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Impact of Climate Change on Equity Markets

Evidence from a Global Sample of 45 Countries

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Abstract

Climate change and its effects on our daily life are one of the most visited research topics in the last few years. A growing number of this literature focuses on the impact of climate change on the economy and financial markets, and the threat it may pose on long-term investments. In this study, we examine the relationship between equity returns and climate risk factors using a revised version of the ND-GAIN vulnerability and readiness index along with macroeconomic and global control factors for 45 countries over 80 quarters from 2001Q1 till 2020Q4. We further examine the impact of climate risk factors on equity returns for a different group of countries which represent some commonalities such as development, geographical position, and weather-based factors. We employ a fixed effect panel regression model with modifications towards cross-section independence and white residuals. We are using seemingly unrelated regression (SUR) features of generalized least squares (GLS) and white (diagonal) standard errors. We find that equity returns are negatively correlated with the climate vulnerability index and positively correlated with the climate readiness index at the full panel sample. Implementing our novel clustering strategies, we also find that there are significant contrasts among countries clustered based on some commonalities.

Key words: ND-GAIN, climate vulnerability, climate readiness, equity index returns, fixed-effects model, cross-section (SUR)

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1 Introduction

Global warming is one of the strongest indicators of likely climate change that inevitably affects our lives today. Wildfires, hurricanes, summer storms, floods, droughts, deadly summer temperatures, etc. set just some examples of devastating events with enormous impacts on our lives originating from climate change. According to NASA GISS (2021), the average temperature has globally risen more than 1.2C degrees since the 1880s. Furthermore, global warming has escalated during the last 60 years and reached record high degrees in the last 5 years (Climate Central, 2020; GISTEMP Team, 2021; Lenssen et al., 2019). The highest temperature on Earth was measured at the Death Valley, US with a record of 54.4C in mid-August 2020 (BBC News, 2020). 2020 (tied with 2016) has registered as the warmest year since the 1880s (NASA GISS, 2021).

Climate change is unfortunately not free of cost. It causes frequent environmental, humanitarian, and economic costs to humanity, which are damaging the livability of our planet Earth's atmosphere and losing some spatial areas including global metropolises because of an increase in sea levels remain the most important ones. In case all glaciers in the world melted down, the sea level is estimated to increase by 60-70 meters (USGS, 2021), which will cause lots of today's coastlines including some metropolitan cities hosting millions of people to sink.

Although it is not straightforward to calculate the exact number of people under the risk of forced migration due to climate change, several studies attempt to come up with an estimation. The most cited number remain 200 million people by 2050 (Myers, 2005; Stern et al., 2006). However, some recent studies postulate even higher numbers. A recent report by the Institute for Economics & Peace (2020) forecasts 1.2 billion people from 43 countries to be at risk of displacement in the next 30 years due to the resource scarcity and natural disasters caused by climate change. Deforestation, desertification, dried-up lakes, and rivers, drought, water stress, food insecurity, extreme weather events, rising sea levels, etc., apart from holding huge environmental costs, are just some of the channels through which the impacts of climate change are translated into the economic costs.

The literature that tries to explain the relationship between climate change and economic performance is predominantly focused on the long-term effects (Kahn et al., 2019). Kahn et al. (2019) indicate that a rise of mean global temperatures by 3.2°C until 2100 will result in decreasing the global real GDP per capita by more than 7% in case of no mitigation activities. Burke et. al. (2015) also find that climate change might reduce global average incomes by 23% by 2100 relative to a no climate change scenario. OECD (2015) highlights that GDP could be 12% lower by 2100 due to the negative impacts of climate change. Hsiang et al. (2017) find that the 1.5 C degree scenario will affect the GDP by -1.7%, the 4.0 C degrees by -5.6%, and 8.0 C degrees by -15.7%. Arbex and Batu (2020) show that an uninterrupted temperature increase will decrease the output level up to 1.61% of GDP. As it can be seen, estimates are quite different across studies chiefly because of the differences in their assumptions for the climate damage function. Even though the literature on climate change on the economy is somehow established, the literature on the impact of climate change on the financial markets is however limited. Of which CISL (2015) finds that the value of a typical investor's portfolio could be 50% lower in a scenario without climate change mitigation as compared to a 2.0 C degree scenario. As per Spedding et. al. (2013)'s assessment of the transition risks for the listed European oil and gas companies, the estimated value at risk is 40-60% of their market capitalization.

