
Δhc_{it}	0.89	0.63	4.64	-0.69	2,430

Notes: This table contains descriptive statistics for: Mean; SD = standard deviation; Max = maximum value; Min = minimum value; Obs. = number of observations. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. Δhc_{it} represents the growth rate of human capital index. Sample of 81 advanced and emerging countries from 1992 to 2021.

3.4 Results

3.4.1 Descriptive Statistics

We begin our empirical analysis by providing some descriptive statistics; see Table 3.1 for our full sample and the Appendix for the advanced and emerging economies' samples. The evidence from our entire sample shows that the average economic growth is 3.19%, with a standard deviation of 4.59%. Emerging economies during the sample period had a higher average and higher variability of economic growth as expected; see Appendix. From the descriptive statistics, we also see that our measure of green growth is positive on average. In contrast to economic growth, advanced economies exhibit relatively higher green growth. This is notable and prima facie evidence that we should account for the heterogeneous nature and relationship between economic growth and green growth.

3.4.2 Econometric Pre-Tests

We also conduct some formal econometric pre-tests to assess cross-sectional dependency (CD) and slope heterogeneity. The cross-sectional dependency (CD) test has a null hypothesis of no or weak cross-sectional dependence (Pesaran, 2015, 2021). If the CD test statistic has a $p<0.05$ and α value significantly exceeds 0.5, the null hypothesis is rejected, and we ave no

Table **3.2:** Cross-sectional dependence and slope heterogeneity

Statistics	CD	α	Adj.Δ
Δy_{it}	95.80*** [0.00]	0.79	
Δl_{it}	50.36*** [0.00]	0.68	
Δk_{it}	17.74*** [0.00]	0.63	
Δg_{it}	188.36*** [0.00]	1.00	
Δhc_{it}	30.26*** [0.00]	0.67	
Slope Heterogeneity			
1. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}$			9.14*** [0.00]
2. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}$			0.98 [0.33]

Notes: This table presents cross-sectional dependence tests, denoted as CD and α from Pesaran (2015, 2021). We reject the null hypothesis of weak cross-sectional dependence when the CD statistics shows a p-value less than 0.05. Cross-sectional dependency is considered strong when $\alpha = 1$, semi-strong $0.5 \leq \alpha \leq 1$, weak $\alpha = 0$, and semi-weak $0 < \alpha < 0.5$. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital is denoted as Δk_{it}, green growth is denoted as Δg_{it}. This table also contains a test statistics for estimation parameter heterogeneity, Adj.Δ from Pesaran and Yamagata (2008) where we reject the null hypothesis of no cross-sectional heterogeneity when the test statistics have a p-value less than 0.05. P-values are presented in the square brackets. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

evidence of cross-sectional dependency; see Pesaran (2015, 2021). Our results in Table 3.2 for the full sample indicate that α is consistently greater than 0.5 for all series with small associated p-values, hence there is semi-strong to strong cross-sectional dependence. It was observed that the slope heterogeneity exists for the full sample. Using Pesaran (2007) unit root tests, we observed that all the panel time series are stationary. That is, we are able to reject the null hypothesis of panel unit root against an alternative of no panel unit root at 1% statistical significance level. We can therefore assume that our data series are stationary and will not be susceptible to a spurious regression problem. The results are presented in Table 3A-6 in the Appendix.

3.4.3 Econometric Evidence

Benchmark Results

We begin our formal analysis of the relationship between economic activity and green growth by presenting benchmark results. Initially, we use an Auto-Regressive Distributed Lag (ARDL) model based upon equation (3.5) with up to one lag and a general to specific methodology to systematically examine our core relationships. We use mean group estimation to tackle cross country heterogeneity in estimated parameters and account for cross country spillovers by having common factors. Table 3.3 is our first set of core results.

Table 3.3 column (1) contains a dynamic fixed effects (DFE) estimation with homogeneous coefficients. In particular, in column (1) lagged green growth (i.e. the coefficient on Δg_{it-1}) is statistically significant at the 1% significance level, indicating a powerful relationship between green growth and economic activity. However, the dynamic fixed effects estimator may not be robust to spillovers and parameter heterogeneity. In contrast, column (2) is a full ARDL(1,1,1,1) model estimated by dynamic mean group estimation with common correlates. This empirical model may be overparameterized, and the CD-stat for cross-sectional dependence rejects the null of no cross-sectional dependence. Therefore, cross-sectional dependence still exists in the estimated model. Columns (3) and (4), using a general-to-specific approach, illustrate that lagged green growth, similar to DFE in column (1), again dominates a contemporaneous impact, here at the 10% level. We also considered replacing labour with human capital in the estimated results in Table 3.4. With human capital, we also observed a positive and statistically significant coefficient for lagged green growth. This could be due to adjustment costs or delays in the impact of green economic activity on macro growth.

We consequently focus in what follows on the relationship between economic activity and lagged green growth. Having established our fundamental relationship using an ARDL model with a general to specific methodology, we now consider whether this approach is robust to a variety of estimators. These estimators take account of potential parameter heterogeneity, error cross sectional correlation and endogeneity. The estimators are: Fixed Effects (FE), Dynamic Fixed Effects (DFE), Common Correlated Effects Mean Group MG(+CCE), Dynamic Common Correlated Effects Mean Group, DMG (+CCE), and Common Correlation Effects Mean Group instrumental variable, MG-IV(+CCE) estimators. Fixed effects, with and without dynamic terms from the dependent variable, is a standard estimator in empirical applications. It is also a useful benchmark but may not fully deal with cross-sectional hetero-

Table **3.3:** Baseline regression evidence

Estimator	DFE	DMG(+CCE)	DMG(+CCE)	DMG(+CCE)
Δg_{it}	-0.44	0.55	0.45	
	(0.65)	(0.59)	(0.53)	
Δg_{it-1}	3.41***	0.81		1.26*
	(0.67)	(0.71)		(0.70)
Δl_{it}	0.62***	0.37**	0.31**	0.23**
	(0.05)	(0.13)	(0.11)	(0.11)
Δl_{it-1}	-0.21***	-0.02		
	(0.05)	(0.12)		
Δk_{it}	0.88***	1.70***	0.64***	0.65***
	(0.08)	(0.25)	(0.09)	(0.10)
Δk_{it-1}	-0.57***	-1.32***		
	(0.07)	(0.24)		
Δy_{it-1}	0.12***	0.09**	0.11**	0.10**
	(0.02)	(0.03)	(0.03)	(0.03)
Constant	-0.73	-2.02	-2.43***	-2.63***
	(0.50)	(0.70)	(0.54)	(0.58)
Common factors	No	Yes	Yes	Yes
NxT	2,349	2,187	2,187	2,187
R^2	0.25	0.43	0.60	0.58
F-stat	68.16***	1.90***	1.60***	1.70***
F-test: All $u_i = 0$	1.33 [0.03]			
CD-stat.		8.94***	1.04	0.86
CD-stat. [p-value]		[0.00]	[0.30]	[0.39]

Notes: This table presents the results on the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. In this table we use an ARDL model with economic growth explained by green growth, labour and capital. The estimators are (1) DFE denotes Dynamic Fixed Effects ARDL. Columns (2) to (4) use Dynamic Common Correlated Effects Mean Group estimation based upon a general to specific ARDL specification. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent; p-values are in the square brackets. The CD-stat represents a cross-sectional dependence test of the residuals with a null hypothesis of no or weak cross-sectional dependence from Pesaran (2015, 2021). We do not reject this null at the 5% significance level but if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

geneity, cross-sectional dependency and endogeneity.[12] In contrast, mean group estimation more fully accounts for parameter heterogeneity. We have established in Table 3.2 evidence of heterogeneity in the estimated coefficients. If this heterogeneity was not accounted for, there would be heterogeneity bias. Also evidence of cross-sectional correlation due perhaps

[12]Failure to consider these issues can lead to biased and inconsistent estimation results; see Ditzen (2021) and Pesaran (2015, 2021).

Table **3.4:** Baseline regression evidence with human capital

Estimator	DFE	DMG(+CCE)	DMG(+CCE)	DMG(+CCE)
Δg_{it}	-0.24	0.81	0.61	
	(0.67)	(0.52)	(0.59)	
Δg_{it-1}	3.72***	1.06		1.73**
	(0.70)	(0.74)		(0.76)
Δhc_{it}	-0.20	-2.53**	-1.76	-1.79
	(0.38)	(1.08)	(1.27)	(1.20)
Δhc_{it-1}	0.45	1.44		
	(0.37)	(1.23)		
Δk_{it}	0.95***	1.79***	0.77***	0.81***
	(08)	(0.27)	(0.12)	(0.13)
Δk_{it-1}	-0.59***	-1.47***		
	(08)	(0.26)		
Δy_{it-1}	0.13***	0.04	0.07*	0.04
	(0.02)	(0.03)	(0.04)	(0.04)
Constant	-0.68	-2.43	-1.30	-1.50
	(0.54)	(1.49)	(1.07)	(1.00)
Common factors	No	Yes	Yes	Yes
NxT	2,349	2,106	2,106	2,106
R^2	0.20	0.45	0.62	0.60
F-stat	39.58***	1.40***	1.17***	1.80***
F-test: All $u_i = 0$	1.26 [0.06]			
CD-stat.		9.37***	2.20**	1.31
CD-stat. [p-value]		[0.00]	[0.03]	[0.19]

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. In this table we use an ARDL model with economic growth explained by green growth, human capital and capital. The estimators are (1) DFE denotes Dynamic Fixed Effects ARDL. (2) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL full model. (3) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL intermediate model. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL final model. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in human capital index is denoted as Δhc_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent; p-values are in the square brackets [ ]. We do not reject the null hypothesis with p-value > 0.05. The CD-stat represents a cross-sectional dependence test of the residuals with a null hypothesis of no or weak cross-sectional dependence from Pesaran (2015, 2021). We do not reject this null at the 5% significance level but if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

to common shocks, suggest it is imperative to address this aspect. In such instances, the preference lies in employing the mean group plus common correlated effects estimator, given the presence of both heterogeneity as confirmed by the heterogeneity test and cross-sectional correlation. Finally, we use the mean group-instrumental variable with a common correlated effect estimator to deal with potential endogeneity since our Granger causality test confirms evidence of reverse causality. Most importantly, in a growth model, there is the tendency to experience reverse causality in that capital accumulation and GDP growth are considered endogenous; see, for example, Temple (1999) and Durlauf et al. (2005). Table 3.5 illustrates the outcome of our findings for the full sample.[13]

The findings from our benchmark analysis with green growth, as presented in Table 3.5, indicate that green growth has a substantial impact on economic growth, as exhibited in columns (1) to (4). In contrast, we find less evidence of a link between economic activity and green growth, as shown by the common correlated mean group instrumental variable (MG-IV+CCE) estimator in column (5).[14] This evidence differs from what was observed in columns (1) to (4). Perhaps this further suggests endogeneity between economic activity and green growth and potential reverse causality. The MG-IV(+CCE) estimator is capable of dealing with this issue while also addressing cross-sectional heterogeneity and cross-sectional spillovers; see Ditzen (2018).

Whilst our mean group estimation methods are robust to country heterogeneity, there are potentially differences in behaviour across advanced and emerging economies. Lin and Zhu (2019b), Su and Fan (2022), Zhao et al. (2022a) and Zhou et al. (2022) argue that the influence of green growth indicators on economic growth varies significantly across different regions, given that countries with more stringent environmental regulations, greater technological innovation, and a higher level of environmental awareness tend to experience a more pronounced effect. To give a sense of the global heterogeneity of the country estimations, we mapped country coefficients to illustrate considerable country heterogeneity, which is also consistent with the formal parameter heterogeneity tests in Table 3.2, from Pesaran and Yamagata (2008). Our country results illustrate that the impact of green growth on GDP growth is considerably heterogeneous, for example, countries including Cyprus, Greece, and Ireland are more likely to experience positive effects whereas Argentina, Ethiopia and Panama could

[13] In the Table 3A-9, we present the evidence observed from the advanced and emerging economies subsample to comprehend the heterogeneity of our sample

[14] Throughout the MG-IV(+CCE) estimations, we instrument physical capital as an endogenous variable with one-year and two-year lags, and the one-year lag of economic growth as exogenous variables following Ditzen (2018) given as $\Delta k_{it} = \Delta k_{it-1}$, Δk_{it-2}, Δy_{it-1}.

potentially experience adverse effects of green growth on GDP growth, as shown in Figure 3A-1 in the Appendix. In addition, our evidence presented in Table 3A-9 indicates that the indicator of green growth are more strongly associated with the growth of gross domestic product (GDP) in advanced countries than emerging economies, as observed across the estimators used for the full sample. This reflects the theoretical position of the EKC hypothesis, which suggests that at the initial stage of economic development, countries experience environmental destruction but this is reversed after a certain income threshold is achieved. In view of this, advanced economies having achieved this income threshold are better able to invest in cleaner and green technologies, ensure stricter environmental regulations and environmental sustainability policies. By constrast, developing or emerging economies are at the early stage of economic development and are closely tied to resource-intensive and environmentally straining activities. Given the structural difference in policy, access to cleaner and green techologies, and institutional capacity, the relationship between green growth and GDP appears to be insignificant.

Extended Model

We go on now and consider the relationship between green growth and economic activity in an extended model. We consider in particular whether there may be other environmental and economic factors that could mediate the relationship between green growth and economic growth. Chudik and Pesaran (2015) argue that adding covariates to account for the effects of many common factors that are not observed can improve the consistency of estimation. Here, we extend our baseline model by combining the production function model with three inputs and the IPAT model. Consequently, we apply the same approach used for the benchmark model. First, we assess the relationship with an ARDL model and subsequently rely on the significant measure of green growth. Whilst there is evidence that both current period and lagged green growth positively impact economic activity in Table 3.6, we find stronger evidence associated with the lagged indicator. This is also consistent with

Table **3.5:** Regression evidence with multiple panel estimators

Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	3.41***	3.27***	1.28*	1.26*	0.92
	(0.67)	(0.67)	(0.73)	(0.70)	(0.75)
Δl_{it}	0.62***	0.59***	0.23**	0.23**	0.23*
	(0.05)	(0.05)	(0.11)	(0.11)	(0.12)
Δk_{it}	0.48***	0.41***	0.75***	0.65***	0.25**
	(0.05)	(0.05)	(0.10)	(0.10)	(0.10)
Δy_{it-1}		0.10***		0.10**	
		(0.02)		(0.03)	
Constant	-1.52***	-1.45***	-2.61***	-2.63***	-1.24**
	(0.43)	(0.42)	(0.60)	(0.58)	(0.64)
Common factors	No	No	Yes	Yes	Yes
NxT	2,349	2,349	2,187	2,187	2,106
R^2	0.21	0.22	0.63	0.58	0.33
F-stat	119.23***	96.21***	1.70***	1.70***	2.18***
F-test: All $u_i = 0$	1.81 [0.00]	1.49 [0.00]			
CD-stat.			1.11	0.86	-1.14
CD-stat. [p-value]			[0.27]	[0.39]	[0.26]

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. The estimators are (1) FE denotes Fixed Effects. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Model 1 to 5 are estimated upon equation (3.5). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent. We do not reject the null hypothesis with p-value > 0.05; p-values are in the square brackets. The CD-stat represents a cross-sectional dependence test of the residuals with a null hypothesis of no or weak cross-sectional dependence from Pesaran (2015, 2021). We do not reject this null at the 5% significance level but if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

the notion that there are adjustment costs in responding to green growth. Given this, we rely on the lagged green growth measure in our subsequent estimations. Table 3.7 presents our extended model results. These results estimate equation (3.6) above, the relationship between green growth and economic activity, conditional upon urban population, environmental technologies, greenhouse gas emissions and FDI, while also accounting for parameter heterogeneity, spillovers and endogeneity. We therefore provided five estimations in Table 3.7; FE, DFE, MG(+CCE), DMG(+CCE) and MG-IV(+CCE). In general, it is evident that there is a strong positive relationship between green growth and economic activity, albeit

Table **3.6:** Regression evidence: extended model

Estimator	DFE	DMG(+CCE)	DMG(+CCE)	DMG(+CCE)
Δg_{it}	-0.71	0.39	0.85*	
	(0.61)	(0.69)	(0.46)	
Δg_{it-1}	2.82***	0.48		1.20*
	(0.64)	(0.94)		(0.71)
Δl_{it}	0.56***	0.37*	0.35*	0.27
	(0.05)	(0.20)	(0.21)	(0.20)
Δl_{it-1}	-0.12**	0.10		
	(0.05)	(0.17)		
Δk_{it}	0.78***	1.57***	0.71***	0.73***
	(0.07)	(0.30)	(0.10)	(0.10)
Δk_{it-1}	-0.48***	-1.08***		
	(0.07)	(0.27)		
Δp_{it}	-0.06	0.83	-0.74**	-0.62**
	(0.16)	(0.70)	(0.33)	(0.31)
Δp_{it-1}	-0.22	-1.14		
	(0.16)	(0.70)		
$\Delta \tau_{it}$	0.00	-0.01***	-0.01*	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
$\Delta \tau_{it-1}$	0.00	-0.01*		
	(0.00)	(0.00)		
Δfdi_{it}	0.01***	0.00	0.02**	0.02**
	(0.00)	(0.00)	(0.00)	(0.00)
Δfdi_{it-1}	0.00	0.00		
	(0.00)	(0.00)		
Δe_{it}	0.20***	0.11***	0.21***	0.20***
	(0.01)	(0.03)	(0.03)	(0.03)
Δe_{it-1}	0.00	-0.03		
	(0.01)	(0.03)		
Δy_{it-1}	0.10***	0.04	0.06*	0.05
	(0.02)	(0.04)	(0.03)	(0.03)
Constant	0.12	-2.11*	-2.36***	-2.60***
	(0.49)	(1.10)	(0.71)	(0.76)
Common factors	No	Yes	Yes	Yes
NxT	2,349	2,187	2,187	2,187
R^2	0.33	0.22	0.40	0.38
F-stat	53.10***	1.49***	1.88***	2.05***
F-test: All $u_i = 0$	1.36 [0.02]			
CD-stat.		1.70	-0.11	0.26
CD-stat. [p-value]		[0.09]	[0.91]	[0.79]

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. The estimators are (1) DFE denotes Dynamic Fixed Effects ARDL. (2) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL full model. (3) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL intermediate model. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group ARDL final model. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gas emissions and growth in green technologies is denoted as $\Delta \tau_{it}$. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent; p-values are in the square brackets. We do not reject the null hypothesis with p-value > 0.05.The CD-stat represents a cross-sectional dependence test of the residuals with a null hypothesis of no or weak cross-sectional dependence from Pesaran (2015, 2021). We do not reject this null at the 5% significance level but if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

Table **3.7:** Extended model with multiple panel estimators

Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	2.86***	2.74***	1.51**	1.61**	1.52**
	(0.63)	(0.63)	(0.74)	(0.73)	(0.78)
Δl_{it}	0.58***	0.57***	0.18	0.31	0.20
	(0.05)	(0.05)	(0.18)	(0.22)	(0.21)
Δk_{it}	0.44***	0.38***	0.93***	0.86***	0.40**
	(0.04)	(0.05)	(0.12)	(0.11)	(0.15)
Δp_{it}	-0.28**	-0.35***	-0.34	-0.18	0.06
	(0.10)	(0.10)	(0.35)	(0.34)	(0.45)
$\Delta \tau_{it}$	0.00	0.00	-0.01*	0.00	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Δe_{it}	0.20***	0.20***	0.18***	0.18***	0.20***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Δfdi_{it}	0.01***	0.01***	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δy_{it-1}		0.09***		0.02	
		(0.02)		(0.04)	
Constant	-0.72*	-0.57	-1.34	-2.91*	-2.34
	(0.42)	(0.42)	(1.56)	(1.61)	(1.72)
Common factors	No	No	Yes	Yes	Yes
NxT	2,349	2,349	2,187	2,187	2,106
R^2	0.29	0.30	0.39	0.37	0.59
F-stat	95.33***	87.30***	1.43***	1.39***	2.08***
F-test: All $u_i = 0$	1.80 [0.00]	1.52 [0.00]			
CD-stat.			0.69	0.54	-0.54
CD-stat. (p-value)			[0.49[	[0.59]	[0.59]

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. In these estimations, we combine the baseline model with three inputs and the IPAT model. The estimators are (1) FE denotes Fixed Effects. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Model 1 to 5 are estimated upon equation (3.6). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force participation rate is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gas emissions and growth in green technologies is denoted as $\Delta \tau_{it}$. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent. We do not reject the null hypothesis with p-value > 0.05; p-values are in the square brackets. The CD-stat represents a cross-sectional dependence test of the residuals with a null hypothesis of no or weak cross-sectional dependence from Pesaran (2015, 2021). We do not reject this null at the 5% significance level but if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

with a lag potentially due to adjustment costs. Our approach accounts for different effects from country specific policies. Environmental policies such as carbon pricing, subsidies for renewable energy, and overall environmental policy stringency. Green growth is arguably the sustainability strategy considered to have a cross-cut and positive impact on countries vulnerable to rising sea level and extreme weather events as these can potentially have severe economic consequences (Bohensky et al., 2011; Potts et al., 2016; Cramer et al., 2018).

To offset the possibility that our results are unduly impacted by over-parameterisation, we introduce urbanisation and green technologies separately to gain insight into the environmental factors that may impact the relationship between green growth and economic activity. The results are presented in the Appendix.[15] Our findings indicate that urbanisation has a negative and substantial impact on GDP growth. Despite the relationship between urbanisation and GDP growth, green growth still positively impacts GDP growth. In contrast the alternative measure of green technologies ($\Delta\tau_{it}$) from the OECD is not found to have a strong relationship with GDP growth, beyond that contained within our main green growth measure. Overall, we observed that the lagged term of green growth significantly contributes to economic growth, even in the presence of unfavourable economic and environmental factors. We find strong evidence that indicators of green growth are major contributors to economic growth, in support of the existing literature. These studies document that green growth indicators, such as fintech (Ren et al., 2022), knowledge-intensive growth (Pretty, 2013; Potts et al., 2016; Wang et al., 2022), environmental taxes (Bohensky et al., 2011; Griggs et al., 2013; Song et al., 2019; Fernandes et al., 2021; Jin et al., 2023), green energy (Yi and Liu, 2015; Li et al., 2022; Mahmood et al., 2022), and green finance (Zhou et al., 2022), have a substantial positive effect on green economic growth.