Climate risk is categorized as a systemic risk and this negative impact arises due to the damage to the physical environment as well as due to the accumulated greenhouse gases (GHGs) emissions (Li, Wang, Zhao, & Qi, 2021). Physical, transition, indirect, and stranded assets risks are widely highlighted risks associated with climate change. Physical risks occur with weather-related events like floods, droughts, etc. which affect the financial institutes and markets directly; whereas transition risks are the result of adjustments to lower carbon emissions. Investors may therefore face significant climate risk without barely recognizing it (Allen, Crawford, Théot, & Toscani, 2015). Indirect risk constitutes a risk that is practically ignored in scientific studies. This risk occurs with companies whose business is not directly affected by climate change, but the business of their key partners is at risk, and this can cause disruptions of global supply chains (Fabris, 2020). Stranded assets risks are related to losses incurred because of written off carbon-based assets such as oil left in the ground. To prevent the negative impacts of climate change, the net carbon emissions should ultimately reach zero. Hence, massive investments will be required to achieve this transition. As per the estimates of the Global Commission on the Economy and Climate, $90 trillion will be invested in infrastructure by 2030 (NCE, 2018). For simplicity, we predominantly focus on physical and transition risks arising due to climate change and follow a top-down approach to evaluate the effect of climate change on the financial markets.

Physical risks primarily comprise three major factors: hazard, exposure, and vulnerability. Vulnerability is one of the most significant climate risk factors as it entails exposure and hazard factors. It is explained as the extent of disruptions on the physical systems and assets which are resulted from exposure to the climate hazard (Tankov & Tantet, 2019), whereas climate resilience is another measure that explains the preparedness to climate risks. As per IPCC (2012), climate resilience is the capacity of a system to absorb shocks and recover from hazardous events.

Researchers are trying to study the impact of climate change on the investment portfolio. Typically, these studies involve temperature as a proxy for the climate risk factor. Bansal et al. (2016) find the increase in temperature lowers equity valuations around the globe. In another study using temperature, Bansal et al. (2019) discuss the likelihood of loss from significant storms, flooding, heatwaves, etc. to be associated with lower and more volatile earnings and cash flows. Moreover, studies are conducted using regional temperature and firm-specific portfolios. The study by Kumar et al. (2019) suggests that stock markets misprice stocks with the highest climate sensitivity which they measured as abnormal temperature. Using Notre Dame Global Adaption Initiative index (ND-GAIN), Kling et al. (2018) identify a severer cost of debt to be uniquely associated with climate-vulnerable countries. Furthermore, Beirne et al. (2020) find the increasing cost of sovereign borrowings on climate-vulnerable countries. However, studies focusing on the impact of climate vulnerability and climate readiness on the global stock market returns are limited.

Relying on these discussions, we aim to estimate the relative impact of climate change risk on the equity market returns of distinct clusters. Hence, our research questions are:

a. What represents the relative impact of climate risk factors on equity market index returns?
b. How do various geographical and economic factors characterize the countries impact the relationship between climate risk factors and equity returns?