Decomposition of Green Growth

Our final empirical exercise in This chapter is to decompose the green growth measure into constituent sub-dimensions, and assess the impact on economic activity. The sub-dimensional measures include natural asset base, policy responses related to the environment, socio-

[15] Refer to Table 3A-10 for the impact of urbanisation (Δp_{it}), and Table 3A-11 for the impact of green technologies ($\Delta\tau_{it}$).

economic outcomes, quality of life, and productivity. Sarkodie et al. (2023) contends that these sub-dimensional measures act as foundational elements for promoting sustainable economic growth. Consequently, we assessed the relationship between these measures and GDP growth for our sample of 81 countries, comprising 27 advanced economies and 54 emerging economies. Our analysis reveals that the sub-dimension of green growth, natural assets base have a consistently and sometimes statistically significant impact on economic activity. This is based upon an empirical model with lagged green growth indicators, consistent with the key results in the main chapter of the chapter. The strongest evidence is for the impact of natural asset base, productivity and socio-economic indicators. However, the latter result for the socio-economic indicator is potentially strongest, as it is accounting for heterogeneity, spillovers and endogeneity. This implies that socioeconomic outcomes are potential contributors to economic growth and perhaps greater and improved socioeconomic policies geared towards green growth has the tendency to drive economic prosperity; see Easton and Walker (1997) and Faria and Montesinos (2009). The result remains unaffected by endogeneity, cross-sectional dependence, and cross-sectional heterogeneity due to our utilisation of the MG-IV(+CCE) estimator, which effectively addresses these concerns through our econometric approach. Results are in the appendix.

3.5 Conclusion

Using a novel dataset we examined whether green growth impacts macroeconomic outcomes for a large number of countries. Our green growth measure is a composite index of natural asset base, environmental productivity, environmental-related policy responses, socio-economic outcomes, and quality of life. In testing our central hypothesis, we used empirical methods robust to panel parameter heterogeneity, cross-sectional correlation, and endogeneity. Our empirical results strongly suggest that green growth has a positive impact on GDP growth, especially in an extended model and for advanced economies. Specifically, our country results illustrate that the impact of green growth on GDP growth is considerably heterogeneous.

Our evidence indicates that the indicator of green growth are more with the growth of gross domestic product (GDP) in advanced countries than emerging economies, as observed across the estimators used for the full sample. Overall, we observed that the lagged term of green growth significantly contributes to economic growth, even in the presence of unfavourable economic and environmental factors. We find strong evidence that indicators of green growth are major contributors to economic growth. Research and Development (R&D) is a recurring topic in the carbon emissions literature. Investments in R&D leads to technological advancement in the production of efficient and cleaner technologies that could aid in the adaptation and mitigation of climate change effects as a result of global warming. Research and development intensity may decrease as knowledge increases, making it harder to make new discoveries. However, economic growth requires more natural resources, potentially causing environmental destruction, raising the question of whether R&D intensity can significantly reduce global warming. In the next chapter, we examine the impact of R&D intensity on global warming.

Chapter 4

R&D Intensity and Global Warming

4.1 Introduction

Over the past decades, there has been an unprecedented rise in greenhouse gases, and global warming has emerged as a global policy concern; see in particular Acemoglu et al. (2012), and Nordhaus (2019a). Since carbon dioxide (CO2) emissions are the primary causes of global warming, a considerable body of knowledge in environmental and energy economics has emerged that explores the causes of carbon emissions as well as alternative mitigation strategies (see for example Arora and Cason, 1996; Dinda, 2004; Churchill et al., 2019; Lin and Zhu, 2019a; Huang et al., 2021). Macroeconomic indicators such as economic growth, population, and trade, among others things, have been studied as determinants of environmental quality in the literature; see Grossman and Krueger (1995), Koop and Tole (1999), and Dinda (2004). Existing studies frequently test the environmental Kuznets curve (EKC) hypothesis, which hypothesises an inverted U-shaped linkage between per capita income and various pollutants, to examine factors influencing environmental quality. Grossman and Krueger (1995), Koop and Tole (1999), and Dinda (2004) have extensively utilised the EKC hypothesis and identified an inverted U-shaped curve between income levels and various environmental quality determinants.

Research and Development (R&D) intensity is the resource allocation commitment to innovation and technological progress; see Levin (1988) and Veugelers (1997). The effectiveness of R&D in combating global warming, meanwhile, differs with various phases of economic development (Mansfield, 1972). The type of R&D spending is practically important. Research and development on energy efficiency has been establised to be more effective in mitigating carbon emissions; see for example, Churchill et al. (2019), Shahbaz et al. (2020), Huang et al. (2021) and Safi et al. (2021). This accentuates the urgency of improving R&D investments toward innovations that directly help to lower greenhouse gas emissions. The EKC hypothesis provides a framework that highlights on how environmental quality and economic growth interact. Including R&D intensity in this model draws attention to the possibility of technological innovation changing conventional EKC path. This, therefore, stresses the importance of strategic R&D investment to properly fight global warming. The assertion that technological advancements will have a positive effect on environmental quality, referred to as the technological effect, is a recurring theme in the extensive literature on the EKC hypothesis (see Churchill et al., 2019; Shahbaz et al., 2020; Huang et al., 2021; Safi et al., 2021). Investments in research and development are focused on boosting productivity as well as improving the quality and diversity of products (Fisher-Vanden and Wing, 2008).

Endogenous growth theory argues that long-term economic growth is driven by factors that influence the opportunities and incentives for knowledge production; see Lucas (1988), Romer (1994) and Aghion et al. (1998). Importantly R&D investment can result in improved efficiency in production and the use of natural resources and energy; see Barbier (1999). As income rises, countries are better able to invest in R&D and, as a result, adopt more efficient technologies (Grossman and Krueger, 1995). More efficient technologies can minimise the strain on natural resources while also reducing greenhouse gas emissions and pollutants (Dinda, 2004), resulting in a clean and healthy environment (Grossman and Krueger, 1995). More R&D investment, for example, is likely to improve environmental quality in situations where effective environmental management systems are in place to ensure proper waste management (Arora and Cason, 1996; Churchill et al., 2019; Huang et al., 2021; Paramati et al., 2021). Although new technology may increase efficiency, increasing output may necessitate the use of additional natural resources, which could result in an increase in carbon emissions. This theory is supported by the fact that R&D has historically produced declining returns (Newell, 2009; Churchill et al., 2019).

There is uncertainty regarding the effect of technological advancement on global warming emanating from greenhouse gas emissions (Meinshausen et al., 2009; Moss et al., 2010; Arent et al., 2011). Two significant uncertainties obscure the future requirements of green technology, Fulkerson et al. (1989) argued that the future of energy technology is shaped by increasing energy demand and the pressing issue of the greenhouse gas effect. This revelation highlights the need for a well-rounded approach to research and development. Higher economic growth and trade openness through the scale effects of larger production is likely to adversely impact environmental quality. Given that new technologies may potentially improve efficiency, output growth may require more natural resource consumption, which may likely increase carbon emissions (Chen et al., 2020). This development may eventually increase atmospheric carbon concentration, potentially altering the average global temperature and leading to global warming (Pindyck, 2021). It seems that the possibility is more likely because the returns on research and development decrease as time goes on. However, it is important to note that economic growth still requires an increasing amount of natural resources and is likely to cause environmental destruction. These arguments beg the question: can R&D intensity lead to a significant reduction in global warming?

Our study makes three important contributions. Our first contribution is to examine the empirical relationship between R&D and individual countries' contributions to global warming. Since the pre-industrial period, anthropogenic emissions of carbon dioxide (CO2), nitrous oxide (N2O) and methane (CH4) have significantly contributed to global warming (Masson-Delmotte et al., 2021). Consequently, international climate policy has concentrated on these emissions. Assessing national contributions to climate change, as well as informing equitable commitments to decarbonisation, are of significant interest; see Jones et al. (2023). Importantly, understanding national contributions to climate change is critical to understanding the burden of responsibility a country carries for global warming and can inform the design of international policies pursuing equitable decarbonisation pathways. The extant literature usually focus on carbon emissions, which is just a single measure of greenhouse gas emissions; see for example, Churchill et al. (2019). However, the ultimate policy objective is to reduce temperature rise, but not just limit carbon emissions. Therefore, temperature, which is the climate variable of concern is more tied to individual countries' greenhouse gas emissions contribution to global temperature changes than just carbon emissions per se. To the best of our knowledge no other research has examined the relationship between R&D and individual countries' contribution to global warming. The closest literature is from Churchill et al. (2019) that studied the relationship between R&D intensity and carbon emissions for the period 1870 to 2014 for G-7 countries. In addition, we use a novel dataset on global warming sourced from Jones et al. (2023) and also extend the span in both time and country dimension over Churchill et al. (2019). This contribution is significant because it moves beyond existing studies. (a) We assess the impact on R&D on climate change, specifically the individual countries' greenhouse gases emission contribution to changes in average global temperature. (b) We study the case of 20 OECD countries over the period 1870 to 2021, as this offers more perspective into recent developments in climate change and R&D spending.

Our second contribution is to decompose R&D at the country level to global R&D and country-level R&D. This is in the spirit of Coe et al. (2009) since it allows for spillovers in R&D, but is different in that foreign and national R&D is not available from 1870 to 2021. While the decomposition of R&D spillovers have been done previously by using domestic and foreign R&D capital stock (Coe and Helpman, 1995; Coe et al., 2009). Our novel approach is to use a multivariate stochastic volatility model and by extension a principal component analysis to decompose R&D into global spillovers and country-specific R&D intensity. This is premised on a common belief that technological spillovers could likely enhance efficiency in production. As it is more likely to lead to lower energy and natural resource use, which would potentially reduce greenhouse gas emissions and eventually limit global warmig (Fisher-Vanden, 2003). Lastly, studying the impact of R&D on global warming over a longer period could be complex and would potentially experience cross-sectional dependence, time-varying volatility, structural breaks, endogeneity, heterogeneity, and non-linearity. Given these, we use multiple econometric methods and approaches that can handle these relevant issues. We use methods such as fixed effects, random effects, fixed effects regression with Driscoll-Kraay standard errors, two-stage least squares fixed effects instrumental variable, as well as sample split based on structural break test to address the econometric concerns emphasised in the existing literature; see Churchill et al. (2019) and Huang et al. (2021).

Our key findings could be set out as follows: (1) R&D intensity significantly reduces global warming across 20 OECD countries from 1870 to 2021. The impact is different across OECD countries. In G7 countries, the effect is significantly positive, while there is a clear negative impact observed in other OECD countries. (2) The effect of R&D intensity on global warming has been less significant after World War II compared to the pre-war period. Potentially this is because of diversification of R&D investments. (3) At the global level, R&D intensity consistently and significantly reduces global warming, underscoring the importance of international research collaborations, knowledge, and technological transfers.

The structure of the chapter is as follows: section one introduces the topic, section two reviews the existing literature to identify gaps and tease out the importance of the phenomenon of interest, section three highlights the empirical model, data, and econometric methods used in the study, section four presents the results and discusses the findings, and section five concludes the study.

4.2 Literature Review

Global warming is highly important for citizens, policy makers and academic researchers. A global climate assessment revealed for the first time that human activities are altering the environment and its biodiversity through climate change; consequently, the effects of global warming are projected to intensify; see Delworth and Knutson (2000) and Kerr (2007). Assessing the global determinants and consequences of global warming is of considerable interest; see also Berg et al. (2024) and Chapter 2 of this thesis. The rise in global temperatures has stimulated an intense academic and international policy debate, highlighting concerns regarding the sustainability of the global economy (Donadelli et al., 2021). While economists and policymakers generally agree that climate change can incur substantial costs on the economy and society, there is no consensus on (*i*) the R&D effects of global warming and (*ii*) the mechanisms through which R&D is more likely to impact global warming.

The existing literature has documented considerable evidence in relation to the R&D-

emissions nexus. For instance, Churchill et al. (2019) used a sample of G7 countries between 1870 and 2014. The authors applied the common correlated effect mean group and non-parametric Local Linear Dummy Variable Estimation (LLDVE) methods. Their findings indicate a time-varying relationship between R&D and CO2 emissions with a notable negative coefficient. However, a positive coefficient function was observed during the second half of the 20th century and a gradual increase for the first 110 years but slightly decreased afterwards. Similarly, Safi et al. (2021) looks into how environmental taxes and research and development influence consumption-based carbon emissions in G-7 countries over the period from 1990 to 2019. The results indicate a consistent long-term relationship among taxes, R&D, imports, exports, GDP, and CO2 emissions. Their findings conclude that taxes, research and development, and exports play a crucial role in lowering emissions, whereas GDP and imports tend to increase them. Policymakers in G-7 countries are encouraged to concentrate on these factors to reach carbon neutrality. Shahbaz et al. (2020) use historical data on the UK from 1870 to 2017 to understand how R&D spending, financial development, and economic growth influence carbon emissions. The authors document an inverted-U-shaped relationship between R&D spending and carbon emissions.[1]

Understanding the relationship between R&D investment and environmental sustainability in European countries, Paramati et al. (2021) confirmed that when countries increase their investments in research and development, it leads to a higher consumption of renewable energy. This, in turn, helps to reduce the amount of CO2 emissions in European countries. The study also suggests that one way to further reduce CO2 emissions is by increasing the proportion of renewable energy in the overall energy mix. This evidence is apparent for 25 European countries for the period 1998 to 2014 by using the Fully Modified Ordinary Least Square (FMOLS). Huang et al. (2021) also studied the energy-saving R&D and carbon intensity in China for 30 provinces between 2000 and 2016. They utilised the fixed effects

[1] The EKC hypothesis suggests an inverted U-shaped curve, that is, due to the trade-off between economic growth and environmental quality, some level of environmental degradation is inevitable in the initial phases of development. Yet, beyond a specific income level, the decline in environmental quality will start to improve; see Grossman and Krueger (1991, 1995).

instrumental variable method, dynamic panel threshold method, and difference generalised method of moment method. According to their findings, when businesses invest in energy-saving research and development, it greatly reduces carbon intensity. The authors further argue that utility-type research and development (R&D) activities have a greater impact on reducing carbon intensity. The analysis found that there was a structural shift in the relationship between energy-saving R&D activities and carbon intensity. This structural shift was influenced by the capacity to absorb technology, which either promoted or alleviated these effects.

In a different context, Fisher-Vanden and Wing (2008) examined how research and development affect energy consumption and greenhouse gas emissions in developing nations. They showed that R&D aimed at improving efficiency and enhancing quality has contrasting impacts on energy and emission intensities. The balance relies on responsive upstream output and responsive downstream output elasticities and the proportion of emissions-intensive inputs used. The research employs a computable general equilibrium simulation to highlight the challenges of integrating these findings into climate policy analysis. Similarly, Van der Zwaan et al. (2002) in an earlier study argued that incorporating endogenous innovation necessitates quicker emission reductions to comply with atmospheric carbon concentration constraints. Donadelli et al. (2021) investigates three mechanisms by which an increase in global temperature adversely impacts the growth of R&D expenditure. They observed that positive temperature shocks adversely impact patent obsolescence, labour productivity, and capital efficiency. However, decreased labour productivity results in diminished resources for R&D investment, whereas elevated temperatures may constrain capital availability, diminish demand for intermediate goods or patents, and adversely affect R&D spending.

The literature on the nexus between R&D intensity and global warming is sparse, despite its relative importance in our quest to deal with climate change externalities. Research and development play a crucial role in tackling global warming. It is important to emphasise that it contributes to the development of new technologies, accelerates the transition to a low-carbon economy (Zeqiraj et al., 2020), and boosts economic competitiveness (Pigato et al., 2020). Wong et al. (2013) found that energy focused research and development expenditure resulted in greater efficiency of economic growth compared to fossil fuel consumption, regardless of oil reserves. Nonetheless, allocating resources to research and development in areas like energy, transportation, and manufacturing can help accelerate the transition to a low-carbon economy—reducing global warming (Joskow, 1998; Kittner et al., 2017; Atar and Durmaz, 2024). Pigato et al. (2020) and Blanco et al. (2022) argue that there is an urgent need to transfer knowledge and low-carbon technologies from advanced countries to developing countries given that future emissions are anticipated to come from these countries in their quest to exponentially increase living standards and eradicate poverty. Understanding the link between research and development and global warming can assist policymakers in crafting effective climate policies and developing strategies for managing risks and adapting to climate changes.

4.3 Model, Data and Econometric Methods

4.3.1 Empirical Model

Following Churchill et al. (2019), we model the relationship between R&D intensity and global warming. Our empirical model examines whether research and development ($R\&D_{it}$) is positively or negatively impacts global warming (GW_{it}). Both R&D and global warming are panel time series. We define global warming as the individual countries' greenhouse gases emissions contribution to the changes in average global temperature. While the relationship itself could be unconditional, it's more likely to be conditional upon other factors (X_{it}). The relationship between global warming and research and development, could be linear but also could be dependent upon the level of development, see for example Grossman and Krueger

(1991, 1995).[2] Some level of environmental degradation seems inevitable in the initial stages of development. Yet, beyond a specific income level, the decline in environmental quality may start to improve. We therefore formulate the following empirical model:

$$GW_{it} = f(R\&D_{it}, X_{it}) = \beta_{i0} + \beta_1 R\&D_{it} + \beta_2 X_{it} + u_{it} \tag{4.1}$$

Equation (4.1) sets out the empirical model, in which β_{i0}, β_1 and β_2 are estimated parameters and u_{it} is the error term at time t for country i. We enhance the general specification in Equation (4.1) by being explicit about the conditional factors in Equation (4.2). These conditional factors include trade ($TRADE_{it}$), financial development ($M2_{it}$), population (POP_{it}), real GDP per capita (Y_{it}); and a quadratic function of real GDP (Y_{it}^2). The extended empirical model is:

$$\begin{aligned} GW_{it} = \beta_{i0} &+ \beta_1 R\&D_{it} + \beta_2 TRADE_{it} + \beta_3 M2_{it} \\ &+ \beta_4 POP_{it} + \beta_5 Y_{it} + \beta_6 Y_{it}^2 + u_{it} \end{aligned} \tag{4.2}$$

β_{i0} represents the individual country-specific effects, β_1 to β_6 are the parameter coefficients to be estimated. GW_{it} denote global warming, and $R\&D_{it}$ denote Research and Development (R&D) intensity. Y_{it} is real GDP per capita; Y_{it}^2 is the quadratic function of Y_{it}; financial development is measured by $M2_{it}$ in Equation (4.2), which is the ratio of broad money to GDP; POP_{it} is the total population; and $TRADE_{it}$ is the ratio of trade (imports plus exports) to GDP. In the early stages of economic growth, higher per capita income leads to increased environmental degradation due to industrialization, urbanization, and increased consumption. Therefore the expected sign on real GDP is (i.e. β_5) is positive. After reaching a certain income threshold (the turning point), further income growth leads to a reduction in environmental degradation as economies shift toward cleaner technologies, better regulations, and increased environmental awareness. Hence, the expected sign on the quadratic term of Real GDP (i.e. β_6) is negative. Our a priori expectation of the coefficients of trade (i.e. β_2), financial development (i.e. β_3) and population (i.e. β_4) are negative signs. Trade openness can

[2] The authors find that concentrations of two pollutants increase with per capita GDP at low-income levels but decrease at higher income levels. However, for most indicators, economic growth leads to an initial phase of environmental destructions, which is later improved as income levels increase.

lead to clean technology spillovers which substantiate the pollution halo effects of advanced economies. The OECD countries are characterised by stronger and well-developed financial sector. These countries have earmarked funds for green R&D and environmentally-friendly technologies. With more cleaner, green and efficient technologies, an increasing population can benefit from such developments, which may lead to lower emissions per capita.

By extension, we decompose R&D intensity into global factors and idiosyncratic (country-specific) factors. Idiosyncratic R&D represents efforts unique to individual countries, focusing on proprietary technologies or processes that may lead to competitive advantages. While the global (common factor R&D) spillovers constitutes collaborative research initiatives, shared technological advancements, or widespread industry practices that collectively influence environmental outcomes. In Section 4.4.4, we analyse how global warming responds to changes in country-specific R&D intensity ($R\&D_{it}^{I}$) and the global (common) component of R&D intensity ($R\&D_{t}^{F}$). This is obtained as a multivariate decomposition of country-level R&D intensity. We derive the model below:

$$GW_{it} = f(R\&D_{it}, X_{it}) = \beta_{i0} + \beta_1 R\&D_{it} + \beta_2 X_{it} + u_{it} \tag{4.3}$$

We decompose R&D as

$$R\&D_{it} = R\&D_{t}^{F} + R\&D_{it}^{I} \tag{4.4}$$

The decomposition of R&D intensity is done by employing a principal component analysis and multivariate factor stochastic volatility model. For the principal component analysis (PCA), we follow this approach: we run a PCA on R&D intensity for country i at time t, as this calculates the principal components. We then generate the scores of the principal components retained, this represents the common factor, also known as global spillovers ($R\&D_{t}^{F}$). Finally, we computer the idiosyncratic scores, the country-specific R&D intensity ($R\&D_{it}^{I}$). The idiosyncratic scores are the difference between the actual R&D intensity values and their modeled values. For the MFSV approach, we estimate our model with one factor ($r = 1$) and implement the MCMC approach with 5000 draws. The common

R&D factor captures cross-border collaborative dynamics as it reflects fluctuations in R&D intensity across countries. It also highlights on shared technological advancements given that R&D advancements in one country often influence innovation trajectories of other countries through trade, licensing, or international patent families. The factor distinguishes global trends from country-specific policies. This allows for straightforward attribution of global collaborative R&D initiatives.

We then formally formulate our extended model as follows:

$$\begin{aligned} GW_{it} &= f(R\&D_t^F, R\&D_{it}^I, X_{it}) \\ &= \beta_{i0} + \gamma_1 R\&D_t^F + \gamma_2 R\&D_{it}^I + \gamma_3 X_{it} + e_{it} \end{aligned} \tag{4.5}$$

Where β_{i0} denotes the individual country fixed effects, γ_1 and γ_2 denote the parameter coefficients of global R&D ($R\&D_t^F$) and country-specific ($R\&D_{it}^I$) R&D spillovers (see equations (4B-1) to (4B-4) in Appendix B for the underlying models), and γ_3 denotes the parameter coefficients of the control variables X_{it}, such as population, trade openness, financial development, GDP per capita, and the quadratic term of GDP per capita. In relation to the decomposition, Gillingham et al. (2008) contend that important issues in empirical modelling include accurately calculating the opportunity costs of creating knowledge about climate change, managing knowledge spillovers, and finding a solid empirical basis for parameterizing technological relationships. These are all important for understanding how technological change affects climate change. However, there is no one approach that works best in all areas, and the analytical goal (positive or normative) may determine which method is preferred.

This chapter argues that innovation that improves efficiency can significantly impact energy consumption and greenhouse gas emissions among countries; see also Fisher-Vanden and Wing (2008). It is commonly believed that when advanced technologies spread from developed countries to developing ones, it will enhance the efficiency of the latter, leading to lower energy consumption and reduced greenhouse gas emissions, thereby inhibiting global warming. While this outcome might indeed happen, it is also probable that greater efficiency will lead to faster growth in output, which could result in higher energy consumption and emissions overall; for example, see Fisher-Vanden (2003). While boosting productivity is a key focus of research and development in many countries, there is a growing emphasis on improving product quality and diversity in innovative efforts. This trend matters because these improvements can influence energy consumption and emissions by altering the mix of output and how value-added is distributed across industries, which is essentially structural change.