We use panel data of 45 countries over 80 quarters from 2001Q1 till 2020Q4. Data is collected from several institutional databases (i.e., OECD, IMF, World Bank, FRED, FAOSTAT, EUROSTAT, ND-GAIN) and country accounts. Our variables include stock market index returns (based on MSCI country indexes), macroeconomic factors like GDP growth, GDP per capita growth, unemployment rate, industrial production, inflation, short-term and long-term interest rates, exchange rates, recession dummy, banking crisis dummy, global factors like MSCI World and volatility index, and climate variables as ND-GAIN vulnerability and readiness index. We employ a fixed-effects panel regression model with cross-section seemingly unrelated regression (SUR) and white (diagonal) standard errors as the generalized least squares (GLS) modifications. We define several clustering strategies to test our results across different clusters.

Our primary contribution to the literature originates from the uniqueness of the study using the ND-GAIN vulnerability and readiness indices as the climate risk and resilience variables to quantify the impact of climate change on equity markets. Additionally, we establish novel weather, geographical and economic factor approach to explain differences across regions provide another source of contribution to the literature. The relevance of our research is in the usage of climate vulnerability measures which can be estimated ex-ante compared to other ex-post climate risk proxies like natural catastrophes.

Our results show that equity returns are negatively correlated with the climate vulnerability index and positively with the climate readiness index on the full panel level. Furthermore, the results indicate significant divergences among countries based on development, proximity to the equator, and weather-related clusterings.

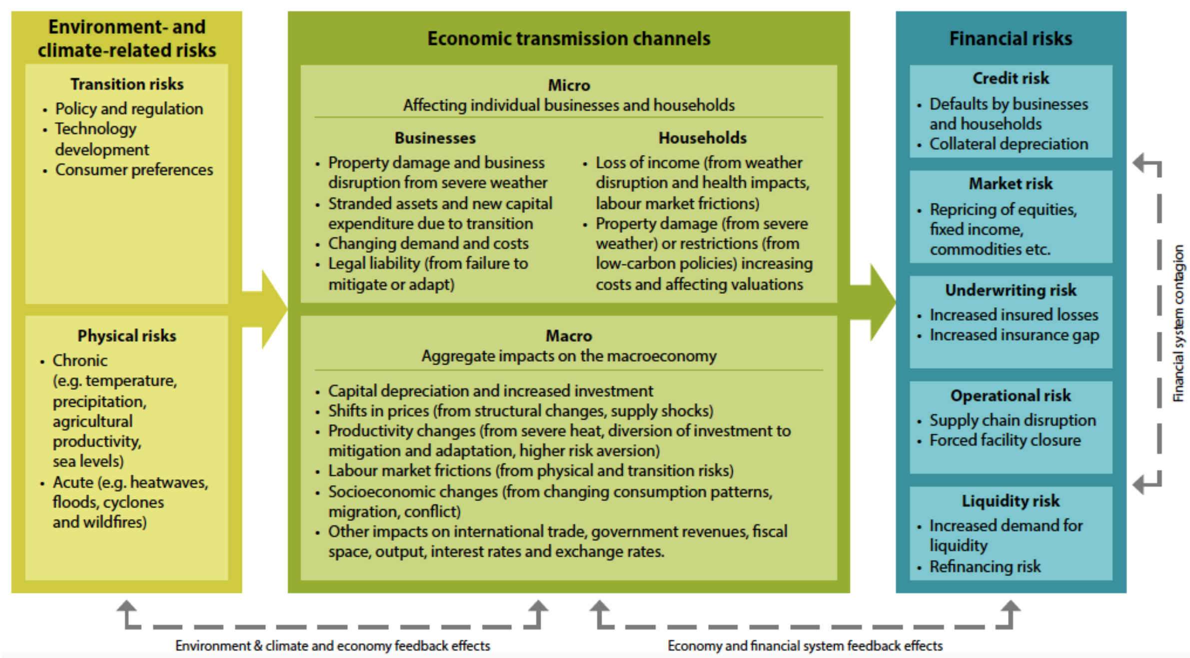
In the following sections, we initially start with a theoretical background and findings from the different literature focusing on the relationship between climate change, the macroeconomy, and equity returns from an empirical point. We subsequently explain the methodology, modeling approach, and data description of the variables used in our model. Lastly, we discuss the empirical results and analyze our results with the literature and conclude the thesis.