Sectors that see more rapid advancements in product quality and variety are likely to grow at a faster pace compared to their less innovative counterparts, altering the general composition of overall output. The energy and emissions intensities of the overall economy could increase or decrease based on the energy consumption patterns of these key industries. In an earlier study, Van der Zwaan et al. (2002) indicated that incorporating endogenous innovation leads to earlier emission reductions in order to comply with atmospheric carbon concentration limits; see also Wang et al. (2020). Nonetheless, the impact is more significant than what the literature indicates. Additionally, developing non-fossil energy technologies presents a significant chance for reducing emissions (Atar and Durmaz, 2024). R&D delivers efficient and environmentally sustainable solutions of green innovations, while economic growth can improve efficiency and reduce carbon intensity; see Lv et al. (2021) and Li and Wei (2021). However, growth driven by R&D may lead to brown innovation if such initiatives are not environmentally-friendly, which could worsen global warming; see also, Chen et al. (2020). Technology diffusion and specialization in cleaner industries can lead to pollution haven effects or clean technology spillovers—that is, pollution halo effects (Letchumanan and Kodama, 2000). Overall, these factors play a crucial role in promoting R&D and reducing emissions, and eventually limiting global warming.

4.3.2 Data

In this section, we provide details of our data and the macroeconomic variables used in our study to test the relationship between climate and innovation activity. We have panel data for 20 OECD countries from 1870 to 2021 sourced from Jones et al. (2023) and Churchill et al. (2019). This is extended to include 2015 to 2021 data sourced from the World Bank's World Development Indicators. We focus on twenty advanced economies while examining whether impacts global warming based on the following: (1) research and development allows for significant innovation in climate-related technologies, such as renewable energy and sustainable manufacturing. (2) OECD countries also have more reliable data on R&D spending, environmental policies, and emissions can be evaluated to reduce emissions globally. Above all, the diverse economic and industrial structures of OECD countries can also highlight the most effective R&D investments in combating climate change.

Central to our analysis is that we seek to explain the impact of R&D on climate change. Our country climate change measure is each country's contributions to global warming via emissions as a ratio. Our climate change variable (GW_{it}) is measured as a percentage of greenhouse gases emissions contribution to the world's temperature change in levels. This is sourced from Jones et al. (2023). The independent variable is research and development intensity ($R\&D_{it}$), measured as the ratio of nominal R&D expenditure to nominal GDP sourced from Churchill et al. (2019) and World Development Indicators in log levels. Other variables include Y_{it}, Y_{it}^2, $M2_{it}$, POP_{it}, and $TRADE_{it}$ are control variables in their natural logarithm. Y_{it} is real GDP per capita; Y_{it}^2 is the quadratic function of Y_{it}; $M2_{it}$ is the ratio of broad money to GDP, a common proxy for financial development; POP is the total population; and $TRADE$ is the ratio of trade (imports plus exports) to GDP sourced from Churchill et al. (2019) and World Development Indicators. These control variables account for the finance, trade, and population-level channels as potential mechanisms to influence R&D and global warming. In Section 4.4.4, we decompose each country's research and development intensity into an idiosyncratic component and a common factor spillovers, representative of country-specific and global spillovers of research and development intensity and their corresponding effects on global warming. We use a multivariate stochastic volatility model and principal component analysis to estimate the country-specific and global R&D spillovers.

We report the correlations among the variables in Table 4A-1 in the Appendix. We observe significant correlations between trade and global warming (negative) as well as population and global warming (positive). Also, a positive correlation between R&D intensity and trade openness is evident. Essentially, countries that invest resources into R&D tend to be more innovative and competitive on the global level, which results in greater trade openness. This promotes the spread of technology through trade, boosting local research and development initiatives (Dechezleprêtre and Glachant, 2014). As the population grows, it can result in increased greenhouse gas emissions and harm to the environment since there is a greater need for resources such as energy, water, and food; see Khan and Hanjra (2009). Liberalising trade can enhance GDP per capita by drawing in foreign investment and facilitating access to international technology and expertise (Henry et al., 2009). On the other hand, an increase in population can lead to a decrease in the resources available for each individual, which can restrict the funds for investments that boost productivity (Bloom et al., 2003). Dependency ratios can restrict the growth of GDP per capita.

The way investment resources are allocated and our willingness to take risks can have an impact on sectors that rely heavily on research and development. Larger populations striving for self-sufficiency and the presence of trade policy barriers can influence the level of trade openness (Ewing-Chow and Slade, 2016). As GDP per capita rises, financial development grows, bolstering banking systems, savings, and investments. An increase in GDP per capita boosts the demand for money, which in turn leads to a larger money supply (Hall, 2009). The connections between macroeconomic factors and environmental variables are clearly evident in these relationships.

4.3.3 Econometric Methods

Understanding the empirical relationship between climate change and macroeconomic variables is not relied on one-sided method. Theoretical climate-economy models, such as Integrated Assessment Models (IAMs), are often underpinned by assumptions that can be investigated empirically; see Churchill et al. (2019). There are also major limitations to understanding of key socioeconomic and physical factors, along with model design choices. Those factors contribute to data limitations in studying climate change and mitigation policies. Studying the impact of R&D on global warming over a longer period could be complex. The relationship might potentially experience time-varying volatility, structural breaks, endogeneity, and non-linearity, as well as the impact being heterogeneous across countries; see also Churchill et al. (2019) and Huang et al. (2021).

To examine our key empirical relationships, we use a variety of estimators. These have various strengths and allow us to examine the robustness of our results with different estimators. The objective, however, is to address potential cross-sectional dependence, and endogeneity while estimating the relationship between R&D intensity and greenhouse gas emissions contribution to global warming. First, we use a fixed effects estimator, assuming that the individual-specific effects are jointly significantly and are correlated to the explanatory variables. We also assume that there are issues with endogeneity with the individual-specific effects and the other explanatory variables. If endogeneity is apparently not an issue, then the random effects estimator would confirm that. The relationship between R&D intensity and global warming could potentially have reverse causality. Given that global warming can lead to increased R&D intensity to mitigate its effects, the nature of R&D activities can either contribute to or reduce global warming. This can be attributed to underlying factors such as economic growth, policy frameworks, and social awareness that shape both R&D intensity and global warming. A strong economy, for instance, may allocate more R&D resources while also boosting industrial activity generating emissions. This widespread dependency might obscure the link between R&D intensity and climate change. Churchill et al.

(2019) argues that R&D intensity can have a detrimental impact on environmental quality due to increased production, which is referred to as the scale effect that comes with higher economic growth (Omri et al., 2015) and trade openness (Chen et al., 2022). Although new technology has the capacity to enhance efficiency, achieving higher output may still necessitate the utilisation of additional natural resources, potentially resulting in an increase in CO2 emissions (Chen et al., 2020). This may cause atmospheric carbon concentration, and eventually altering average global temperature, leading to global warming (Pindyck, 2021). Given this, we suspect endogeneity between R&D intensity and global warming. Hence, we employ the two-stage least square fixed effects instrumental variable estimator as the final method coupled with per capita income and the one-year lag of per capita income as valid instruments that can correct for this bias. We use the fixed effects regression with Discroll-Kraay standard errors to address cross-sectional dependence among the countries, in the spirit of Driscoll and Kraay (1998).

To address non-linearity, heterogeneity, and time-varying effects, we use a polynomial (quadratic) function of research and development intensity, split the sample period into pre-World War II and post-World War II following Churchill et al. (2019) and also based on structural break tests. Further, country groupings into G7 and others are used to throw more light on the heterogeneous effects of R&D intensity. The relationship between R&D and global warming may not remain constant over time. By splitting the sample or testing for breaks, we can account for changes in how they interact, such as shifts in policy, technology, or economic conditions. This averts the assumption of a single linear relationship from oversimplifying the dynamics. Moreover, different time periods or subgroups may exhibit distinct characteristics or responses. Most especially, countries at different stages of development or facing different levels of climate risk might respond differently to similar policies. Splitting the sample allows for separate analysis of these differences, capturing the heterogeneity and time-varying effects.

Table **4.1:** Descriptive statistics

	Mean	SD	Max.	Min.	Obs.
GW_{it}	2.35	5.61	29.68	0.09	3,040
$R\&D_{it}$	0.12	0.52	3.49	0.00	3,040
$TRADE_{it}$	-2.62	2.48	16.15	-7.22	3,040
POP_{it}	16.32	1.50	19.62	0.00	3,040
$M2_{it}$	4.03	0.95	10.46	0.00	3,040
Y_{it}	8.94	1.52	26.13	-9.80	3,040
Y_{it}^2	82.30	37.64	682.65	32.78	3,040

Notes: This table contains descriptive statistics for: Mean; SD = standard deviation; Max = maximum value; Min = minimum value; Obs. = number of observations.

4.4 Results and Discussion

4.4.1 Descriptive Statistics

This section reports on the descriptive statistics of the variables, as presented in Table 4.1. The descriptive statistics indicate a substantial variation across most variables, particularly in global warming, R&D intensity, and trade openness (see the standard deviations). These variations highlight the diverse economic and environmental contexts represented in the data. These variations are important in understanding the relationship between R&D activities, economic factors, and their potential impacts on global warming. The large standard deviations across most variables suggest that our study needs to account for the significant heterogeneity in the sample.

4.4.2 Preliminary Tests

We begin our investigation by first testing for cross-sectional dependence in the spirit of Pesaran (2015, 2021). The null hypothesis of the cross-sectional dependence assumes weak cross-sectional correlations among the units. The alternate hypothesis confirms cross-sectional dependence, suggesting that the units are strongly correlated. The outcome of the test is presented in Table 4.2. We reject the null hypothesis of cross-sectional dependence at 1% significance level. Also, the cross-sectional exponent α indicates strong cross-sectional de-

Table **4.2:** Unit root and cross-sectional dependence tests

	CIPS	Lags	Remarks	CD test	CD [α]
GW_{it}	-2.64***	4	I(0)	164.45***	0.88
$R\&D_{it}$	-3.97***	1	I(0)	169.45***	1.00
$TRADE_{it}$	-2.63***	1	I(0)	151.20***	1.00
POP_{it}	-2.52***	1	I(0)	144.68***	1.00
$M2_{it}$	-2.36***	1	I(0)	39.72***	0.90
Y_{it}	-2.27**	1	I(0)	125.41***	1.00

Notes: This table reports the unit tests. CIPS represents cross-sectional IPS unit roots developed by Pesaran (2007). The null hypothesis suggests all panels have unit roots. The alternate hypothesis suggests at least one series in the panel has no unit root for CIPS test and some (but not necessarily all) have not unit root for IPS test. CD and α denote cross-sectional dependence tests by Pesaran (2015, 2021). We reject the null hypothesis of weak cross-sectional dependence when the CD statistics shows a p-value less than 0.05. Cross-sectional dependency is considered strong when $\alpha = 1$, semi-strong $0.5 \leq \alpha \leq 1$, weak $\alpha = 0$, and semi-weak $0 < \alpha < 0.5$. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

Table **4.3:** Cointegration tests

Westerlund Cointegration Tests	
(1) GW_{it}, $R\&D_{it}$, $TRADE_{it}$, POP_{it}, $M2_{it}$, Y_{it}, Y_{it}^2	8.87***
(2) GW_{it}, $R\&D_{it}^2$, $TRADE_{it}$, POP_{it}, $M2_{it}$, Y_{it}, Y_{it}^2	8.97***
(3) GW_{it}, $R\&D_{it}^I$, $R\&D_{it}^F$, $TRADE_{it}$, POP_{it}, $M2_{it}$, Y_{it}, Y_{it}^2	1.67**

Notes: This table contains a test statistics for estimating cointegration, variance ratio test from Westerlund (2005) where we reject the null hypothesis of no cointegration when the test statistics have a p-value less than 0.05. P-values are presented in the square brackets. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

pendence among the variables. We strongly confirm evidence of cross-sectional dependence among the selected variables.

We then test for stationarity, and structural breaks of the variables given the longer time span of the data. In particular, we use Pesaran (2007) test for testing the stationarity levels of the variables. We present the outcome of our unit root tests in Table 4.2. We therefore find no evidence that there is pervasive non-stationarity in the data nor the possibility that there can be spurious relationships. This is contrary to what Churchill et al. (2019) observed for variables such as carbon emissions, population, and GDP. On the other hand, we further test for cointegration of the variables in the models. The outcome, which is exhibited in Table 4.3, indicates that the null hypothesis of no cointegration or spurious regression is rejected at 1% significance levels for models (1) and (2), and at 5% significance level for model (3). Finally, we test for structural breaks in our model using the test developed by Ditzen et al. (2021).

While testing for structural breaks, we also account for heteroskedasticity, autocorrelation, and cross-sectional dependence. The outcome is presented in Table 4.7. It is important to emphasise that upon accounting for cross-sectional dependence of R&D intensity for the structural break test, we observe a one-year break point, i.e., 1967. When we account for the cross-sectional dependence of global warming, then the break points turn out to be two years, i.e., 1908 and 1968. Furthermore, we consider the cross-sectional dependence of all variables and identify a one-year breakpoint in 1946.

4.4.3 Benchmark Results

Empirical Linear Model

For the initial estimations, we use the four estimators discussed to capture and address the major econometric issues raised in the existing literature in order to produce reliable and valid results for robust inference; see, for example, Churchill et al. (2019) and Huang et al. (2021). We assess whether our empirical results are robust to different empirical estimators. These estimators are fixed effects (FE), random effects (RE), fixed effects with Driscoll-Kraay standard errors (FE-DK), and two-stage least squares fixed effects instrumental variable regression (FE-IV).

Global warming could be influenced in diverse ways such as through industrial policies, energy mix, technological diffusion, population, trade, financial development, etc. If these factors are omitted from the analysis, the projected direct impact of R&D on global temperature could be negligible. In as much as a direct bivariate regression could be important, it may be misleading when R&D affects emissions since it could be indirect, potentially mediated by technology adoption, regulation, or economic growth. We formally assess the relationship between R&D intensity and global warming in our benchmark model including factors such as population, trade openness, financial development, economic growth, and exponential rise in economic growth.

We present the results for our benchmark model in Table 4.4 for the linear estimations.

Table **4.4:** Benchmark climate change model

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.17***	-0.17***	-0.17**	-0.16**
	(0.05)	(0.05)	(0.07)	(0.05)
$TRADE_{it}$	-0.03*	-0.03**	-0.03*	-0.03**
	(0.02)	(0.02)	(0.01)	(0.02)
$M2_{it}$	-0.06**	-0.06*	-0.06	-0.04
	(0.03)	(0.03)	(0.05)	(0.03)
POP_{it}	-0.33***	-0.32***	-0.33***	-0.60***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.10**	0.09**	0.10	0.69**
	(0.05)	(0.05)	(0.09)	(0.31)
Y_{it}^2	-0.01***	-0.01***	-0.09**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.72***	7.65***	7.72***	8.88***
	(0.57)	(1.29)	(0.41)	(0.87)
R^2	0.19	0.19	0.08	0.23
F-stat.	44.26***		400.51***	
$\mathcal{X}^2$		263.07***		17980.53***
F-test: All $\beta_i = 0$	3590.72			3523.79
	[0.00]			[0.00]
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the results of R&D intensity's impact on global warming (GW_{it}). FE = Fixed Effects. RE = Random Effects. FE-DK = Fixed Effects with Discroll-Kraay standard errors addressing cross-sectional dependence. FE-IV = Fixed Effects Instrumental Variable. The F-test assumes the joint significance of the fixed effects. If the p-value is low (< 0.05), we reject null hypothesis, suggesting that individual-specific effects are significant, and FE should be used instead of pooled OLS. Square brackets [ ] exhibits the p-values of the F-tests. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Our analysis indicates a significant inverse relationship between R&D intensity and global warming. Specifically, a 1% increase in R&D intensity is associated with a reduction in greenhouse gas emissions' contribution to global warming by approximately 0.16% to 0.17%. Fixed Effects (FE) and Random Effects (RE) estimators both yield a coefficient of -0.17, significant at the 1% level, while the Fixed Effects-Instrumental Variables (FE-IV) estimator produces a coefficient of -0.16, significant at the 5% level. These findings underscore the substantial impact of R&D intensity on mitigating global warming. We use the fixed effects estimator to robust-check the random effects estimator. Subsequently, we estimate the extended model by excluding the quadratic term of per capita income (Y_{it}^2). This would allow us to comprehend whether the estimation of the benchmark model would be spurious. This is because, in our initial unit root tests, we observe that the variable Y_{it}^2 is non-stationary and perhaps may be an unbalanced regression if included in the model. The outcome of our findings is presented in Table 4A-4. Our evidence suggests that the sign on the coefficient of R&D intensity is unaffected except the magnitude that slightly decreases. Moreover, the estimated coefficient of R&D intensity loses its significance upon addressing cross-sectional dependence with the FE-DK estimator. This implies that the inclusion of Y_{it}^2 in the benchark model is substantial as it allows us to assess the scale effects of the environment-economic development nexus.

To shed light on the conditional variables, we observe negative sign on coefficients for trade, financial developmment, population and the quadratic term of real GDP per capita. With exception of real GDP per capita which shows positive sign. This implies that the role of trade openness, population and financial development are beneficial to the effects of R&D on global warming. However, the sign on financial development becomes insignificant after addressing cross-sectional dependence and endogeneity issues. In view of this, we can argue that population and trade openness serve as moderators to amplify the positive environmental impacts of R&D by facilitating the diffusion of clean technologies (Klette and Kortum, 2004) or fostering economies of scale and increased public pressure for sustainable policies (Dai, 2025). In addition, as income levels of countries' increase, they are better able to invest in the development of cleaner and efficient technologies that could exert positive effects on environmental quality (Grossman and Krueger, 1995). This is because some level of environmental degradation is inevitable in the initial phases of development. The implication is, beyond a specific income level, the extent to which environmental quality declines will diminish.

In the context of model comparisons, we find that the estimated coefficients for the fixed effects results of our extended model are similar to those of the random effects estimations, as presented in Table 4.4. In contrast, according to our Hausman test presented in Table

4A-3 in the appendix, the fixed effects estimations are preferable to the random effects estimations. We observed that the individual-country specific effects and the explanatory variables are correlated. In addition, the Hausman (1978) test statistic for both Fixed Effects and Random Effects are consistent under the null, but RE is more efficient. In contrast, the FE is consistent under the alternative. Rejecting the null of equivalence of FE and RE suggests that we normally should adopt FE.

Empirical Non-Linear Model

Turning now to the estimates of the non-linear models' estimations, we assess the relationship between the quadratic term of R&D and global warming coupled with the other control variables. We argue there may be non-linearity in the relationship between R&D and global warming; a negative coefficient is consistent with dimisnishing marginal returns. R&D intially is very powerful in reducing a country's contribution to global warming but the effect diminishes with more R&D. We present the results in Table 4.5. We find negative relationship between the quadratic term of R&D and global warming. The evidence suggests that a percentage point increase in R&D intensity is most likely to lead to a reduction in the share of greenhouse gas emissions contribution to global warming by 0.06% and 0.07% at 1% and 5% significance levels. We find that higher R&D intensity could possibly reduce the share of greenhouse gas emissions contribution to average global temperature changes. However, the relationship between R&D intensity and global warming is nonlinear, given that for all our estimations we observed a consistent negative, significant and reduced coefficients. In contrast, the magnitude of the impact is likely to diminish over time, as compared to the results of the linear estimations in Table 4.4.

This revelation is in support of Newell (2009)'s assertion that as the stock of existing knowledge increases, it becomes more difficult to make new discoveries, which results in lower levels of R&D intensity over time. Also, Aleluia Reis et al. (2023) argue that a strong initial investment is crucial to kickstart the transition, after which R&D spending can slowly

Table **4.5:** Benchmark climate change non-linear model

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}^2$	-0.06***	-0.06***	-0.06**	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
$TRADE_{it}$	-0.03**	-0.03**	-0.03**	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
$M2_{it}$	-0.06**	-0.06**	-0.06	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)
POP_{it}	-0.33***	-0.32***	-0.33***	-0.61***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.10**	0.10**	0.10	0.71**
	(0.05)	(0.05)	(0.09)	(0.31)
Y_{it}^2	-0.01***	-0.01***	-0.01**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.70***	7.64***	7.70***	8.92***
	(0.56)	(1.29)	(0.39)	(0.87)
R^2	0.19	0.19	0.08	0.23
F-stat.	45.08***		391.65***	
$\mathcal{X}^2$		267.99***		18018.41***
$N \times T$	3040	3040	3040	3020

Notes: This table presents the estimations of the impact of long run impact of the quadratic term of R&D intensity on global warming for a sample of 20 OECD countries from 1870 to 2021. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

decrease as the benefits of learning-by-doing take over. Initially, investment in research and development might be entirely focused on tackling climate change—that is, on renewable energy and green innovations. In the likely event, R&D may change to other priorities, such as artificial intelligence, biotech, and defense as economies grow, which may potentially reduce its ability to slow down global warming.

We conclude that the relationship between R&D intensity and global warming is negative and substantial, as well as could potentially persist for a longer period. Additionally, we confirm an inverted U-shaped curve relationship between real GDP per capita and global warming in our sample. A U-shaped curve is suggested by Grossman and Krueger (1991, 1995), as it indicates that as income increases, countries are better able to invest in R&D and may adopt more efficient technologies. This would perhaps likely minimise the overdependence on natural resources while also mitigating emissions and pollutants (Dinda, 2004), leading to a clean and healthy environment (Grossman and Krueger, 1995). A substantial amount of R&D investment is likely to improve environmental quality when stringent and effective environmental policies and management systems are in place to ensure proper waste management, pollution, and emissions mitigation (Arora and Cason, 1996; Churchill et al., 2019; Huang et al., 2021; Paramati et al., 2021). Our findings are robust to cross-sectional dependence, unobserved heterogeneity, non-linearity, and endogeneity. The relationship is conditional upon per capita income, population, financial development, and trade openness.

4.4.4 R&D Common Factors

Further, we assess the relationship between R&D intensity and global warming by using the decomposition into country-specific and global spillovers in the extended model. Following Coe et al. (2009), we decompose R&D intensity on the assumption that there may be potential spillover effects internationally from one country to another. Our method is different from Coe et al. (2009) who model foreign R&D as a means of identifying spillovers, while we model spillovers looking at a common factor and the extent to which each country locks on to the common with a factor loading. Our factor model approach also has the advantage of being able to model spillovers for a long data period, while Coe et al. (2009) may not be feasible given the absence of data sources that span 150 years. Country level or idiosyncratic R&D involves exclusive efforts by individual countries, while global (common) R&D spillovers involves collaborative research, shared technologies, and industry practices influencing environmental outcomes.

Our common factor approach also has considerable advantages in terms of generality. We model common factors in two ways: in terms of growth rates and in terms of volatility. First we use the principal component analysis (PCA) to extract the common factor of research and development intensity and further compute the idiosyncratic components. For robustness sake, second we model commonalities by using a multivariate factor stochastic volatility

Table **4.6:** Climate change and R&D PCA decomposition

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}^{I}$	0.03***	0.03***	0.03**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
$R\&D_{t}^{F}$	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
$TRADE_{it}$	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.02)
$M2_{it}$	-0.05*	-0.05*	-0.05	-0.02
	(0.03)	(0.03)	(0.05)	(0.03)
POP_{it}	-0.19***	-0.18***	-0.19***	-0.48***
	(0.05)	(0.05)	(0.05)	(0.14)
Y_{it}	0.14**	0.14**	0.14	0.78**
	(0.05)	(0.05)	(0.09)	(0.32)
Y_{it}^{2}	-0.01**	-0.01**	-0.01*	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
constant	5.05***	4.92***	5.05***	6.18***
	(0.85)	(1.43)	(0.66)	(0.97)
R^2	0.10	0.09	0.09	0.18
F-stat.	40.85***		534.89***	
$\mathcal{X}^2$		284.34***		18093.87***
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the results decomposed R&D intensity's impact on global warming. Here, the decomposition is done using a principal component analysis. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

(MFSV) model created by Hosszejni and Kastner (2021a) and estimating it using Bayesian methods. The factor stochastic volatility model's Bayesian estimation is based on standard univariate stochastic volatility implementations and includes a number of new features to make it work efficiently. The major advantage of using the MFSV is that it aids in understanding the intricate connections among various factors and their fluctuations in a dynamic manner, as shown in Equation 4.4 in Section 4.3.1. Essentially, instead of addressing the volatility of each variable on its own, it posits that a limited number of underlying factors influence the overall volatility across all variables. This diminishes the complexities while still capturing essential patterns in the data. The objective, however, is to augment the PCA approach as the multivariate factor stochastic volatility approach uses the log-volatilities as against the levels that is used by the former.

The outcome of the findings is presented in Table 4.6 for the principal component analysis decomposition of R&D. We observe a negative and statistically significant relationship between global R&D spillovers and global warming. However, the PCA computation of country-specific research and development intensity exhibits consistent positive and significant relationship with global warming.[3] A study shows that research and development spending and renewable energy consumption negatively correlate, further affirming that an increase in country-level research and development investment may not inherently lead to renewable energy consumption. Meanwhile, greater investments in physical assets, such as machinery and infrastructure, frequently result in higher emissions, as numerous industrial and infrastructure initiatives are energy-intensive.[4]

In retrospect, we show that the intensity of global R&D spillovers have a notable negative effect on global warming, suggesting that an increase in global R&D spillovers could potentially decrease global warming. This indicates that advancements in technology and innovations fuelled by global research and development and the transfer of advanced technologies as well as knowledge from developed countries to developing countries can result in more efficient or cleaner technologies that could help address climate change; see Pigato et al. (2020) and Blanco et al. (2022). In addition, the influence of country-level R&D intensity on global warming is devastatitng, indicating that tackling climate change requires a coordinated global approach. The research highlights the importance of working together globally in areas like research and development, implementing flexible climate policies, and

[3] Table 4A-5 presents the findings for the multivariate stochastic volatility decomposition of R&D intensity. Our evidence suggests that global R&D intensity has a negative and significant relationship with global warming as a result of global spillovers. As shown for all the estimators, a percentage point increase in global R&D spillovers could potentially reduce global warming by about 0.07% and 0.09%. Moreover, we find that the country-level R&D intensity has an inconsistent impact on global warming across all estimations. In terms of the two approaches, the outcome of our findings does not differ except that there is slight difference in the magnitude of coefficients and R^2.

[4] Naz et al. (2024) find a positive and moderate correlation among GDP, gross capital formation, labor, and greenhouse gas (GHG) emissions, most especially in the G7 countries.

using a mix of policy measures, technology, and current innovation to enhance the beneficial effects of R&D on climate change.

4.4.5 Structural Breaks

Recognising structural breaks is key to assessing R&D intensity's long-term impact on global warming. These breaks lead to important changes in how R&D relate to global warming over time, including shifts in historical events and policy, advancements in technology, global economic changes, variations in data availability and measurement, and an increasing awareness of climate change (Ditzen et al., 2021). Historical events such as industrial revolutions, major wars, and environmental policies like the Kyoto Protocol and the Paris Agreement may have changed the dynamics of global warming and R&D intensity; see Atar and Durmaz (2024). Technological breakthroughs in renewable energy and advancements in energy efficiency might have changed how R&D efforts affect emissions; see Acheampong et al. (2022) and Abbas et al. (2024). Shifts in how data is collected and a growing awareness of climate change might lead to structural breaks in the data, suggesting a change in the focus and effectiveness of R&D efforts to combat global warming.

We conduct structural break tests on the assumption that the break dates are unknown and there may be potential cross-sectional dependence of R&D intensity and global warming. The structural break tests are presented in Table 4.7 for all variables' cross-sectional dependence specification. Other specifications include R&D cross-sectional dependence and global warming cross-sectional dependence while assessing the structural breaks, as presented in Table 4A-2 in the Appendix. In the spirit of Ditzen et al. (2021), we performed structural tests against the null of no structural breaks. The alternate hypothesis suggests at least one structural break. The outcome of the test indicates a critical value of 10.25, which is above the critical value of 4.08 at 1% significance level. We, however, reject the null hypothesis of no structural break, as presented in Table 4.7. Based on these structural break tests, we include dummies of the break years as exogenous variables in the baseline models. The

Table **4.7:** Structural break tests

	Stat.	1% Critical value	5% Critical value	10% Critical value
Structural Break Test 1				
$\mathrm{GW}_{it} = \mathrm{f}(R\&D_{it}, TRADE_{it}, POP_{it}, M2_{it}, Y_{it}, Y_{it}^2)$				
F(1|0)	10.25***	4.08	3.35	2.99
F(2|1)	3.31	4.32	3.69	3.34
F(3|2)	3.77*	4.51	3.84	3.53
F(4|3)	3.73*	4.59	3.96	3.68
F(5|4)	6.93***	4.70	4.07	3.77
Cross-section dependence = GW_{it}, $R\&D_{it}$, $TRADE_{it}$, POP_{it}, $M2_{it}$, Y_{it}, Y_{it}^2, Break points = 1 year: **1946**				

Notes: This table presents the results for structural break tests. The structural break test accounts for heteroskedasticity, autocorrelation, and cross-sectional dependence where the cross-sectional variables are exhibited in parentheses for each test. The test is developed by Ditzen et al. (2021). Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. F(1|0) rejects the null of no structural breaks against the alternate hypothesis of one structural break. F(2|1) accepts null of structural break hence we conclude that there is evidence of structural break. Critical values from 1% to 10% significance levels.

outcome of the estimations, including dummies of the break years, are presented in Table 4.8 taking into account the cross-sectional dependence of all variables with 1946 as the break year, Table 4A-6 taking into account the cross-sectional dependence of R&D intensity with 1908 and 1968 as break years, and Table 4A-7 taking into account the cross-sectional dependence of global warming with 1967 as the break year. Our findings indicate that R&D intensity has a significant negative impact on global warming across all estimations. The results are consistent with the other findings in terms of the sign of the coefficients. This indicates that, despite addressing structural breaks and the cross-sectional dependence of both R&D intensity and global warming, as well as the other variables, R&D intensity may have the potential to mitigate the effects of global warming. While the formal test finds evidence of one break, the estimator does not suggest that the break is statistically significant.

Table **4.8:** Climate change and R&D: structural breaks

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.17***	-0.17***	-0.17**	-0.16**
	(0.05)	(0.05)	(0.07)	(0.05)
$BREAK_{dummy}$	0.07	0.07	0.07**	0.12
	(0.22)	(0.22)	(0.03)	(0.22)
$TRADE_{it}$	-0.03*	-0.03*	-0.03*	-0.03**
	(0.02)	(0.02)	(0.01)	(0.02)
$M2_{it}$	-0.06**	-0.06**	-0.06	-0.04
	(0.03)	(0.03)	(0.05)	(0.03)
POP_{it}	-0.33***	-0.32***	-0.33***	-0.61***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.10**	0.10**	0.10	0.70**
	(0.05)	(0.05)	(0.09)	(0.31)
Y_{it}^2	-0.01***	-0.01***	-0.01**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.72***	7.65***	7.72***	8.90***
	(0.57)	(1.29)	(0.41)	(0.88)
R^2	0.19	0.19	0.08	0.23
F-stat.	37.94***		1203.25***	
$\mathcal{X}^2$		263.09***		17975.71***
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 20 OECD countries from 1870 to 2021. Here, we focused on the cross-sectional dependence of all variables while considering the structural breaks: Test (1). The null hypothesis of test the presence of a break against the alternative of one more break, as it is estimated against lower and upper limits of breaks. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

4.4.6 Other Results

We further decompose our sample into pre- and post-World War II to understand the time-varying effects, as these events may have influenced economic priorities and industrial activity. The outcome of these estimations is presented in Table 4A-8 for the pre-World War II and Table 4A-9 for post-World War II samples, respectively. Our findings indicate that the impact of R&D intensity on global warming does not vary in sign but rather in magnitude. The evidence indicates that the effect of R&D intensity has been minimal following World War II in comparison to the period preceding it. The findings imply that while R&D intensity has consistently influenced global warming, the post-World War II shift in economic priorities, diversification of R&D fields, environmental policies, and slower growth in emission-intensive industries reduced the magnitude of its impact. During pre-World War II period, R&D was strongly tied to industrial growth, leading to a more pronounced effect on emissions and global warming, whereas post-World War II, the connection between R&D and global warming weakened due to a more complex global economic and technological landscape.

Subsequently, we assess the heterogeneity assumption of our sample. We split our sample of 20 OECD countries into G7 and other 13 countries to better assess the heterogeneous effects of R&D intensity on global warming. These results are presented in Table 4A-10 for the G7 countries and Table 4A-11 for the other 13 countries in the Appendix. With their industrialisation, technological leadership, and larger R&D budgets, G7 countries are likely to show a stronger historical link between R&D intensity and global warming. In contrast, the other 13 OECD countries may have different R&D and energy policies that affect emissions, especially in recent years. This separation highlights the different roles of economic history, policy, and technology in these groups. Our estimations reveal a consistently positive relationship between R&D intensity and global warming in the G7 countries, whereas a consistent negative and significant impact of R&D intensity on global warming is evident in the other 13 OECD countries. In G7 countries, the relationship is positive, which may likely be due to factors like legacy fossil fuel innovations, and industrial R&D. On the other hand, the other 13 OECD countries, with a more consistent focus on cleaner technologies and less reliance on emissions-intensive industries, show a clearer and more consistent negative relationship between R&D intensity and global warming.

4.5 Conclusion

This chapter examined the relationship between R&D intensity and global warming in the OECD countries. Research and Development is vital for economic growth and mitigating or adapting to the impact of climate change. Investment in R&D may, therefore, lead to technical change that could have positive effects on environmental quality. Against this backdrop, we assessed the impact of R&D intensity on global warming for a sample of twenty OECD countries for over one hundred and fifty years of data. Our multiple estimations suggest that R&D intensity is empirically relevant for global warming. Increasing R&D intensity is significantly associated with a reduction in global warming. This relationship is also time invariant in terms of sign of the coefficient. In addition, there are potential global R&D spillovers that are likely to scale up the efforts in reducing global warming. This implies that global R&D spillovers are more important than country-specific intensity. We find that the magnitude of R&D intensity's impact on global warming has been diminishing post-World War II as compared to pre-World War II. The findings are robust to cross-sectional dependence, endogeneity, and structural breaks.

Chapter 5

General Discussion and Policy Implications

This chapter of the thesis shall discuss the policy implications of the research in greater detail. We begin by examining *"The Macroeconomic Impact of Global and Country-Specific Climate Risk, "* followed by *"The Economic Consequences of Green Growth: A Multi-Country Empirical Study"* and finally, *"R&D Intensity and Global Warming."*

5.1 The Macroeconomic Impact of Global and Country-Specific Climate Risk

Chapter two of the thesis highlighted the critical role of global climate risk in impacting macroeconomic activity. While the literature has primarily examined country-specific climate risk, our results suggest that such risks, although negative in their impact, are relatively less significant in comparison to global climate risk. Our results imply long-term and substantial negative effects of global climate risk on GDP growth across both advanced and emerging economies. Emphasising the interconnected nature of climate-related shocks and implying a need for coordinated global policy responses. A key insight from our study is the delayed and persistent effect of global climate risk shocks on macroeconomic performance. The lagged impact, peaking around the third year, highlights the structural vulnerabilities economies face when adjusting to climate-induced disruptions. Furthermore, the temporary overshooting of GDP following an initial decline suggests that global climate risk shocks introduce volatility into economic activity before eventual stabilisation. The finding is comparable to those from Alessandri and Mumtaz (2021) and Donadelli et al. (2022). This finding is crucial for policymakers in designing adaptive economic strategies that can buffer against such economic fluctuations. Below are the policy implications for our findings:

Global Climate Governance: Given the dominant role of global climate risk in macroeconomic activity, policy measures must prioritise international cooperation. The estimated adverse impact observed across advanced and emerging economies calls for strengthened multilateral frameworks, such as enhanced commitments to the Paris Agreement, and better integration of climate-related risks into global financial stability assessments; see Han and Cheng (2023).

Structural Reforms: The delayed effects of climate shocks necessitate forward-looking policies that enhance economic resilience. Governments should invest in climate adaptation infrastructure, diversify their energy sources towards renewables, and promote sustainable agriculture to mitigate long-term economic disruptions; see also, Chen et al. (2023).

Monetary and Fiscal Policy: Central banks and financial regulators must incorporate climate risk into macroeconomic forecasting and monetary policy frameworks; see Campiglio et al. (2018) and Batten et al. (2020). The findings indicate that global climate risk induces additional economic volatility, which suggests the need for countercyclical fiscal measures, green financial instruments, and climate stress testing in financial markets; see also, Battiston et al. (2017) and Lamperti et al. (2021).

Advanced and Emerging Economies: Although both advanced and emerging economies are adversely affected by climate risk shocks. It is important to emphasise that advanced economies should ensure reducing carbon emissions through stringent environmental policies and regulations; see Ahmed (2020). In addition, advanced economies should invest in critical technologies that could aid decarbonisation; see also, Jägemann et al. (2013). Emerging economies, on the other hand, require financial and technological support to transition towards climate-resilient growth models while maintaining economic development goals (Nhamo and Chapungu, 2024). This is in line with notion that developing countries face financial challenges in addressing the pressing climate change effects whereas advanced economies contribute the chunk of emissions that causes global warming.

Climate Risk Monitoring: The factor stochastic volatility approach used in this chapter highlights the importance of high-quality climate and macroeconomic data. The available data on climate change and macroeconomic activity indicate that an increase in annual average temperature has an effect on macroeconomic growth; see, for example, Alessandri and Mumtaz (2021), Donadelli et al. (2022), and Kotz et al. (2022). However, a number of macroeconomic activities are affected by deviations in daily temperature from seasonal expectations that are not adequately reflected in annual averages; see Kotz et al. (2021). Governments and international institutions should invest in climate risk monitoring to enhance prediction of climate risk.

The macroeconomic effects of climate risk are no longer confined to individual countries but manifest through globally interconnected channels. This thesis's findings reinforce the argument that mitigating climate risk requires proactive and coordinated global efforts rather than isolated national policies. The long-term and significant adverse effects of global climate risk on GDP emphasise the need for immediate and sustained policy actions. Without such interventions, economies may continue to experience heightened volatility and structural economic downturns, reinforcing the urgency of integrating climate risk considerations into economic policymaking.

5.2 The Economic Consequences of Green Growth: A Multi-Country Empirical Study

Chapter three of this thesis highlights the significant and positive relationship between green growth and macroeconomic performance, particularly in advanced economies. The comprehensive green growth measure, which incorporates environmental productivity, policy responses, and socio-economic factors, demonstrates that transitioning towards a greener economy does not necessarily come at the cost of economic expansion; see Easton and Walker (1997) and Faria and Montesinos (2009). Instead, the results suggest that well-designed green growth policies that can lead to sustainable economic development; see also, Fay (2012). One of the key results from this chapter is the heterogeneity in the effects of green growth across countries. These variations underscore the importance of country-specific conditions, such as economic structure, labour force composition, and policy implementation for the effectiveness of green growth policies—in consistent with Iqbal et al. (2025) and Sharma et al. (2025). The presence of significant lagged effects further reinforces the notion that green growth policies require time to have their full effect. Given these findings, we make the following policy recommendations:

Particular Country Approaches: Given the heterogeneous effects of green growth, policymakers must adopt country-specific approaches. While advanced economies can use their existing infrastructure and skilled labour force to ensure green innovation, emerging economies may need transitional policies that mitigate potential short-term economic disruptions. Targeted investments in renewable energy, sustainable agriculture, and green infrastructure can minimise negative consequences; see, for example, Choi et al. (2021) and Zhang et al. (2022).

Policy and Institutional Stability: The significant lagged effects of green growth on GDP highlight the necessity for long-term policy commitment. It is instructive to suggest that investment incentives (Di Falco and Sharma, 2018), environmental policy stringency (Song and Knaap, 2004), and maintaining policy consistency (Basheer et al., 2022), would repose confidence in businesses and investors at large, to participate in sustainable economic activities. Therefore, policymakers need to pay critical attention to these issues. Short-term political or economic disruptions should not derail long-term green growth strategies.

Balancing Economic and Environmental Goals: While green growth contributes positively to economic performance, there is the need to ensure that sustainable development goals are primarily the focus of every facets of government policies. Essentially, countries that experience initial negative effects should prioritise a gradual and adaptive approach. This may include incorporating compensatory measures such as green subsidies, carbon pricing mechanisms, and financial support for industries transitioning to sustainable models (Knopf et al., 2010; Feng and Ge, 2024).

Climate Finance: Emerging economies may require additional financial and technical support to transition towards green growth; see Liu and Liu (2025). International cooperation, climate finance mechanisms, and public-private partnerships can help bridge investment gaps. Multilateral institutions should play a central role in facilitating access to green finance and ensuring that funds are efficiently allocated to projects with high economic and environmental impact; see Chen et al. (2024).

Measurement of Green Growth: Accurate and comprehensive data collection is critical for assessing green growth policies; see, for instance, Sarkodie et al. (2023). Governments should better track environmental productivity, policy effectiveness, and socio-economic outcomes. This will enable evidence-based policymaking and allow for adjustments to strategies as needed.

The empirical evidence strongly supports the positive economic implications of green growth, particularly in advanced economies. However, the heterogeneous effects across different countries highlight the need for adaptive and country-specific strategies. Policymakers must consider financial constraints when designing green growth policies. By ensuring policy consistency, and improving financial and policy support, countries can benefit from green growth while minimising potential short-term economic disruptions. Green growth can have a powerful impact if the right policy mix is adopted.

5.3 R&D Intensity and Global Warming

Chapter four of this thesis emphasises the role of R&D intensity in addressing global warming. The evidence suggests that increased investment in R&D has been important in reducing global warming. Technology potentially has a powerful impact upon global warming. Increasing R&D intensity is significantly associated with the reduction in global warming, which is time-invariant in terms of sign of the coefficient but the size differs. A notable insight from this research is the significance of global R&D spillovers, which are more important for global warming than country-specific R&D efforts. This suggests that international collaboration and knowledge spillovers in research and development play a pivotal role in the global fight against climate change. However, the observed decline in the effectiveness of R&D intensity in mitigating global warming post-World War II, compared to the pre-World War II period, raises important questions about the evolving nature of technological progress and its environmental impact.

Furthermore, the confirmation of an inverted U-shaped curve between per capita income and global warming indicates that economic growth initially contributes environmental degradation but eventually leads to improvements in environmental quality as economies mature and invest more in green technologies. This finding is in support with the broader literature on the relationship between economic development and environmental sustainability; see, for example, Grossman and Krueger (1991), Grossman and Krueger (1995), Koop and Tole (1999), Dinda (2004) and Shahbaz et al. (2020). These studies suggest the need for specific policies that accelerate the transition to cleaner and sustainable developent. Here are some policy implications for our findings:

Global R&D Collaboration: Given the importance of global R&D spillovers, policymakers should aim to promote international research collaborations, joint innovation projects, and technology-transfer arrangements; see, for example, Debackere and Veugelers (2005) and Proskuryakova et al. (2017). It is worth noting that strengthening cross-border collaboration in clean energy research and climate-friendly technologies that can propagate the positive effects of R&D investment on global warming reduction is essential. Becker (2015) argues that R&D cooperation through university research and high-skilled human capital usually escalates private sector R&D. According to Becker (2015), there are three categories that public policies are usually considered. (*i*) Policies that considers R&D tax credits and direct subsidies, (*ii*) policices in support of the university research system and (*iii*) policies in support of the formation of high-skilled human capital, and support of formal R&D cooperations across a variety of institutions. In order to ensure sustainable and effective research and development of climate-related innovations, governments and policymakers should provide condusive environment for all players; see Elia et al. (2020) and Omri and Jabeur (2024). This can include tax credits and subsidies, and direct investment for green technology projects. More importantly, public-private partnerships should be encouraged for development and deployment of sustainable production and climate solutions.

Post-WWII Decline in R&D Intensity: The chapter's revelation of diminishing impact of R&D intensity on global warming after the World War II indicates the need to re-examine R&D policy initiatives. R&D policies should focus on ensuring that research efforts are effectively translated into practical, scalable, and impactful solutions; see David and Hall (2000). This may involve strengthening stronger industry-academia collaborations. Sakakibara (1997) argues that complementary knowledge spillovers are the underlying benefit of R&D collaboration. This may be attributed to the rapid diffusion of knowledge and technology among stakeholders. In this instance, it supports the deployment and development of pilot projects for nascent green technologies. By contrast, it is important for governments to ensure environmental policy stringency that could support the commercialisation of environmentally-friendly innovations. Since we find that an inverted U-shaped curve relationship exists between economic development and environmental quality. It is important to emphasise that early investments in sustainable infrastructure, ensuring stringent environmental management, and economic diversification polices should be of high priority to achieve low-carbon economy.

The chapter's findings highlight the fundamental role of R&D intensity in mitigating global warming and underscores the importance of global R&D spillovers in achieving environmental sustainability. Despite R&D investment being an important policy initiative to address climate change, we find that its intensity has evolved over time. This implies that continuous and sustainable policy implementation and adaptation is strongly needed; such as strengthening international collaboration, improving financial support for environmental-related R&D investment, and adoption of cleaner and green technologies.

Chapter 6

Summary and Conclusion

This chapter provides a summary and conclusion to the thesis. We begin with a conclusion and summary of our first study, *"The Macroeconomic Impact of Global and Country-Specific Climate Risk, "* followed by the second study, *"The Economic Consequences of Green Growth: A Multi-Country Empirical Study"* and final the study, *"R&D Intensity and Global Warming."*

6.1 The Macroeconomic Impact of Global and Country-Specific Climate Risk

Temperature increases have been shown to have an adverse effect on economic growth, especially in developing countries (see Dell et al., 2012; Burke et al., 2015; Feng and Kao, 2021; Kotz et al., 2021, among otherss). This study demonstrates how climate change affects macroeconomic activity via a volatility channel. We used the Bayesian Panel VAR with hierarchical prior to estimate the VAR coefficients of macroeconomic activity and climate risk for 17 advanced and 13 emerging economies for the period 1901 to 2020. No other papers as far as we are aware have applied factor stochastic volatility to model global risk, consistent with the notion from Stern (2008) that climate change is global in character. Our results highlight that there is a powerful negative impact from global climate risk on macroeconomic activity.