2 Theoretical Background and Literature Review

2.1 Overview

The 6th assessment report by IPCC predicts the rise in the global surface temperature to continue until the mid-century and the global warming to rising above 2 degrees scenario until the greenhouse gas reduction steps are in place (IPCC, 2021). This temperature rise is projected to cause devastating effects on the economy (Marshal Burke & Tanutama, 2019; Kahn et al., 2019). The economic damage due to climate change will further increase the global financial risk. Hence it is important to understand the estimated impact of climate change on the economy and further how the impact will spread be on the financial markets (NGFS, 2020b, 2020c). Figure 1 exhibits the climate change risk transmission channel affecting the different financial risks such as – credit risk, market risks, underwriting risks, operational risks, and liquidity risks. the transmission effect is observed via the microeconomic and macroeconomic channels. In this paper, we study the impact on the equity returns (market risk) using a global sample via the macroeconomic channel.

Figure 1: Transmission Channels for Climate Risks to Financial Risks



Source: (NGFS, 2020a, p. 9)

Jones and Mearns (2005) describe climate risk as a measure of hazard, probability, and vulnerability. They discuss two approaches for measuring climate risk, A hazard-based approach and a vulnerability-based approach. Physical risks are those types of risks that arise due to the physical damage caused due to climate-related hazards whereas Transition risks arise due to the transition towards to low-carbon economy. From an economic perspective – the physical risks affect the business operations and demand due to property damages alongside household finance. These risks further flow down on the insurance underwriters and increase the financial risk of the creditors. These effects are visible at a macroeconomic level through various channels, broadly via demand (consumption pattern), production capacity, agricultural output, prices, and labor that are significantly increasing the investment requirements from the governments, corporate institutions, and households.

As per Tankov and Tantet (2019), physical risk can be expressed as a function of three major factors, hazard, exposure, and vulnerability. Hazard is described as uncertain weather patterns and events with different damaging intensities. Exposure refers to the entity and assets under the risk from the climate hazard and vulnerability is defined as the extent of disruptions on the physical systems and assets coming from the exposure to the climate hazard. Whereas the key drivers of transition risk are mitigation policies, technological changes, and preference changes. (Semieniuk, Campiglio, Mercure, Volz, & Edwards, 2021).

The effects of climate risks on financial markets are primarily modeled using two methodologies, a top-down approach in which the impact of climate change is studied on a broad cross-section of stock market returns. This approach involves the development of macroeconomic financial models. This approach can be observed in the research work of Bansal et al. (2019) and Kumar et al. (2019), whereas another approach includes a bottom-up analysis in which firm and investor specific characteristics are critical. The bottom-up approach generally involves microeconomic and firm-specific parameters in modeling. For instance, as observed in studies by Addoum et al. (2020) and Krueger et al. (2020). In this study, we follow a top-down approach.

Researchers have modeled the impact of physical and transition risks on equity returns using various climate risk proxies. For instance, Bansal et al. (2019) use temperature as a climate change risk factor and reveal significant negative impacts on the global equity returns. Research by Kumar et al. (2019) estimates the equity returns using temperature sensitivity. Bolton and

Kacperczyk (2020) study the carbon transition risk using emissions data and identify equity returns as to be linked to a firm's both direct and indirect emissions. Engle et al. (2020) create an environmental score from MSCI and Sustainalytics to hedge climate change risk. Using Palmers drought severity index (PDSI), Hong et al. (2019) find stock markets are inefficient in pricing droughts which can be attributed as one of a significant climate change risk. Given climate vulnerability is one of the important factors of physical risk, studies focusing on the impact of climate vulnerability on equity returns are limited.

ND-GAIN vulnerability and readiness index are created by Notre Dame Global Adaptation Initiative. The data captures the climate vulnerability at a level and measures the change in the country's vulnerability risk profile over years. Given it includes the parameters from critical sectors covering the exposure, sensitivity, and adaptive capacity, this index is being used by researchers within the financial economics sphere. For instance, Kling et al. (2018) use the ND-GAIN vulnerability index to evaluate the impact on bond yields of V20 countries. In another study, Kling et al. (2021) evaluate the impact of the ND-GAIN climate vulnerability index on the cost of capital at a firm level. Beirne et al. (2020) study the climate vulnerability impact on the cost of sovereign borrowing and identify cost effects at a global and regional level. More recently, Cheema-Fox et al. (2021) research the impact of climate vulnerability on currency returns. Inspired by these studies, we take a similar approach of incorporating the ND-GAIN vulnerability index as a climate vulnerability variable and try to analyze its effects on the stock market returns.

As per IPCC (2012), climate resilience is the capacity of a system to absorb shocks and recover from hazardous events. Moreover, Tyler and Moench (2012) define climate resilience as a critical factor for managing the future implications arising from the climate risks and altering the policies to manage the negative impacts. Hence, it is also important to capture the effects arising from the climate resilience of a country as the effect of climate risks affects countries in different proportions. In our study, we include the ND-GAIN readiness index which captures the preparedness and resilience to climate risks.

2.2 Literature Review

2.2.1 The Overall Impact of Climate Change on Economy

The global economy is exposed to risks due to extreme weather changes arising due to climate change. Many researchers have studied this relationship, for instance, Nordhaus (2006) studies the linkage between economic activities and a country's geographical positioning and identifies a negative relationship between temperature and output per capita. Similarly, in another study, Dell et al. (2012) use the variations in the temperature across various countries to analyze the effects on the aggregate economic outcomes and associate diminishing economic growth with the increase in temperature along with the growth rate. Temperature is widely used in empirical studies as a yardstick for modeling the economic loss due to climate change. Dell et al. (2014) identify agricultural outputs, industrial outputs, labor productivity, energy demand to be the channels through which weather shocks impact the economy. Bansal and Ochoa (2012) show that temperature acts as a significant risk factor that affects the economic growth of countries. Using the long-run risk model and global markets returns, they further find the negative effect of temperature is also visible in form of risk premium in the case of hotter countries that are closer to the equator whereas the impact is not material in the case of countries situated at higher latitudes. Inspired by this finding, we further create a cluster based on the geographical positioning of the country.

Hsiang et al. (2017) estimate the economic damage caused by climate change by integrating climate sciences, econometrics, and process. They define the damage on agriculture, crime, coastal storms, energy, human mortality, and the labor sector is quadratically increased with global mean temperature and costing 1.2% GDP for every 1C increase in temperature. They also project that the damage for the poorest countries would be between 2% to 20% of the country's income under the business-as-usual scenario. Burke and Tanutama (2019) analyze the district level panel data set on climate - explained using temperature, precipitation, and GDP and find the local level growth in output is non-linearly linked with the changes in the temperature. This research also estimates that the European Union (EU) and the United States of America (USA) have suffered from an output loss of ~4 trillion dollars and tropical countries are at least 5% poorer because of this warming. Learning from Burke and Tanutama (2019)'s findings, we further incorporate similar variables in our model for capturing the climate effect on the macroeconomic factors.