To allow for country heterogeneity, we also differentiate the impact of climate risk upon advanced and emerging economies. We discover that both advanced and emerging countries are negatively affected by climate risk shocks. Existing literature has focused on country-based risk shocks, but our findings indicate that idiosyncratic or country-specific climate risk shocks are relatively unimportant. On the other hand, global climate risk has a negative and relatively more important impact on macroeconomic activity. In accordance with Stern (2008), we also find that the impact of climate risk on macroeconomic activity is far-reaching and potentially long-lasting. It is essential to recognise that countries' temperature changes are interconnected, as evidenced by substantial spillovers. This discovery supports and justifies the significance of our findings. In addition, the capability of our econometric method to capture cross-sectional heterogeneity and spillovers makes our findings robust and noteworthy.

One potential limitation to our research is that we do not differentiate various forms of shocks. We leave to future research discussion of modelling underpinning shocks to climate variability and how they can impact GDP depending upon the source of shock. Additionally, our study fails to consider additional external factors, such as policy responses, adaptive strategies, or technological advancements, which have the potential to either mitigate or exacerbate the effects of climate risks. Hence, it is plausible that dynamic models that effectively capture the dynamic nature of the relationship between climate risk and macroeconomic activity, taking into consideration the temporal changes in climate patterns, economic conditions, and policies, may provide valuable insights into this phenomenon. A future extension to this research could be that we focus on a wider range of countries, with more global coverage, albeit over a short time period. This could also encompass the examination of policy measures, international cooperation, and their resultant effects.

6.2 The Economic Consequences of Green Growth: A Multi-Country Empirical Study

Climate change has led to country adaptation policies via promotion of green growth policies. Comparable data on green economic activity has been hard to find; see Hammer et al. (2011); Shao et al. (2020). This study examines the dynamic relationship between green growth and GDP growth, thereby contributing to the expanding body of research on the economic consequences of climate adaptation. Estimators robust to cross sectional error correlation, parameter heterogeneity and potential endogeneity are used for a sample of 81 countries from 1992 to 2021. The methodology relies on estimating the common factors by utilising cross-sectional averages of the dependent and independent variables. We use dynamic common correlated effects, mean group, and mean group instrumental variable estimators, along with static and dynamic fixed effects.

To summarise our main findings, we support the notion that green growth positively and significantly contribute to economic growth. The relationship between green growth and GDP growth is robust to accounting for the impact of physical capital investment, urbanisation, human capital, and green technologies. The relationship between green growth and GDP growth is bidirectional, although there is a noticeable delay in the effect, suggesting that the influence of green growth on GDP growth is more rapid in advanced economies than in emerging economies. Our analysis reveals that the sub-dimension of green growth known as environmental-policy-related response and social economic opportunities have a positive and significant impact on the increase in GDP growth. However, other sub-dimensions such as natural asset base, environmental productivity, and quality of life do not have an immediate effect on GDP growth.

Considering the approach used, it is crucial to emphasize that the estimators for the dynamic common correlated effect were found to be consistent when assessing the dynamic relationship using our sample size of $T < N$ than the fixed effects estimators. Given that they are robust and flexible to address cross-sectional dependence, cross-sectional heterogeneity, and endogeneity; see Ditzen (2021). Everaert and De Groote (2016) confirm that the properties of the common correlated effect estimator, when applied to small samples, can be utilised for estimating dynamic panel data models, as long as the sample size (T) is not excessively small. Chudik and Pesaran (2015) show that using a dynamic common correlated effect mean group estimator and adding covariates to account for the effects of many common factors that are not observed can help lower the bias in small sample time series analysis. This ensures consistent rates and enables the derivation of the asymptotic distribution. We acknowledge the presence of possible constraints in the study. Owing to the limited availability of data, the quality and reliability of data from different countries may differ, posing a challenge in deriving significant conclusions and restricting the extent of the analysis. Examining the drivers of heterogeneity of country results through time could be a promising avenue.

6.3 R&D Intensity and Global Warming

This study explores how research and development relates to global warming. Emphasising the impact of R&D spillovers at both global and country levels. Our analysis shows that R&D mitigates climate change impacts in 20 OECD countries. Our results show that increased R&D intensity significantly mitigates global warming, highlighting the environmental benefits of technological progress. Most essentially, investment in R&D that might lead to development of efficient technologies is likely to improve efficiency in production, natural resource and energy use. In effect, as countries experience growth in per capita income, they are better able to invest in R&D that could reduce the strain on natural resources, mitigate emissions and improve biodiversity. Our analysis reveals heterogeneity: R&D intensity increases global warming in G7 countries but reduces it in the other 13 OECD countries. Our findings reveal that R&D intensity had a much greater impact before World War II than afterward. On the other hand, the findings indicate that global R&D spillovers have a negative and statistically significant impact on global warming.

Our findings also show that global collaborative R&D effectively combats climate change, while country-specific research may hinder progress potentially due to inconsistent policies, fossil fuel dependence, and rebound effects. This emphasizes the importance of working together across borders in research and development related to climate and transferring technology to achieve beneficial outcomes across the globe. This further highlights the essential importance of global research and development initiatives in fostering technological advancements that aid in addressing climate change. The study also reveals that R&D intensity at the country level could positively and significantly affect global warming, emphasising the need for international collaboration and collective action in promoting effective climate-related innovations. The dependence on national R&D investments alone might not be enough to tackle climate change; we need to tap into knowledge and technological transfers as well. These findings highlight the importance of ongoing and collaborative global research and development efforts, especially in green technologies, to effectively address global warming.

Policymakers need to take into account not just the immediate advantages of investing in R&D, but also the long-term interactions and responses within the global climate system. As we forge ahead, adopting a global strategy for research and development, backed by global partnerships and steady financial support, will be crucial in tackling the climate crisis. We acknowledge the potential limitation of our study in using aggregate data on R&D to understudy the country-level and global impact of global warming. Given that the results using aggregated data are harder to interpret, and also use to advocate for very specific policy recommendations.

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Appendix - Chapter 2

Appendix A: Supplementary Results and Methodology

Modelling Univariate Climate Risk ($\mathbf{H}^{\mathbb{T}}_{it}$)

To estimate univariate climate risk $\mathrm{H}^{\mathbb{T}}_{it}$ for all countries i at time t, we apply a univariate stochastic volatility estimation model country-by-country, with $\mathbb{T}_t$ representing a country time series representing temperature changes. Univariate stochastic volatility is constructed independently for each country. We use a stochastic volatility (SV) model to estimate univariate climate risk $\mathrm{H}^{\mathbb{T}}_{it}$ for each country, based upon the following framework for $\mathbb{T}_t$:

$$\begin{aligned} \mathbb{T}_t &= exp(h_t/2)\epsilon_t, \\ h_{t+1} &= \mu + \varphi(h_t - \nu) + \sigma\eta_t, \\ \epsilon_t &\sim \mathcal{N}(0,1), \eta_t \sim \mathcal{N}(0,1), \end{aligned} \tag{2A-1}$$

The random variables ϵ_t and η_t are assumed to be independent. Whereas the log-variance process h_t is initialised with h_0 drawn from a normal distribution with mean μ and variance $\sigma^2/(1-\varphi^2)$. The SV parameters, denoted as $\upsilon = (\mu, \varphi, \sigma)$, are used in our study. Here, μ represents the level, φ represents the persistence, and σ (also known as *volvol*) represents the standard deviation of the log-variance.

Modelling Global Climate Risk ($\sigma^{\mathbb{T}}_{Ft}$)

In the factor Stochastic Volatility model, Bayesian estimation improves on the univariate Stochastic Volatility implementations and offers multiple options to enhance efficiency (Andersen et al., 1999; Hosszejni and Kastner, 2021b). To circumvent the issue of sluggish convergence in high dimensions, our model is estimated with a sampler that uses multiple interweaving strategies (Hosszejni and Kastner, 2021b).[1] Several factors are influenced by

[1]The efficiency of sampling in Bayesian inference for stochastic volatility models using Markov Chain Monte Carlo (MCMC) methods is heavily contingent upon the specific values of the parameters being estimated. The standard centre parameterization of posterior draws is inadequate in cases where the volatility of the volatility parameter in the latent state equation is low. Conversely, non-centered versions of the model

a small number of random sources, which explain how the observations interact with one another. In addition, latent factor models provide an effective method for estimating the dynamic covariance matrix. They decrease the number of unknowns. In a typical latent factor model with r factors, the decomposition is the diagonal matrix, which contains the variances of the idiosyncratic errors (Hosszejni and Kastner, 2021b).

A significant issue with dynamic covariance estimate is the large number of unknowns relative to the number of observations. To be precise, a quadratic expression in N have $N(N+1)/2$ degrees of freedom which has a corresponding covariance matrix Σ_t when the cross-sectional dimension is N. Using latent factors, one can make Σ_t appear sparser in order to overcome the dimensionality curse. When creating latent factor models, it is essential to keep in mind that even multidimensional systems can be governed by a limited number of random sources.

Against this backdrop, this research employed a factor stochastic volatility method to measure climate risks in order to assess its impact on macroeconomic activity. In the factor stochastic model, the covariance matrix of $\overline{\Sigma}_t$ and $\tilde{\Sigma}_t$ is representing independent univariate stochastic volatility processes which are both diagonal. Identification issues relative to factor stochastic volatility are relevant. Some of the identification assumptions are the sign, the order, and the scale of the factors is unidentified. In the factor Stochastic Volatility model, Bayesian estimation improves on the univariate SV implementations and offers multiple options to enhance efficiency. To circumvent the issue of sluggish convergence in high dimensions, it is performed with a sampler that employs several ancillarity-sufficiency interweaving strategy (ASIS) types.[2]

exhibit shortcomings when applied to highly persistent latent variable series. The efficacy of the ancillarity-sufficiency interweaving technique in addressing these challenges across various multilevel models has been substantiated (Yu and Meng, 2011; Kastner and Frühwirth-Schnatter, 2014).

[2]The efficiency of sampling in Bayesian inference for stochastic volatility models using Markov Chain Monte Carlo (MCMC) methods is heavily contingent upon the specific values of the parameters being estimated. The standard centre parameterization of posterior draws is inadequate in cases where the volatility of the volatility parameter in the latent state equation is low. Conversely, non-centered versions of the model exhibit shortcomings when applied to highly persistent latent variable series. The efficacy of the ancillarity-sufficiency interweaving technique in addressing these challenges across various multilevel models has been

In this chapter we model global climate risk using a Factor Stochastic Volatility model.

$$\begin{aligned} &\mathbb{Z}_{it} \mid \boldsymbol{\beta}, \boldsymbol{\Lambda}, \boldsymbol{f}_t, \overline{\boldsymbol{\Sigma}}_t \sim \mathcal{N}_N(\boldsymbol{\beta} + \boldsymbol{\Lambda} \boldsymbol{f}_t, \overline{\boldsymbol{\Sigma}}_t), \\ &\boldsymbol{f}_t | \tilde{\boldsymbol{\Sigma}}_t \sim \mathcal{N}_r(0, \tilde{\boldsymbol{\Sigma}}_t), \end{aligned} \tag{2A-2}$$

where $\mathcal{N}(\boldsymbol{\beta} + \boldsymbol{\Lambda} \boldsymbol{f}_t, \overline{\boldsymbol{\Sigma}}_t)$ denotes the normal distribution for the matrix $\mathbb{Z}_{it}$ with mean temperature changes represented by $\boldsymbol{\beta} = (\beta_1,...,\beta_N)^\top$ with temperature change factors $\boldsymbol{f_t} = (f_{1t},....,f_{rt})^\top$. The factor loadings are $\boldsymbol{\Lambda} \in \mathbb{R}^{N \times r}$ in equation (2A-2). The covariance matrices $\overline{\boldsymbol{\Sigma}}_t$ and $\tilde{\boldsymbol{\Sigma}}_t$ are both diagonal and can be written as:

$$\begin{aligned} &\overline{\boldsymbol{\Sigma}}_t = diag(exp(\overline{h}_{it}), ..., exp(\overline{h}_{Nt})), \\ &\tilde{\boldsymbol{\Sigma}}_t = diag(exp(\tilde{h}_{1t}), ..., exp(\tilde{h}_{rt}))), \\ &\overline{h}_{it} \sim \mathcal{N}(\overline{\mu}_i + \overline{\varphi}_i(\overline{h}_{it-1} - \overline{\mu}_i), \overline{\sigma}_i^2, \quad i = 1, ..., N, \\ &\tilde{h}_{jt} \sim \mathcal{N}(\tilde{\mu}_j + \tilde{\varphi}_j(\tilde{h}_{jt-1} - \tilde{\mu}_j), \tilde{\sigma}_j^2, \quad j = 1, ..., r, \end{aligned} \tag{2A-3}$$

The total variance ($\boldsymbol{\Sigma}_t$) of temperature changes can be decomposed into factor and idiosyncratic variance.

$$\boldsymbol{\Sigma}_t = \tilde{\boldsymbol{\Sigma}}_t + \overline{\boldsymbol{\Sigma}}_t, \tag{2A-4}$$

Where $\overline{\boldsymbol{\Sigma}}_t$ consists of variances of the idiosyncratic errors while $\tilde{\boldsymbol{\Sigma}}_t = r < N$. Equation (2A-4) can be modified utilising equation (2A-2) to become:

$$\boldsymbol{\Sigma}_t = \boldsymbol{\Lambda} \tilde{\boldsymbol{\Sigma}}_t \boldsymbol{\Lambda}^\top + \overline{\boldsymbol{\Sigma}}_t, \tag{2A-5}$$

In essence, identification issues relative to factor stochastic volatility are relevant at this stage. For any generalised permutation matrix $\boldsymbol{P}$ of size $r \times r$, there is some other viable decomposition $\boldsymbol{\Sigma}_t = \boldsymbol{\Lambda'} \ \tilde{\boldsymbol{\Sigma}}'_{\boldsymbol{t}} \ (\boldsymbol{\Lambda'})^\top + \overline{\boldsymbol{\Sigma}}_t$, where $\boldsymbol{\Lambda'} = \boldsymbol{\Lambda} \boldsymbol{P}^{-1}$ and $\tilde{\boldsymbol{\Sigma}}'_t = \boldsymbol{P} \ \tilde{\boldsymbol{\Sigma}}_{\boldsymbol{t}} \ \boldsymbol{P}^\top$. However, the uncertainty in the scale of the factors is resolved by setting their log-variance level to zero. In the second stage of our empirical analysis examining the relationship between macroeconomic activity and climate risk, we denote country specific climate risk ($\overline{\boldsymbol{\Sigma}}_t$) as $\sigma_{it}^{\mathbb{T}}$ and global climate risk ($\boldsymbol{\Lambda} \tilde{\boldsymbol{\Sigma}}_t \boldsymbol{\Lambda}^\top$) as $\sigma_{Ft}^{\mathbb{T}}$.

substantiated (Yu and Meng, 2011; Kastner and Frühwirth-Schnatter, 2014).

Optimal Lag Length Selection

The table below highlights information criteria for optimal lag length selection for PVAR($\sigma^{\mathbb{T}}_{it}$, $\sigma^{\mathbb{T}}_{Ft}$, y_{it}). The optimal lag length for the PVAR, as indicated by the table, is four. According to the evidence, the values of each criterion are lower at a lag length of four than at other lag lengths in support of Donadelli et al. (2022). See Table 2A-1 for details.

Table **2A-1:** Panel VAR lag length selection

Model	*MBIC*	*MAIC*	*HQIC*
PVAR(1)	−23.686	−5.717	−12.186
PVAR(2)	−23.641	−5.672	−12.141
PVAR(3)	−23.254	−5.285	−11.754
PVAR(4)	−23.228*	−5.259*	−11.729*

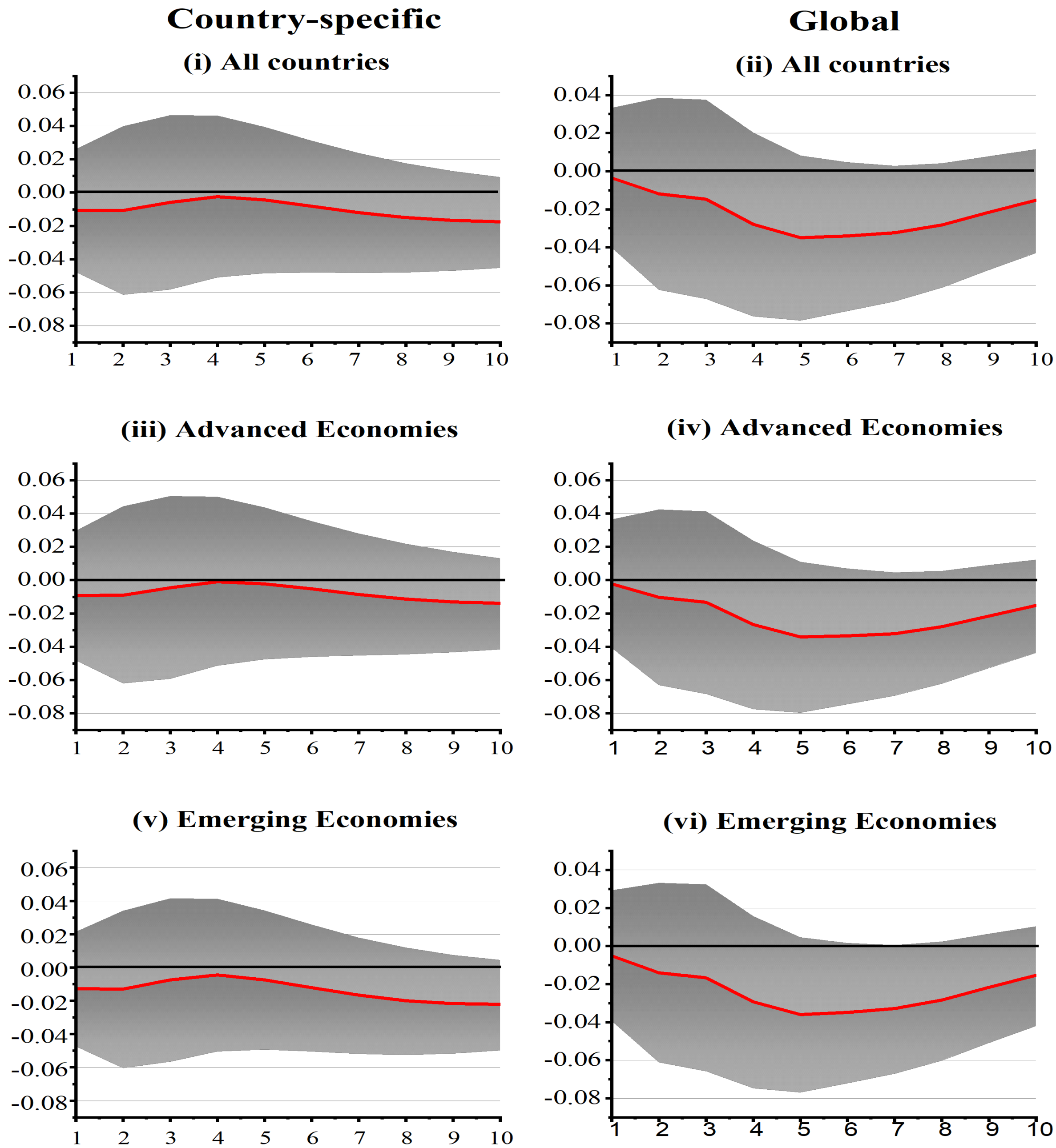
Notes: This table provides information criteria used to select the optimal lag length for our benchmark Panel VAR model. Hence we include several information criteria and varying the lag length from the PVAR(1) to PVAR(4). * indicates lag order selected by the criterion. MBIC: MMSC-Bayesian information criterion. MAIC: MMSC-Akaike Information Criterion. MQIC: MMSC-Hannan and Quinn Information Criterion. This method is developed by Andrews and Lu (2001).

Climate Risk Impact on GDP Volatility

Higher temperature risks increase growth risks; perhaps a GDP contraction arises from the combined impact of higher climatic and economic uncertainty. As a result, the transmission mechanism is based on risk rather than actual temperature changes.[3] In contrast to this argument, we show that the impact of shocks on country-specific climate risk is not important for GDP growth volatility, as shown in Figures 2A-1 and 2A-2. It is worth noting that even with our later sample, the impact of both country-specific and global climate risk are not important for GDP growth volatility. Overall, we find that climate risk impact on GDP growth is homogeneous.

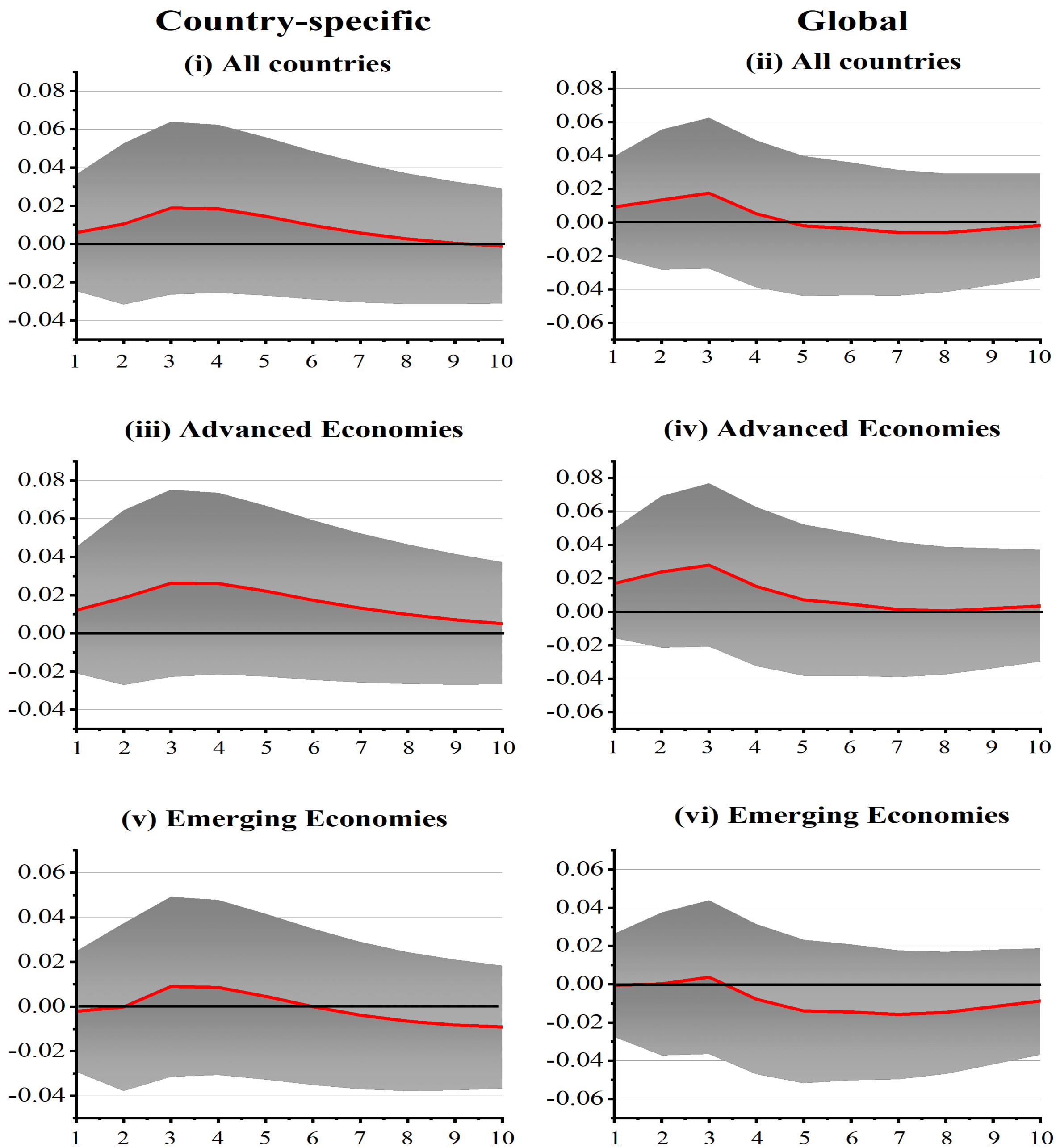
[3] Alessandri and Mumtaz (2021) argue that shocks to temperature volatility trigger a positive impact on GDP growth volatility.

Figure **2A-1:** Climate risk impact on GDP volatility: full sample



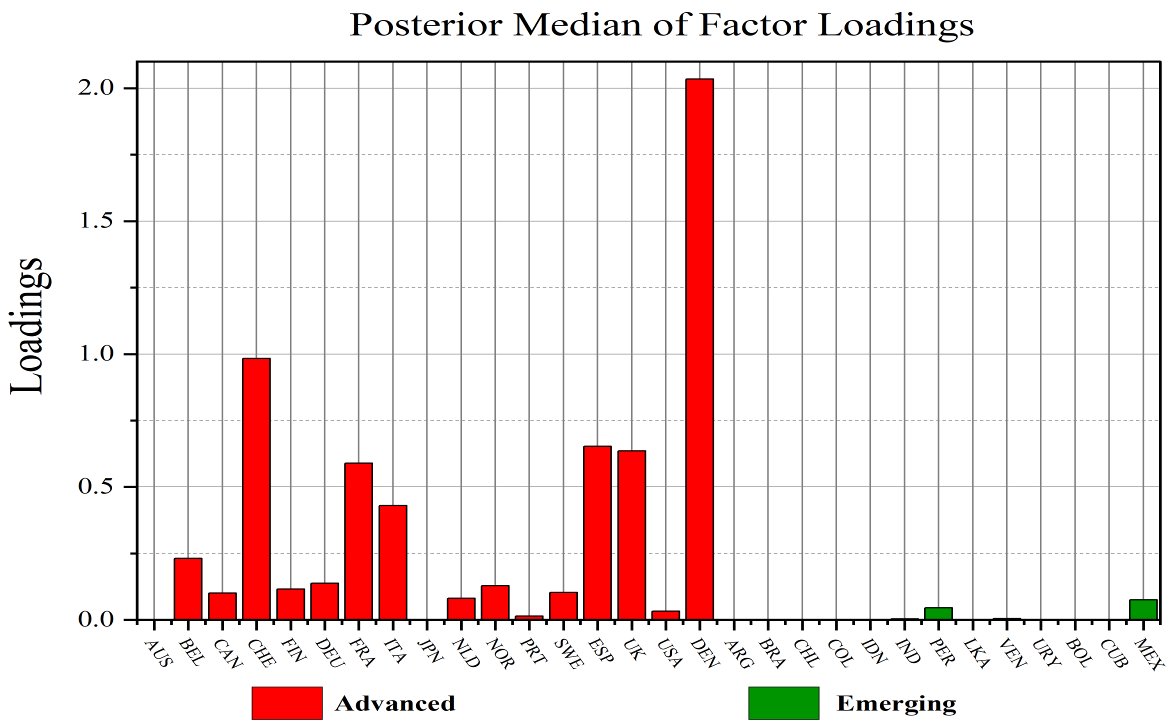
Notes: This figure presents evidence of the impact of climate risk on macroeconomic volatility. Specifically the left panel is the impulse response function from a shock to country climate risk ($\sigma^{\mathbb{T}}_{it}$) upon GDP growth volatility (σ^{y}_{it}). The right column of panels are global climate risk ($\sigma^{\mathbb{T}}_{Ft}$) upon GDP growth volatility (σ^{y}_{it}). GDP volatility is derived from factor stochastic volatility model which is idiosyncratic volatility of GDP growth. Our sample of 30 advanced and emerging economies between 1901 and 2020. We use a trivariate Panel VAR, PVAR($\sigma^{\mathbb{T}}_{it}$, $\sigma^{\mathbb{T}}_{Ft}$, σ^{y}_{it}). The evidence suggests the impact on macroeconomic volatility of a climate risk shock is not important and noticeable. The shock is a one standard deviation increase in risk. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

Figure **2A-2:** Climate risk impact on GDP volatility: post 1950



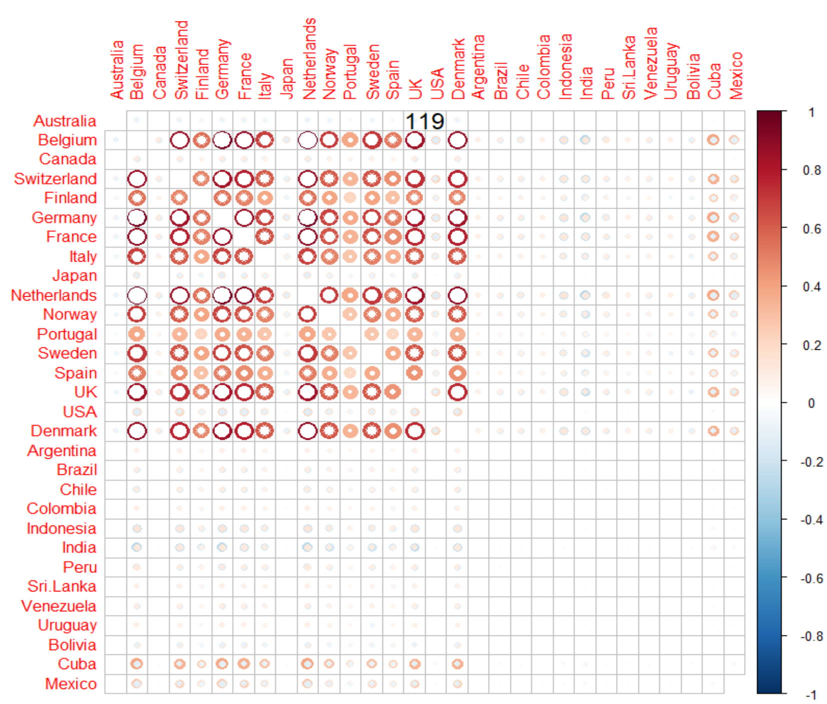
Notes: This figure presents evidence of the impact of climate risk on macroeconomic volatility. Specifically the left panel is the impulse response function from a shock to country climate risk ($\sigma_{it}^{\mathbb{T}}$) upon GDP growth volatility (σ_{it}^{y}). The right column of panels are global climate risk ($\sigma_{Ft}^{\mathbb{T}}$) upon GDP growth volatility (σ_{it}^{y}). GDP volatility is derived from factor stochastic volatility model thus idiosyncratic volatility of GDP growth. Our sample of 30 advanced and emerging economies between 1950 and 2020. We use a trivariate Panel VAR, PVAR($\sigma_{it}^{\mathbb{T}}$, $\sigma_{Ft}^{\mathbb{T}}$, σ_{it}^{y}). The evidence suggests the impact on macroeconomic volatility of a climate risk shock is not important and noticeable. The shock is a one standard deviation increase in risk. We include the posterior median of the shock (red) and 68% critical band or posterior coverage band (grey).

Figure **2A-3:** Factor loadings of common factor: temperature



Notes: Factor loadings of common factor of idiosyncratic volatility of temperature growth. Data from 1901 to 2020. See Table 2A-4 for components corresponding countries.

Figure **2A-4:** Idiosyncratic temperature volatility correlation



Notes: Correlation among countries' residuals of idiosyncratic temperature volatility. Data from 1901 to 2020.

Table **2A-2:** Panel unit root tests

Panel Time Series	LLC	IPS
$\mathbb{T}_{it}$	-27.733***	-43.827***
$\sigma_{it}^{\mathbb{T}}$	-17.663***	-47.936***
y_{it}	-18.042***	-31.779***
$CO2_{it}$	-48.787***	-30.724***
Univariate Time Series	ADF	
$\sigma_{Ft}^{\mathbb{T}}$	-2.898**	

Notes: This table presents panel unit root tests of Levin et al. (2002) (LLC) and Im et al. (2003) (IPS). The null hypothesis posited by panel unit root tests implies the presence of a unit root within the panels whereas the alternative hypothesis suggests no evidence of unit root in the panels. ADF denotes augmented Dickey-Fuller test for unit root. Critical values for ADF test: -3.504 (1%); -2.889 (5%) and -2.579 (10%). This is univariate time series test for unit root. The alternative hypothesis posits that the variable was generated by a process that remains constant over time, whereas the null hypothesis suggests that the variable includes a unit root. Temperature changes is denoted as ($\mathbb{T}_{it}$), idiosyncratic climate risk ($\sigma_{it}^{\mathbb{T}}$), country annual real GDP growth (y_{it}), country carbon emissions ($CO2_{it}$) and global climate risk ($\sigma_{Ft}^{\mathbb{T}}$). The data time span is 1901 to 2020 for 30 countries. Asterisk ***, ** and * denote 1%, 5% and 10% significance levels where we reject the null hypothesis of unit root.

Table **2A-3:** Description of variables

Indicator	Variable
y_{it}	GDP growth
ypc_{it}	GDP per capita growth
σ_{it}^{y}	GDP growth volatility
$\mathbb{T}_{it}$	Temperature change
$\sigma_{it}^{\mathbb{T}}$	Idiosyncratic volatility of temperature change
$\sigma_{Ft}^{\mathbb{T}}$	Common factor of volatility of temperature risk
$H_{it}^{\mathbb{T}}$	Univariate volatility of temperature change
$H_{it}^{\mathbb{T}_L}$	Univariate volatility of temperature levels
$CO2_{it}$	Carbon emissions per capita

Table **2A-4:** Factor loadings: components and corresponding countries

Component	Indicator	Country
1	AUS	Australia
2	BEL	Belgium
3	CAN	Canada
4	CHE	Switzerland
5	FIN	Finland
6	DEU	Germany
7	FRA	France
8	ITA	Italy
9	JPN	Japan
10	NLD	Netherlands
11	NOR	Norway
12	PRT	Portugal
13	SWE	Sweden
14	ESP	Spain
15	UK	UK
16	USA	USA
17	DEN	Denmark
18	ARG	Argentina
19	BRA	Brazil
20	CHL	Chile
21	COL	Colombia
22	IDN	Indonesia
23	IND	India
24	PER	Peru
25	LKA	Sri Lanka
26	VEN	Venezuela
27	URY	Uruguay
28	BOL	Bolivia
29	CUB	Cuba
30	MEX	Mexico

Table **2A-5:** Model estimation information bear and factor stochastic volatility model

Specification	**Details**
Factors specification	1
VAR specification	Bayesian PVAR random hierarchical effects
Iterations	20000
Burn-in iterations	2000
Lag length	4
Horizon	10
Hyperparameters	
Autoregressive coefficient	0.75
Overall tightness	0.1
Cross-variable weighting	0.5
Lag decay	1
Exogenous variable tightness	100
IG shape on overall tightness	0.001
IG scale on overall tightness	0.001

Table **2A-6:** Data source and classification

Variable	Countries	Data - start	Data - end	Interpolation	Source
Temperature	all countries	1901	2020	substantial	World Bank Climate Knowledge Portal
GDP per capita and population	All countries except Cuba and Indonesia	1901	2018	substantial	Maddison Project
GDP per capita and population	Indonesia	1901 - 1941	1950 - 2018	1942 - 1949	Maddison Project
GDP per capita and population	Cuba	1903	2018	1901 - 1902	Maddison Project
GDP growth rate	All countries	2019	2020		World Development Indicators
CO_2 emissions per capita (Metric tonnes)	Bolivia	1929	2018	1901 - 1928	Carbon Emission Information Analysis C
CO_2 per capita (Metric tonnes)	Colombia	1922	2018	1901 - 1921	"
CO_2 per capita (Metric tonnes)	Cuba	1941	2018	1901 - 1940	"
CO_2 per capita (Metric tonnes)	Uruguay	1932	2018	1901 - 1931	"
CO_2 per capita (Metric tonnes)	Venezuela	1913	2018	1901 - 1912	"
CO_2 per capita (Metric tonnes)	Sri Lanka	1949	2018	1901 - 1948	"

Notes: The climate knowledge on climate change portal offers a platform for accessing and analysing extensive data on climate change and development. https://climateknowledgeportal.worldbank.org/download-data: The Maddison Project Database includes data on long-term comparative economic growth and income levels. The World Development Indicators are repository of development variables from the World Bank. https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2020. The World Development Indicators are repository of development variables from the World Bank. https://databank.worldbank.org/source/world-development-indicators. Climate Watch. 2020. GHG Emissions. Washington, DC: World Resources Institute. Available at: https://www.climatewatchdata.org/ghg-emissions.SeeSP.POP.TOTLforthedenominator'ssource. The data are sourced from Carbon Dioxide Information Analysis Center of the U.S. Department of Energy at https://cdiac.ess-dive.lbl.gov/.

Appendix B: Robustness/Extension – Cont'd

Generated Regressor Issue

Global climate risk ($\sigma^{\mathbb{T}}_{Ft}$) by construction in the factor stochastic volatility model equation (1) is orthogonal to idiosyncratic climate risk ($\sigma^{\mathbb{T}}_{it}$). Whether country GDP is predominantly or indeed exclusively impacted by global and/or idiosyncratic climate risk is the focus of the chapter. We firstly observe that latent factors can be considered as though they are observed, provided that N and T are both large. In particular, Bai and Ng (2006, 2008b) and Bai and Ng (2008a) show in linear models that the factor estimates can be treated as known if $\sqrt{T}/N \to 0$. Indeed assuming the factors are known is common in the empirical literature using a two step approach, see Jurado et al. (2015)) and Creal and Wu (2017). Carriero et al. (2018) also suggest that factor estimation uncertainty can be small when $\sqrt{T}/N \to 0$. The latter is the case for our panel of temperature change data.

Secondly, to show that our empirical results are robust to any potential uncertainty in the estimation of the factors, we follow Pagan (1984). He recommends using Instrumental Variables to account for potential measurement error in econometric models. We use the Dynamic Panel Systems Generalised Method of Moments (GMM) estimator, which under certain conditions is the same as Instrumental Variables. The properties of the dynamic panel GMM estimator are considered in Blundell and Bond (1998), Blundell et al. (2001) and Blundell and Bond (2000). Windmeijer (2005) suggests that incorporating a correction for estimated standard errors using robust standard errors enhances inference in the size of the Wald test. We present both uncorrected and corrected standard errors in our Panel GMM results in Table 2.2 for our full sample and 2B-1 for the later sample. Overall, therefore, our approach is to use dynamic panel GMM with robust standard error estimators to analyze the impact upon country GDP growth of idiosyncratic and global climate risk, which should account for potential measurement error.

Our dynamic panel data system GMM and robust standard errors techniques in both Table 2.2 and 2B-1 suggest that global climate risk is more important for economic growth than idiosyncratic climate risk. In columns 2 to 4 using the conventional GMM estimator suggest that the global risk factor $\sigma^{\mathbb{T}}_{Ft}$ has a large and statistically significant negative impact upon real GDP. This is consistent with the key results from the Panel VAR impulse responses. This is also the case with GMM with robust standard errors at the 10% significance level in column 7. Idiosyncratic climate risk factor $\sigma^{\mathbb{T}}_{it}$ has a positive effect, albeit with a small estimate coefficient. Reassuringly idiosyncratic climate risk is important, in terms of statistical significance, when we use robust standard errors in columns 5 to 7. The findings indicate overall that global climate risk has a significantly adverse effect on GDP growth, while the impact of country-specific climate risk on GDP growth is less important and this is consistent with the key results in the chapter. This provides evidence that our Panel VAR results are not an artefact of measurement error and global climate risk is relatively more important in impacting macroeconomic activity.

Table **2B-1:** Dynamic panel system GMM and robust estimations: Later Sample

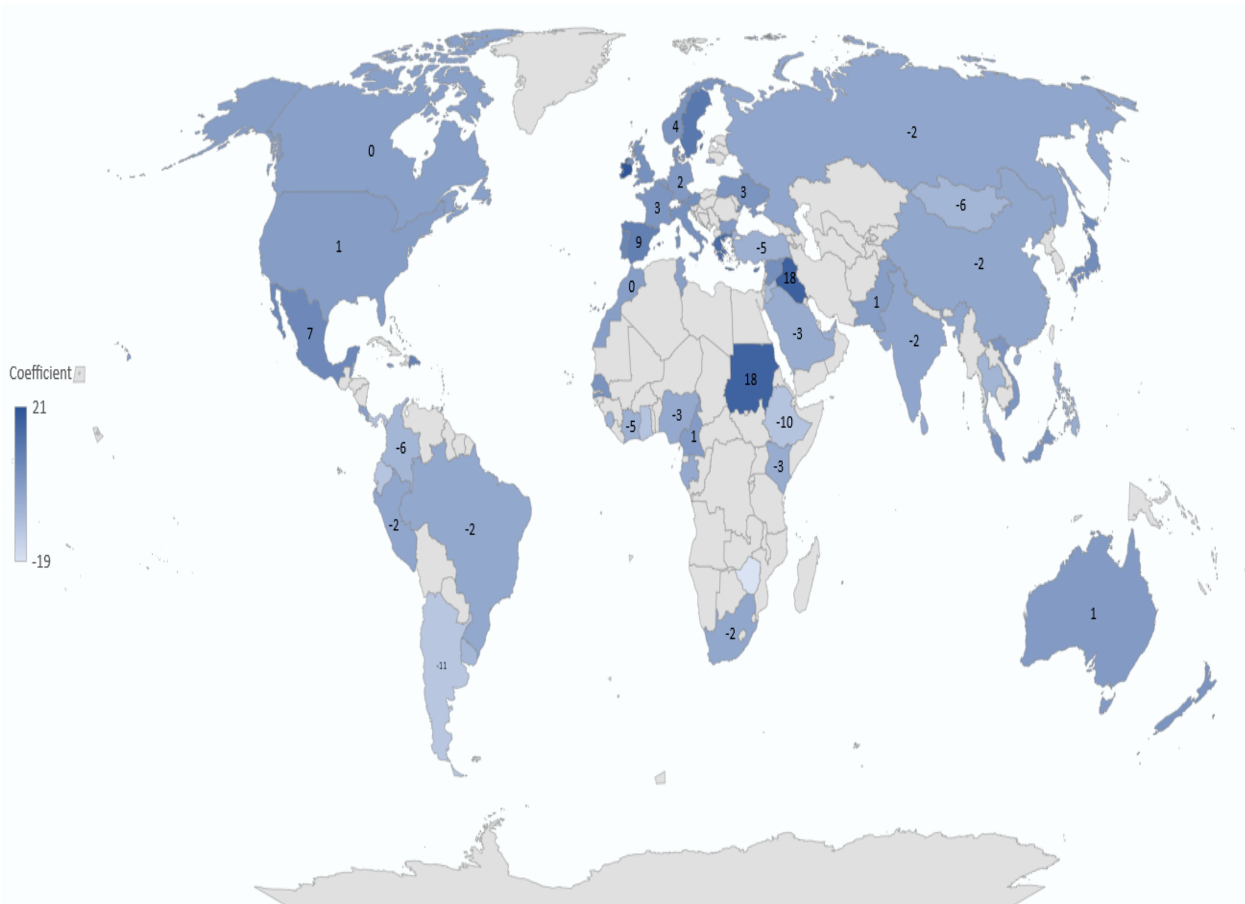
	GMM M1	GMM M2	GMM M3	ROBUST M1	ROBUST M2	ROBUST M3
y_{it-4}	0.03***	0.04***	0.03**	0.03	0.04	0.03
	(0.01)	(0.01)	(0.01)	(0.05)	(0.04)	(0.06)
$\sigma^{\mathbb{T}}_{it}$	-0.21***	—	-0.20***	-0.21***	—	-0.20**
	(0.02)	—	(0.02)	(0.06)	—	(0.05)
$\sigma^{\mathbb{T}}_{Ft}$	—	-18.48***	-19.31***	—	-18.48**	-19.31*
	—	(4.31)	(5.02)	—	(8.40)	(10.86)
Constant	3.13***	3.53***	2.83***	3.13***	3.53***	2.83**
	(0.22)	(0.35)	(0.27)	(0.80)	(0.82)	(1.02)
Wald chi^2	517.32***	191.64***	382.57***	15.44**	16.55**	25.23***
Instruments	428	427	428	428	427	428
AR(2)						
Z-stats.	-0.58	-0.44	-0.42	-0.45	-0.34	-0.32
P-value	0.56	0.66	0.67	0.65	0.73	0.75
Sargan Test						
Chi^2	70.11	69.77	67.77	—	—	—
P-value	1.00	1.00	1.00	—	—	—
Obs.	1,846	1,846	1,846	1,846	1,846	1,846

Notes: This table presents dynamic panel data estimation with the two-step system generalised method of moment (GMM) (Blundell and Bond (1998)) and Windmeijer (2005) Robust (ROBUST) standard errors techniques. Idiosyncratic climate risk ($\sigma^{\mathbb{T}}_{it}$), global climate risk ($\sigma^{\mathbb{T}}_{Ft}$), and country annual real GDP growth (y_{it}). Data period 1950 to 2020 for 30 countries. Asterisk ***, ** and * denote 1%, 5% and 10% significance levels, respectively. Standard errors are in parentheses. M1 represent the model [$y_{it} = \mathrm{F}(y_{it-1}, \sigma^{\mathbb{T}}_{Ft}, \sigma^{\mathbb{T}}_{it})$], M2 represent the model [$y_{it} = \mathrm{F}(y_{it-1}, \sigma^{\mathbb{T}}_{it})$], and M3 represent the model [$y_{it} = \mathrm{F}(y_{it-1}, \sigma^{\mathbb{T}}_{Ft})$]. The Z-statistics for the AR(2) model represents the Sargan test for over-identifying restrictions. H0: The over-identifying restrictions are valid. Wald Chi^2 assess the validity of the instruments employed in the estimation. The null hypothesis for the Wald chi-squared test is that the instruments are valid, meaning they are uncorrelated with the error term and meet the necessary assumptions.

Appendix - Chapter 3

Appendix A: Supplementary Results

Figure **3A-1:** Country-specific green growth impact on GDP growth



Notes: This figure presents heatmap evidence of country-specific impacts of green growth on GDP growth for our sample of 81 countries for the period spanning 1992 to 2021. The heatmap is a reflection of the results illustrated in Table 3.5 using the MG-IV(+CCE) estimator for the benchmark model. The solid blue-shaded countries depicted positive coefficients, while the mid- to light-blue-shaded countries exhibited zero to negative coefficients. Cyprus, Greece, Ireland, Iraq, and Sudan exhibited positive and significant coefficients, whereas Argentina, Ethiopia, and Panama showed negative and significant coefficients of 5% or less.

Table **3A-1:** Variables and data sources

Variables	Indicators	Units of Measurement	Sources
GDP growth	Δy_{it}	log growth rate of GDP (constant 2015 US$)	World Development Indicators, World Bank
Physical capital	Δk_{it}	log growth rate of capital stock. The capital stock is measured in millions of 2017 US dollars at constant national prices.	Penn World Tables
Labour	Δl_{it}	log growth rate of total labour force	World Development Indicators, World Bank
Green Growth	Δg_{it}	Green growth indicator. Index scores for the Green Growth Index range from 0 to 1. Sub-dimensions: natural asset base, environmental-related policy responses, quality of life, environmental productivity, and socio-economic outcomes.	Sarkodie et al. (2023)
Green Technologies	$\Delta \tau_{it}$	log growth rate of the number of environmental-related patent registrations	OECD statistics Database
Urbanisation	Δp_{it}	log growth rate of Urban population	World Development Indicators, World Bank
Greenhouse gas emissions	Δe_{it}	log growth rate of total greenhouse gas emissions (kt of CO2 equivalent)	World Development Indicators, World Bank
Foreign Direct Investment	Δfdi_{it}	log growth rate of foreign direct Investment inflows (BoP, current US$)	World Development Indicators, World Bank
Human capital index	Δhc_{it}	log growth rate of human capital index. The Human Capital Index (HCI) is a metric that evaluates the level of human capital in a given population. It is determined by considering two key factors: the number of years individuals have spent in formal education and the economic benefits.	Penn World Tables

Table **3A-2:** Correlation matrix

	Full Sample			
Correlation	Δy_{it}	Δg_{it}	Δk_{it}	Δl_{it}
Δy_{it}	1.00			
Δg_{it}	0.02	1.00		
Δk_{it}	0.37***	-0.01	1.00	
Δl_{it}	0.32***	0.01	0.22***	1.00
	Advanced Economies			
Correlation	Δy_{it}	Δg_{it}	Δk_{it}	Δl_{it}
Δy_{it}	1.00			
Δg_{it}	0.10***	1.00		
Δk_{it}	0.45***	0.09**	1.00	
Δl_{it}	0.40***	0.10***	0.48***	1.00
	Emerging Economies			
Correlation	Δy_{it}	Δg_{it}	Δk_{it}	Δl_{it}
Δy_{it}	1.00			
Δg_{it}	0.03	1.00		
Δk_{it}	0.34***	0.02	1.00	
Δl_{it}	0.29***	0.04*	0.12***	1.00

Notes: This table presents the correlation matrix $\Delta y_{it} = \Delta l_{it}$, Δk_{it} ,Δg_{it} for our full sample (81 countries), advanced economies (27 countries), and emerging economies (54 countries) from 1992 to 2021. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}.

Table **3A-3:** Descriptive statistics — cont'd

Full Sample	Mean	SD	Max.	Min.	Obs.
$\Delta\tau_{it}$	-0.47	56.19	315.75	-268.98	2,430
Δp_{it}	1.95	1.60	18.58	-8.83	2,430
Δfdi_{it}	10.64	85.77	632.73	-689.52	2,430
Δe_{it}	1.17	6.10	107.12	-89.68	2,430
Advanced Economies	Mean	SD	Max.	Min.	Obs.
Δy_{it}	2.36	3.15	21.89	-11.84	810
Δl_{it}	1.03	1.40	7.85	-4.36	810
Δk_{it}	2.61	1.70	11.94	-0.93	810
Δg_{it}	0.58	0.12	1.00	0.10	810
$\Delta\tau_{it}$	0.14	39.32	315.75	-243.61	810
Δp_{it}	0.96	0.76	5.32	-4.17	810
Δfdi_{it}	9.36	92.60	632.73	-689.52	810
Δe_{it}	-0.43	4.60	23.83	-27.33	810
Δhc_{it}	0.60	0.58	4.64	-0.51	810
Emerging Economies	Mean	SD	Max.	Min.	Obs.
Δy_{it}	3.60	5.11	42.78	-45.66	1,620
Δl_{it}	2.05	2.35	19.64	-11.49	1,620
Δk_{it}	4.20	3.03	18.80	-3.44	1,620
Δg_{it}	0.54	0.14	1.00	0.00	1,620
$\Delta\tau_{it}$	-0.78	62.96	270.22	-268.98	1,620
Δp_{it}	2.44	1.68	18.58	-8.83	1,620
Δfdi_{it}	11.28	82.16	550.02	-464.22	1,620
Δe_{it}	1.96	6.58	107.12	-89.68	1,620
Δhc_{it}	1.03	0.60	3.48	-0.69	1,620

Notes: SD = standard deviation; Max = maximum value; Min = minimum value; Obs. = number of observations. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gases emission and growth in green technologies is denoted as $\Delta\tau_{it}$. growth in human capital index is denoted as Δhc_{it}. Sample of 81 advanced and emerging countries from 1992 to 2021.

Table **3A-4:** Cross-sectional dependence and slope heterogeneity

Statistics	CD	α	Adj.Δ
$\Delta\tau_{it}$	3.63*** [0.00]	0.56	
Δp_{it}	34.28*** [0.00]	0.80	
Δfdi_{it}	16.62*** [0.00]	0.80	
Δe_{it}	41.10*** [0.00]	0.56	
Slope Heterogeneity			
3. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta\tau_{it}, \Delta fdi_{it}$			11.59*** [0.00]
4. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta\tau_{it}, \Delta fdi_{it}$			10.80*** [0.00]

CD and α denote cross-sectional dependence tests by Pesaran (2015, 2021). We reject the null hypothesis of weak cross-sectional dependence when the CD statistics shows a p-value less than 0.05. Cross-sectional dependency is considered strong when $\alpha = 1$, semi-strong $0.5 \leq \alpha \leq 1$, weak $\alpha = 0$, and semi-weak $0 < \alpha < 0.5$. GDP growth is denoted as Δy_{it}, growth in labour force participation rate is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gas emissions and growth in green technologies is denoted as $\Delta\tau_{it}$. Adj.Δ denotes test statistics of heterogeneity by Pesaran and Yamagata (2008) where we reject the null hypothesis of no cross-sectional heterogeneity when the test statistics have a p-value less than 0.05. P-values are presented in the square brackets [ ]. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

Table **3A-5:** Cross-sectional dependence and slope heterogeneity

Advanced Economies	CD	α	Adj.Δ
Δy_{it}	61.51***	1.00	
Δl_{it}	9.72***	0.83	
Δk_{it}	36.05***	0.91	
Δg_{it}	59.91***	1.00	
$\Delta \tau_{it}$	20.36***	0.83	
Δp_{it}	6.20***	0.67	
Δfdi_{it}	3.59***	0.61	
Δe_{it}	28.46***	0.62	
Δhc_{it}	9.10***	0.65	
Slope Heterogeneity			
1. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}$			1.51 [0.13]
2. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}$			-0.80 [0.43]
3. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta \tau_{it}, \Delta fdi_{it}$			4.69 [0.00]
4. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta \tau_{it}, \Delta fdi_{it}$			5.30 [0.00]
Emerging Economies	CD	α	Adj.Δ
Δy_{it}	50.85***	0.81	
Δl_{it}	45.56***	0.74	
Δk_{it}	21.27***	0.79	
Δg_{it}	130.60***	1.00	
$\Delta \tau_{it}$	-1.13	0.68	
Δp_{it}	38.56***	0.81	
Δfdi_{it}	14.90***	0.82	
Δe_{it}	19.97***	0.53	
Δhc_{it}	20.61***	0.71	
Slope Heterogeneity			
1. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}$			9.94 [0.00]
2. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}$			1.42 [0.16]
3. $\Delta y_{it} = \Delta k_{it}, \Delta l_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta \tau_{it}, \Delta fdi_{it}$			10.27 [0.00]
4. $\Delta y_{it} = \Delta k_{it}, \Delta hc_{it}, \Delta g_{it}, \Delta p_{it}, \Delta e_{it}, \Delta \tau_{it}, \Delta fdi_{it}$			8.90 [0.00]

Notes: GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in human capital index is denoted as Δhc_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gas emissions and growth in green technologies is denoted as $\Delta \tau_{it}$. CD and α denote cross-sectional dependence tests by Pesaran (2015, 2021). We reject the null hypothesis of weak cross-sectional dependence when the CD statistics shows a p-value less than 0.05. Cross-sectional dependency is considered strong when $\alpha = 1$, semi-strong $0.5 \leq \alpha \leq 1$, weak $\alpha = 0$, and semi-weak $0 < \alpha < 0.5$. Adj.Δ denotes test statistics of heterogeneity by Pesaran and Yamagata (2008) where we reject the null hypothesis of no cross-sectional heterogeneity when the test statistics has a p-value less than 0.05. P-values are presented in the square brackets [ ]. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

Table **3A-6:** Panel unit root tests

Full Sample	CADF	CIPS
Δy_{it}	-10.93***	-3.76***
Δl_{it}	-7.56***	-3.55***
Δk_{it}	-11.05***	-2.38***
Δg_{it}	-12.85***	-4.52***
$\Delta \tau_{it}$	-23.60***	-5.59***
Δp_{it}	-3.82***	-2.01*
Δfdi_{it}	-26.91***	-5.83***
Δe_{it}	-17.41***	-4.91***
Δhc_{it}	-4.47***	-2.10**
Advanced Economies	CADF I(0)	CIPS I(0)
Δy_{it}	-6.83***	-4.00***
Δl_{it}	-4.84***	-3.42***
Δk_{it}	-4.06***	-2.60***
Δg_{it}	-7.60***	-4.46***
$\Delta \tau_{it}$	-14.43***	-5.74***
Δp_{it}	-1.53	-1.69
Δfdi_{it}	-15.23***	-5.98***
Δe_{it}	-13.10***	-5.37***
Δhc_{it}	-1.91**	-2.79***
Emerging Economies	CADF I(0)	CIPS I(0)
Δy_{it}	-9.60***	-4.01***
Δl_{it}	-8.10***	-3.51***
Δk_{it}	-9.24***	-2.48***
Δg_{it}	-10.41***	-4.51***
$\Delta \tau_{it}$	-22.99***	-5.96***
Δp_{it}	-3.34***	-1.72
Δfdi_{it}	-21.88***	-5.80***
Δe_{it}	-13.60***	-4.72***
Δhc_{it}	-4.09***	-2.13**

Notes: This table shows the panel unit root tests for the variables in the study. CIPS and CADF represent cross-sectional IPS and ADF unit roots developed by Pesaran (2007). The null hypothesis suggests evidence of a unit root in the series. The alternate hypothesis suggests no evidence of a unit root. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Critical values for CIPS tests: -2.07 (10%); -2.15 (5%); -2.30 (1%). GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in human capital index is denoted as Δhc_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth index is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}, growth in foreign direct investment inflows is denoted as Δfdi_{it}, Δe_{it} represents the growth in greenhouse gases emission and growth in green technologies is denoted as $\Delta \tau_{it}$.

Table **3A-7:** Granger causality

Full Sample	Lags	Z-bar tilde	P-value	Remarks
$\Delta g_{it} \longrightarrow \Delta y_{it}$	1	7.38***	0.00	Bidirectional
$\Delta y_{it} \longrightarrow \Delta g_{it}$	1	3.60***	0.00	
Advanced Economies	Lags	Z-bar tilde	P-value	Remarks
$\Delta g_{it} \longrightarrow \Delta y_{it}$	1	11.86***	0.00	Bidirectional
$\Delta y_{it} \longrightarrow \Delta g_{it}$	1	4.33***	0.00	
Emerging Economies	Lags	Z-bar tilde	P-value	Remarks
$\Delta g_{it} \longrightarrow \Delta y_{it}$	2	2.12**	0.03	Bidirectional
$\Delta y_{it} \longrightarrow \Delta g_{it}$	1	1.98**	0.05	

Notes: This table shows the Granger causal relationship between green growth indicators and GDP growth for our full sample and advanced and emerging economies' samples. The data are from 1992 to 2021. We assess the Granger causal linkage on the optimal lag lengths as depicted in the table. $\longrightarrow$ denotes the direction of causality. Bidirectional means a feedback effect and a two-way causal relationship. Models are estimated upon equation (3B-1). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, and green growth is denoted as Δg_{it}.

Table **3A-8:** Regression evidence: contemporaneous green growth

Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it}	0.42	0.14	0.68	0.45	0.20
	(0.65)	(0.54)	(0.56)	(0.53)	(0.68)
Δl_{it}	0.64***	0.61***	0.28**	0.31**	0.30**
	(0.05)	(0.05)	(0.10)	(0.11)	(0.12)
Δk_{it}	0.47***	0.39***	0.75***	0.64***	0.26**
	(0.05)	(0.05)	(0.11)	(0.09)	(0.12)
Δy_{it-1}		0.10***		0.11**	
		(0.02)		(0.03)	
Constant	0.12	0.32	-2.44***	-2.43***	-1.11*
	(0.41)	(0.41)	(0.54)	(0.54)	(0.66)
Common factors	No	No	Yes	Yes	Yes
NxT	2,430	2,349	2,268	2,187	2,106
R^2	0.20	0.21	0.65	0.60	0.32
F-stat	110.67***	89.25***	1.63***	1.60***	2.07***
F-test: All $u_i = 0$	1.71 [0.00]	1.45 [0.01]			
CD-stat.			1.02	1.04	-0.52
CD-stat. (p-value)			0.31	0.30	0.60

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries from 1992 to 2021. The estimators are (1) FE denotes Fixed Effects. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Model 1 to 5 are estimated upon equation (3.5). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent; p-values are in the square brackets [ ]. We do not reject the null hypothesis with p-value > 0.05. The CD-stat represents a cross-sectional dependence test with a null hypothesis of no or weak cross-sectional dependence. We do not reject this null if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

Table **3A-9:** Baseline regression evidence: country heterogeneity

Sample	Advanced Economies				
Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	8.44***	8.73***	1.44*	1.23	1.40*
	(0.83)	(0.84)	(0.84)	(0.91)	(0.82)
Δl_{it}	0.47***	0.52***	0.38***	0.30**	0.40***
	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)
Δk_{it}	0.54***	0.64***	0.49**	0.36	0.12
	(0.09)	(0.10)	(0.60)	(0.17)	(0.21)
Δy_{it-1}		-0.11**		0.11**	
		(0.04)		(0.05)	
Constant	-4.47***		-1.36**	-1.24**	-0.54
	(0.53)		(0.60)	(0.58)	(0.75)
Common factors	No	No	Yes	Yes	Yes
NxT	783	783	702	702	702
R^2	0.32	0.32	0.63	0.59	0.30
F-stat	74.26***	54.46***	1.33**	1.32**	2.52***
F-test: All $u_i = 0$	1.81 [0.01]	2.07 [0.00]			
CD-stat.			-0.53	-0.11	-1.05
CD-stat. (p-value)			0.60	0.91	0.29
Sample	Emerging Economies				
Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	1.40	1.29	0.63	1.44*	2.19
	(0.89)	(0.88)	(0.79)	(0.81)	(2.07)
Δl_{it}	0.64***	0.61***	0.13	0.26	0.13
	(0.06)	(0.06)	(0.16)	(0.18)	(0.27)
Δk_{it}	0.46***	0.38***	0.69	0.68***	0.28*
	(0.05)	(0.06)	(0.14)	(0.14)	(0.15)
Δy_{it-1}		0.13***		-0.02	
		(0.02)		(0.04)	
Constant	-0.38	-0.36	-2.34**	-2.74**	1.61
	(0.57)	(0.56)	(0.85)	(0.95)	(1.99)
Common factors	No	No	Yes	Yes	Yes
NxT	1,566	1,566	1,512	1,404	1,350
R^2	0.17	0.20	0.65	0.59	0.36
F-stat	74.43***	63.54***	2.01***	1.29***	1.80***
F-test: All $u_i = 0$	1.89 [0.00]	1.50 [0.02]			
CD-stat.			1.67	1.92	1.39
CD-stat. (p-value)			0.10	0.06	0.17

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of advanced (27) and emerging (54) countries, from 1992 to 2021. The estimators are (1) FE denotes Fixed Effects. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Model 1 to 5 are estimated upon equation (3.5). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent; p-values are in the square brackets [ ]. We do not reject the null hypothesis with p-value $>$ 0.05. The CD-stat represents a cross-sectional dependence test with a null hypothesis of no or weak cross-sectional dependence. We do not reject this null if the CD-stat p-value $>$ 0.05. Standard errors are presented in the parentheses.

Table **3A-10:** Robustness: baseline model + urbanisation

Sample	Full sample				
Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	3.45***	3.30***	1.64**	1.39**	1.35*
	(0.67)	(0.66)	(0.73)	(0.71)	(0.80)
Δl_{it}	0.70***	0.69***	0.39**	0.34**	0.39**
	(0.05)	(0.05)	(0.14)	(0.14)	(0.17)
Δk_{it}	0.50***	0.43***	0.94***	0.94***	0.68***
	(0.05)	(0.05)	(0.14)	(0.15)	(0.21)
Δp_{it}	-0.27**	-0.35***	-0.82**	-0.79**	-1.47**
	(0.10)	(0.10)	(0.40)	(0.40)	(0.60)
Δy_{it-1}		0.11***		0.00	
		(0.02)		(0.03)	
Constant	-1.19**	-1.02**	-2.79***	-2.84***	-0.88
	(0.44)	(0.44)	(0.82)	(0.84)	(0.95)
Common factors	No	No	Yes	Yes	Yes
NxT	2,349	2,349	2,106	2,106	2,025
R^2	0.20	0.22	0.57	0.54	0.38
F-stat	91.43***	79.63***	1.42***	1.34***	1.98***
F-test: All $u_i = 0$	1.89 [0.00]	1.58 [0.00]			
CD-stat.			1.24	1.36	-0.00
CD-stat. (p-value)			0.21	0.17	1.00

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries, consisting of advanced (27) and emerging (54) countries, from 1992 to 2021. In these estimations, we include urbanisation (Δp_{it}) in equation (3.5) to assess the individual factors of the IPAT model. The estimators are (1) FE denotes Static Fixed Effets. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in urban population is denoted as Δp_{it}. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent. We do not reject the null hypothesis with p-value > 0.05; p-values are in the square brackets [ ]. The CD-stat represents a cross-sectional dependence test with a null hypothesis of no or weak cross-sectional dependence. We do not reject this null if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

Table **3A-11:** Robustness: baseline model + green technologies

Sample	Full sample				
Estimator	SFE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δg_{it-1}	3.40***	3.26***	1.38*	1.28*	1.42*
	(0.67)	(0.67)	(0.76)	(0.73)	(0.85)
Δl_{it}	0.62***	0.59***	0.18	0.17	0.18
	(0.05)	(0.05)	(0.12)	(0.11)	(0.14)
Δk_{it}	0.48***	0.41***	0.74***	0.64***	0.38**
	(0.05)	(0.05)	(0.11)	(0.11)	(0.13)
$\Delta \tau_{it}$	0.00	0.00	0.00	-0.01*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Δy_{it-1}		0.10***		0.08**	
		(0.02)		(0.04)	
Constant	-1.52***	-1.44***	-2.57***	-2.57***	-1.78**
	(0.43)	(0.42)	(0.62)	(0.58)	(0.76)
Common factors	No	No	Yes	Yes	Yes
NxT	2,349	2,349	2,106	2,106	2,025
R^2	0.21	0.22	0.60	0.57	0.36
F-stat	89.66***	77.17***	1.25***	1.22***	1.82***
F-test: All $u_i = 0$	1.81 [0.00]	1.49 [0.00]			
CD-stat.			0.38	-0.23	-0.75
CD-stat. (p-value)			0.70	0.82	0.45

Notes: This table presents the estimations of the impact of green growth indicators on GDP growth for a sample of 81 countries, consisting of advanced (27) and emerging (54) countries, from 1992 to 2021. In these estimations, we include green technologies ($\Delta\tau_{it}$) in equation (3.5) to assess the individual factors of the IPAT model. The estimators are (1) FE denotes Static Fixed Effets. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, green growth is denoted as Δg_{it}, growth in green technologies is denoted as $\Delta\tau_{it}$. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent. We do not reject the null hypothesis with p-value > 0.05; p-values are in the square brackets [ ]. The CD-stat represents a cross-sectional dependence test with a null hypothesis of no or weak cross-sectional dependence. We do not reject this null if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

Table **3A-12:** Decomposition of contemporaneous green growth

Sample	Full sample				
Estimator	FE	DFE	MG (+CCE)	DMG (+CCE)	MG-IV (+CCE)
Δgna_{it-1}	1.89***	1.78***	0.85*	0.85*	0.28
	(0.41)	(0.41)	(0.51)	(0.46)	(0.63)
Δgpr_{it-1}	-0.38	-0.20	-0.93	-0.95	-0.08
	(0.57)	(0.57)	(0.68)	(0.82)	(0.95)
Δgse_{it-1}	0.61	0.63	0.49	0.30	1.19*
	(0.53)	(0.53)	(0.67)	(0.72)	(0.65)
$\Delta gprod_{it-1}$	3.13***	2.86***	0.54	0.52	0.21
	(0.66)	(0.66)	(0.77)	(0.90)	(0.94)
Δgql_{it-1}	0.23	0.28	1.45	1.54	0.40
	(0.66)	(0.66)	(0.93)	(0.97)	(0.95)
Δl_{it}	0.59***	0.57***	0.24**	0.25**	0.23*
	(0.05)	(0.05)	(0.11)	(0.11)	(0.13)
Δk_{it}	0.48***	0.42***	0.74***	0.68***	0.22*
	(0.05)	(0.05)	(0.11)	(0.11)	(0.12)
Δy_{it-1}		0.09***		0.06	
		(0.02)		(0.04)	
Constant	-2.74***	-2.62***	-3.50***	-3.59	-2.40**
	(0.64)	(0.63)	(0.78)	(0.80)	(0.97)
Common factors	No	No	Yes	Yes	Yes
NxT	2,349	2,349	2,187	2,187	2,106
R^2	0.21	0.23	0.49	0.45	0.46
F-stat	54.37***	50.18***	1.51***	1.52***	0.46
F-test: All $u_i = 0$	1.80 [0.00]	1.50 [0.00]			
CD-stat.			1.26	1.17	0.59
CD-stat. (p-value)			0.21	0.24	0.55

Notes: This table presents the estimations of the impact of decomposed green growth measure on GDP growth for a sample of 81 countries from 1992 to 2021. The estimators are (1) FE denotes Fixed Effects. (2) DFE denotes Dynamic Fixed Effects. (3) MG (+CCE) denotes Common Correlated Effects Estimator - Mean Group. (4) DMG (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group. (5) MG-IV (+CCE) denotes (Dynamic) Common Correlated Effects Estimator - Mean Group IV. Model 1 to 5 are estimated upon equation (3.5). Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. GDP growth is denoted as Δy_{it}, growth in labour force is denoted as Δl_{it}, growth in physical capital accumulation is denoted as Δk_{it}, growth in natural asset base indicators is denoted as Δgna_{it}, environmental-related policy response is denoted as Δgpr_{it}, quality of life is denoted as Δgql_{it}, socio-economic outcomes is denoted as Δgse_{it}, and environmental productivity is denoted as $\Delta gprod_{it}$. F-test: All $u_i = 0$ assumes that unobservables and regressors are mean independent. We do not reject the null hypothesis with p-value > 0.05; p-values are in the square brackets [ ]. The CD-stat represents a cross-sectional dependence test with a null hypothesis of no or weak cross-sectional dependence. We do not reject this null if the CD-stat p-value > 0.05. Standard errors are presented in the parentheses.

Appendix B: Empirical Methods

Granger Causality

In order to examine the question of Granger causality, we assess the nature of the relationship between the green growth index and GDP growth. According to Granger (1969), in a bivariate framework, the first variable is considered to be the causal factor for the second variable if the predictive accuracy of the second variable improves when lagged values of the first variable are taken into account. Granger-causality tests are commonly employed in the analysis of vector autoregressive (VAR) models, specifically in relation to the examination of individual equations within VAR systems. The individual equations in vector autoregressive (VAR) models can be represented as autoregressive distributed lag (ADL) relationships:

$$\Delta y_{it} = c_0 + \sum_{l=1}^{p} \alpha_{1it} \Delta y_{it-l} + \sum_{l=1}^{p} \alpha_{2it} \Delta g_{it-l} + e_{it} \tag{3B-1}$$

The variables Δy_{it} and Δg_{it} represent the first and second variables, correspondingly. The determination of the value of variable p is contingent upon the inclusion of lagged terms in the model. The formulation of the hypothesis that there is no Granger-causality between the variables Δg_{it} and Δy_{it} involves conducting a test on the coefficients α_{1it} and α_{2it}, with l ranging from 1 to p, to determine if they are equal to zero. The rationale for conducting such an experiment is clear-cut. As stated by Hamilton (1994), when episode Δg_{it} is perceived as the causal factor for episode Δy_{it}. It is anticipated that episode Δg_{it} would precede episode Δy_{it}. The computation of the test statistic entails summing the squared residuals (RSS) obtained from both the restricted equation and the unrestricted equation, as follows:

$$\mathbb{Y}_{it} = c_0 + \sum_{l=1}^{p} \alpha_{it} \mathbb{Y}_{it-l} + e_{it} \tag{3B-2}$$

Where $\mathbb{Y}_{it}$ represents the dependent variables Δy_{it} and Δg_{it}. The formula for conducting joint-significance tests, as described in the existing literature, is employed in this analysis:

$$F = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T - 2p - 1)} \tag{3B-3}$$

The variable under consideration follows a distribution that can be described as $F(p, T -$

$2p-1$). Equation (3B-3) uses the residual sum of squares from the restricted (RSS_0) and unrestricted (RSS_1) models. The test's validity is constrained to asymptotic conditions due to the incorporation of a lagged dependent variable in the regression model. A test that exhibits asymptotic equivalence is presented by:

$$F_a = \frac{T(RSS_0 - RSS_1)}{RSS_1} \tag{3B-4}$$

The variable follows a chi-squared distribution with p degrees of freedom.

In our endeavour to examine the causal relationship between green growth and economic growth, we also conducted a Granger causality test. The Granger causality test examines the unidirectional and bidirectional causal relationship between green growth and GDP growth. This relationship is observable irrespective of economic status. Even though the green growth indicators and GDP growth are linked in both directions, there is a clear time lag effect that shows how quickly green growth indicators affect GDP growth in advanced economies compared to emerging economies. We present the outcome of the Granger causality test in Table 3A-7.

Appendix - Chapter 4

Appendix A: Supplementary Results

Table **4A-1:** Correlation matrix

	GW_{it}	$R\&D_{it}$	$TRADE_{it}$	POP_{it}	$M2_{it}$	Y_{it}
GW$_{it}$	1					
$R\&D_{it}$	-0.01	1				
$TRADE_{it}$	-0.09***	0.62***	1			
POP_{it}	0.46***	0.02	-0.03*	1		
$M2_{it}$	0.02	-0.35***	0.01	-0.05**	1	
Y_{it}	0.00	0.33***	0.50***	-0.27***	0.09***	1

Notes: $R\&D_{it}$ denote research and development intensity (log levels of nominal R&D spending over GDP). GW$_{it}$ denote global warming (levels), $TRADE_{it}$ denote log levels of trade openness, $M2_{it}$ denote log levels of broad money, POP_{it} denote log levels of total population. Y_{it} denotes log levels of real GDP per capita. Y_{it}^2 denote quadratic function of the log levels of real GPD per capita. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

Table **4A-2:** Structural break tests

	Stat.	1% Critical value	5% Critical value	10% Critical value
Structural Break Test 2				
$\text{GW}_{it} = R\&D_{it}, TRADE_{it}, POP_{it}, M2_{it}, Y_{it}, Y_{it}^2$				
F(1|0)	7.26***	4.08	3.35	2.99
F(2|1)	3.92**	4.32	3.69	3.34
F(3|2)	3.32	4.51	3.84	3.53
F(4|3)	4.01**	4.59	3.96	3.68
F(5|4)	3.20	4.70	4.07	3.77
Cross-sectional dependence = GW_{it}, Break points = 2 years: **1908, 1968**				
Structural Break Test 3				
$\text{GW}_{it} = R\&D_{it}, TRADE_{it}, POP_{it}, M2_{it}, Y_{it}, Y_{it}^2$				
F(1|0)	8.69***	4.08	3.35	2.99
F(2|1)	3.26	4.32	3.69	3.34
F(3|2)	4.35**	4.51	3.84	3.53
F(4|3)	4.08**	4.59	3.96	3.68
F(5|4)	2.15	4.70	4.07	3.77
Cross-sectional dependence = $R\&D_{it}$, Break point = 1 year: **1967**				

Notes: This table presents the results for structural break tests. The structural break test accounts for heteroskedasticity, autocorrelation, and cross-sectional dependence where the cross-sectional variables are exhibited in parentheses for each test. The null hypothesis of test the presence of a break against the alternative of one more break, as it is estimated against lower and upper limits of breaks. The test is developed by Ditzen et al. (2021). Asterisks ***, **, and * denote 1%, 5% and 10% significance levels.

Table **4A-3:** Hausman test

	(b^{RE})	(B^{FE})	$(\text{b}^{RE}\text{-B}^{FE})$	Std. err.
$R\&D_{it}$	-0.167	-0.168	0.001	0.002
$TRADE_{it}$	-0.030	-0.029	0.001	0.001
$M2_{it}$	-0.059	-0.059	0.000	0.001
POP_{it}	-0.323	-0.328	0.005	0.001
Y_{it}	0.095	0.098	0.003	0.001
Y_{it}^2	-0.008	-0.008	0.000	0.000
$\boldsymbol{\mathcal{X}^2 = 45.44^{***}}$				

Notes: b^{RE} denotes coefficients of random effects and B^{FE} denotes coefficients of fixed effects. The Hausman (1978) test statistic assumes that under the null, RE is both consistent and efficient. And that FE is consistent under alternative. Rejecting the null of equivalence of FE and RE suggests that we normally should adopt FE. $\mathcal{X}^2$ test statistic suggests that FE is more preferable because the RE is inconsistent as the significance level is less than 5%. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-4:** Benchmark climate change-R&D model without Y_{it}^2

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.14**	-0.13**	-0.14	-0.14**
	(0.06)	(0.05)	(0.09)	(0.05)
$TRADE_{it}$	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.02)	(0.02)
$M2_{it}$	-0.08**	-0.08**	-0.08	-0.08**
	(0.03)	(0.03)	(0.07)	(0.03)
POP_{it}	-0.22***	-0.21***	-0.22***	-0.22***
	(0.02)	(0.02)	(0.02)	(0.02)
Y_{it}	-0.06**	-0.06**	-0.06***	-0.06**
	(0.02)	(0.02)	(0.01)	(0.03)
Constant	6.55***	6.51***	6.55***	6.58***
	(0.48)	(1.22)	(0.33)	(0.56)
R^2	0.12	0.12	0.08	0.12
F-stat.	50.21***		129.48***	
$\mathcal{X}^2$		249.15***		
F-test: All $\beta_i = 0$	3806.26			17749.39
	[0.00]			[0.00]
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the estimations using fixed effects estimator for robustness check. FE denotes fixed effects. FE(DK) denotes Driscoll-Kraay standard errors-fixed effects, and FE-IV denotes fixed effects instrumental variable estimator. The F-test assumes the joint significance of the fixed effects. If the p-value is low (< 0.05), we reject null hypothesis, suggesting that individual-specific effects are significant, and FE should be used instead of pooled OLS. Square brackets [ ] exhibits the p-values of the F-tests. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-5:** Climate change and R&D SV decomposition extended model

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D^I_{it}$	0.01*	0.01*	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
$R\&D^F_t$	-0.07**	-0.07**	-0.07***	-0.09***
	(0.02)	(0.02)	(0.01)	(0.03)
$TRADE_{it}$	-0.05***	-0.05***	-0.05***	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
$M2_{it}$	-0.04*	-0.04*	-0.04	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)
POP_{it}	-0.35***	-0.34***	-0.35***	-0.66***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.08*	0.08*	0.08	0.78**
	(0.05)	(0.05)	(0.10)	(0.33)
Y^2_{it}	-0.01***	-0.01***	-0.01**	-0.04**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.59***	7.52***	7.59***	8.56***
	(0.69)	(1.30)	(0.46)	(0.82)
R^2	0.20	0.19	0.08	0.23
F-stat.	38.88***		385.18***	
$\mathcal{X}^2$		269.19***		18035.44***
$N \times T$	3,040	3,040	3,040	3,020

Notes: In this table, we decompose research and development into idiosyncratic and common factor using multivariate stochastic volatility approach. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-6:** Climate change and R&D: structural break

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.17***	-0.17***	-0.17**	-0.16**
	(0.05)	(0.05)	(0.07)	(0.05)
GW_{dummy}	0.04	0.04	0.04	0.03
	(0.16)	(0.16)	(0.04)	(0.15)
$TRADE_{it}$	-0.03*	-0.03**	-0.03*	-0.03**
	(0.02)	(0.02)	(0.01)	(0.02)
$M2_{it}$	-0.06**	-0.06**	-0.06	-0.04
	(0.03)	(0.03)	(0.05)	(0.03)
POP_{it}	-0.33***	-0.32***	-0.33***	-0.60***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.10**	0.09**	0.10	0.69**
	(0.05)	(0.05)	(0.09)	(0.31)
Y_{it}^2	-0.01***	-0.01***	-0.01**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.72***	7.65***	7.72***	8.89***
	(0.57)	(1.29)	(0.41)	(0.87)
R^2	0.19	0.19	0.08	0.23
F-stat.	37.94***		374.00***	
$\mathcal{X}^2$		263.05***		17974.86***
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 20 OECD countries from 1870 to 2021. Here, we focused on the cross-sectional dependence of global warming while considering the structural breaks: Test (2). The null hypothesis of test the presence of a break against the alternative of one more break, as it is estimated against lower and upper limits of breaks. $\mathcal{X}^2$test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-7:** Climate change and R&D: structural break

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.17***	-0.17***	-0.17**	-0.16**
	(0.05)	(0.05)	(0.07)	(0.31)
$R\&D_{dummy}$	-0.02	-0.02	-0.02	-0.03
	(0.22)	(0.22)	(0.01)	(0.22)
$TRADE_{it}$	-0.03*	-0.03**	-0.03*	-0.03**
	(0.02)	(0.02)	(0.01)	(0.02)
$M2_{it}$	-0.06**	-0.06**	-0.06	-0.04
	(0.03)	(0.03)	(0.05)	(0.03)
POP_{it}	-0.32***	-0.32***	-0.32***	-0.60***
	(0.04)	(0.04)	(0.05)	(0.15)
Y_{it}	0.10**	0.09**	0.10	0.69**
	(0.05)	(0.05)	(0.09)	(0.31)
Y_{it}^2	-0.01***	-0.01***	-0.01**	-0.03**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	7.71***	7.65***	7.71***	8.88***
	(0.57)	(1.29)	(0.41)	(0.87)
R^2	0.19	0.19	0.08	0.23
F-stat.	37.93***		610.12***	
$\mathcal{X}^2$		262.99***		17974.63***
$N \times T$	3,040	3,040	3,040	3,020

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 20 OECD countries from 1870 to 2021. Here, we focus on the cross-sectional dependence of research and development intensity while considering the structural break: Test (3). The null hypothesis of test the presence of a break against the alternative of one more break, as it is estimated against lower and upper limits of breaks. $\mathcal{X}^2$test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-8:** Time-varying effects: Pre-World War II

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-21.05***	-21.09***	-21.05***	-20.68***
	(1.93)	(1.93)	(1.80)	(4.68)
$TRADE_{it}$	-0.02	-0.02	-0.02**	-0.02
	(0.01)	(0.01)	(0.01)	(0.06)
$M2_{it}$	0.01	0.01	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.13)
POP_{it}	0.26***	0.27***	0.26***	0.21
	(0.04)	(0.04)	(0.04)	(0.38)
Y_{it}	0.00	0.00	0.00	0.85
	(0.02)	(0.02)	(0.01)	(7.96)
Y_{it}^2	0.01***	0.01	0.01***	-0.04
	(0.00)	(0.00)	(0.00)	(0.46)
Constant	-2.06***	-2.11	-2.06***	-4.83
	(0.53)	(1.35)	(0.57)	(27.67)
R^2	0.32	0.32	0.16	0.36
F-stat.	29.51***		55.31***	
$\mathcal{X}^2$		177.64***		197917.48***
$N \times T$	1,380	1,380	1,380	1,360

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 20 OECD countries from 1870 to 1938 (PRE-WORLD WAR II). $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisk ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-9:** Time-varying effects: Post-World War II

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.07*	-0.07*	-0.07*	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)
$TRADE_{it}$	-0.07***	-0.07***	-0.07***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.02)
$M2_{it}$	-0.08***	-0.08***	-0.08***	-0.06**
	(0.02)	(0.02)	(0.02)	(0.03)
POP_{it}	-0.54***	-0.52***	-0.54***	-0.82**
	(0.08)	(0.08)	(0.09)	(0.38)
Y_{it}	0.54***	0.50***	0.54**	1.02
	(0.12)	(0.12)	(0.19)	(0.67)
Y_{it}^2	-0.03***	-0.03***	-0.03***	-0.05
	(0.01)	(0.01)	(0.01)	(0.03)
Constant	8.78***	8.52***	8.78***	10.64***
	(0.85)	(1.30)	(0.48)	(2.66)
R^2	0.31	0.31	0.11	0.36
F-stat.	30.53***		1660.60***	
$\mathcal{X}^2$		178.07		14696.82***
$N \times T$	1,520	1,520	1,520	1,500

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 20 OECD countries from 1946 to 2021 (POST-WORLD WAR II). $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-10:** Heterogeneity: G7 countries

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	0.48***	4.82***	0.48***	0.61***
	(0.12)	(0.55)	(0.10)	(0.13)
$TRADE_{it}$	0.20**	-4.25***	0.20***	0.31***
	(0.06)	(0.23)	(0.05)	(0.08)
$M2_{it}$	-0.37***	-1.95***	-0.37***	-0.42***
	(0.06)	(0.25)	(0.09)	(0.07)
POP_{it}	1.99***	3.90***	1.99***	-2.03***
	(0.17)	(0.31)	(0.12)	(0.17)
Y_{it}	22.60***	22.95***	22.60***	27.28***
	(0.99)	(4.19)	(1.34)	(2.56)
Y_{it}^2	-1.29***	-0.96***	-1.29***	-1.57***
	(0.06)	(0.25)	(0.08)	(0.15)
Constant	-54.43***	-193.42***	-54.43***	-72.75***
	(4.79)	(18.96)	(5.74)	(10.58)
R^2	0.09	0.47	0.48	0.08
F-stat.	161.45***		615.75***	
$\mathcal{X}^2$		928.32***		24128.23***
$N \times T$	1,064	1,064	1,064	1,057

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of G7 countries from 1870 to 2021. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Table **4A-11:** Heterogeneity: other 13 countries

Estimator	FE	RE	FE(DK)	FE-IV
$R\&D_{it}$	-0.03***	-0.03***	-0.03***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
$TRADE_{it}$	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
$M2_{it}$	-0.02***	-0.02***	-0.02***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
POP_{it}	-0.04***	-0.04***	-0.04***	-0.12***
	(0.00)	(0.00)	(0.01)	(0.01)
Y_{it}	0.02***	0.02***	0.02	0.21***
	(0.00)	(0.00)	(0.02)	(0.03)
Y_{it}^2	0.00	0.00	0.00	-0.01***
	(0.00)	0.00	(0.00)	(0.00)
Constant	1.02***	1.02***	1.02***	1.27***
	(0.05)	(0.16)	(0.05)	(0.06)
R^2	0.00	0.00	0.18	0.00
F-stat.	72.47***		262.21***	
$\mathcal{X}^2$		435.14***		83941.19***
$N \times T$	1,976	1,976	1,976	1,963

Notes: This table presents the estimations of the impact of long run impact of R&D intensity on global warming for a sample of 13 other OECD countries from 1870 to 2021. $\mathcal{X}^2$ test statistic has a null of poor model fit. Asterisks ***, **, and * denote 1%, 5% and 10% significance levels. Standard errors are presented in the parentheses.

Appendix B: Modelling Research and Development Intensity Spillovers

We model research and development intensity spillovers using an MFSV model:

$$\begin{aligned} &\boldsymbol{R\&D_{it}} \mid \boldsymbol{\beta}, \boldsymbol{\Lambda}, \boldsymbol{f}_t, \overline{\boldsymbol{R\&D}}_t \sim \mathcal{N}_N(\boldsymbol{\beta} + \boldsymbol{\Lambda}\boldsymbol{f}_t, \overline{\boldsymbol{R\&D}}_t), \\ &\boldsymbol{f}_t | \widetilde{\boldsymbol{R\&D}}_t \sim \mathcal{N}_r(0, \widetilde{\boldsymbol{R\&D}}_t), \end{aligned} \tag{4B-1}$$

where $\mathcal{N}(\boldsymbol{\beta} + \boldsymbol{\Lambda}\boldsymbol{f}_t, \overline{\boldsymbol{R\&D}}_t)$ denotes the normal distribution for the matrix $\boldsymbol{R\&D_{it}}$ with mean research and development intensity represented by $\boldsymbol{\beta} = (\beta_1,...,\beta_N)^\top$ with research and development intensity factors $\boldsymbol{f_t} = (f_{1t},....,f_{rt})^\top$. The factor loadings are $\boldsymbol{\Lambda} \in \mathbb{R}^{N\times r}$ in equation (4B-1). The covariance matrices $\overline{\boldsymbol{R\&D}}_t$ and $\widetilde{\boldsymbol{R\&D}}_t$ are both diagonal and can be written as:

$$\begin{aligned} &\overline{\boldsymbol{R\&D}}_t = diag(exp(\bar{h}_{it}), ..., exp(\bar{h}_{Nt})), \\ &\widetilde{\boldsymbol{R\&D}}_t = diag(exp(\tilde{h}_{1t}), ..., exp(\tilde{h}_{rt})), \\ &\bar{h}_{it} \sim \mathcal{N}(\bar{\mu}_i + \bar{\varphi}_i(\bar{h}_{it-1} - \bar{\mu}_i), \overline{R\&D}_i^2), \quad i = 1, ..., N, \\ &\tilde{h}_{jt} \sim \mathcal{N}(\tilde{\mu}_j + \tilde{\varphi}_j(\tilde{h}_{jt-1} - \tilde{\mu}_j), \widetilde{R\&D}_j^2), \quad j = 1, ..., r, \end{aligned} \tag{4B-2}$$

The total variance ($\boldsymbol{R\&D}_t$) of research and development intensity can be decomposed into factor and idiosyncratic variance.

$$\boldsymbol{R\&D}_t = \widetilde{\boldsymbol{R\&D}}_t + \overline{\boldsymbol{R\&D}}_t, \tag{4B-3}$$

Where $\overline{\boldsymbol{R\&D}}_t$ consists of variances of the idiosyncratic errors while $\widetilde{\boldsymbol{R\&D}}_t = r < N$. Equation (4B-3) can be modified utilising equation (4B-1) to become:

$$\boldsymbol{R\&D}_t = \boldsymbol{\Lambda}\widetilde{\boldsymbol{R\&D}}_t\boldsymbol{\Lambda}^\top + \overline{\boldsymbol{R\&D}}_t, \tag{4B-4}$$

For any generalised permutation matrix $\boldsymbol{P}$ of size $r \times r$, there is some other viable decomposition $\boldsymbol{R\&D}_t = \boldsymbol{\Lambda'}\ \widetilde{\boldsymbol{R\&D}}'_{\boldsymbol{t}}\ (\boldsymbol{\Lambda'})^\top + \overline{\boldsymbol{R\&D}}_t$, where $\boldsymbol{\Lambda'} = \boldsymbol{\Lambda}\boldsymbol{P}^{-1}$ and $\widetilde{\boldsymbol{R\&D}}'_t = \boldsymbol{P}\ \widetilde{\boldsymbol{R\&D}}_{\boldsymbol{t}}\ \boldsymbol{P}^\top$. Practically, the uncertainty in the scale of the factors is resolved by setting their log-variance level to zero. In the second stage of our empirical analysis examining the relationship between global warming and research and development intensity, we denote country specific research and development intensity spillovers ($\overline{\boldsymbol{R\&D}}_t$) as $R\&D^I_{it}$ and global research and development intensity spillovers ($\boldsymbol{\Lambda}\widetilde{\boldsymbol{R\&D}}_t\boldsymbol{\Lambda}^\top$) as $R\&D^F_t$.