Kahn et al. (2019) study the impact of climate change on a data set of 174 countries and find the negative relationship between the economic output growth and temperature. In addition, they illustrate the universal long-run negative effects affecting all countries – rich, poor, hot, cold. Kompas et al. (2018) extend a computable general equilibrium model to forecast the various implications of global warming on economic growth using the data for 139 countries. The economic gains of complying with the Paris Accord's 2C target are estimated to be at 17 trillion USD per year in the long run by 2100. Klomp and Valckx (2014) estimate the relationship between natural disasters and the economic growth per capita and define a direct negative effect on the economic growth which is adverse in the case of developing countries

From the literature, the damaging impact of climate change on the economy is visible. Further, this impact is nonlinear and if affecting different countries due to various factors such as preparedness to mitigate climate risks, geographical positioning, economic development, etc. The negative effects arising from the damage in the economy due to climate change are further visible in the financial markets. Kling et al. (2018) use ND-GAIN climate vulnerability as a measure to study the relationship between climate risks and cost of capital and observe a higher financing cost is associated with the firms in countries that have greater exposure to climate risks. Further inspiring from these results, Beirne et al. (2020) study the impact of climate vulnerability on the cost of sovereign borrowing. Using the ND-GAIN vulnerability index for 40 countries, they identify that climate vulnerability affects the sovereign borrowing cost at a global and regional level. This research establishes a linkage between economic damage and climate change. Extrapolating this study, we further try to develop a simpler relationship between equity returns and climate change.

The literature discussed sets the premise for our research question and the modeling approach followed. In our model, we build on the similar approach discussed incorporating ND-GAIN as a climate vulnerability variable. We construct a model including temperature and rainfall (precipitation) as other climate variables. To capture the effects of the macroeconomic factors we use - GDP, Industrial productivity, interest rates, unemployment which is in line with the other empirical work.

2.2.2 The Impact of Macroeconomic Factors on Equity Returns

Arbitrage pricing theory and multifactor model analysis are the foundation for empirically studying the impact of various macroeconomic factors on equity returns. It is described in the early works of Chen et al. (1986), where they model equity returns as a function of several macroeconomic variables e.g., industrial production, expected and unexpected inflation, risk premium – spread between corporate bond portfolio and long-term government bond portfolio, term structure – spread between the long term and short-term treasuries. Their study incorporates Fama and MacBeth's (1973) factor regression and concludes that several macroeconomic variables have a systematic influence on the stock returns. Further, Chen (1991) studies the US market and finds that excess returns are positively correlated with the expectations of the future economic growth and can be explained by using default spread, term spread, short term treasury bill rate, the growth rate of industrial production, and dividend-price ratio.

Mookerjee and Yu (1997) determine a cointegration between stock returns and money supply and foreign exchange reserves. Harvey (2000) studies drivers of stock market return for 47 emerging and developed countries and concludes market variance and skewness to be risk drivers for emerging markets stock returns. Gjerde and Sættem (1999) reveal a relationship between real interest rates, inflation, oil prices, and stock market returns. Rapach (2001) analyzes the impact of money supply, aggregate spending, and aggregate supply shocks on the real US stock prices using a structural vector autoregression (SVAR) model and identifies that each macroeconomic shock has a significant effect on the real stock prices. Patro et al. (2002) use a GARCH method to explore a country's exposure to global market risk for 16 OECD countries and find several factors such as imports, exports, inflation, market capitalization, dividend yields, and price-to-book value ratios to be significant.

From the literature above, the relationship between macroeconomic variables and equity market returns can be well established. With this premise, we include macroeconomic control variables in the model to capture the macroeconomic fluctuations.

2.2.3 The Impact of Climate Change on Equity Returns

Researchers have further studied and extended the relationship between the macroeconomic variables and the financial market returns along with the climate impact. Some empirical studies have identified a significant relationship between climate risks and equity returns.

Cao and Wei (2005) examine many stock markets worldwide and find a statistically significant, negative correlation between temperature and returns across the whole range of temperature. Using the arbitrage pricing theory model and temperature shock as an undiversified market risk factor, Balvers et al. (2017) discuss a negative relationship between temperature factor-beta and asset returns. Another finding reveals a stronger negative relationship between temperature and asset returns in the case of vulnerable industries. Bansal et al. (2016) argue climate risk can significantly damage wealth using capital markets and temperature changes. Moreover, they find the forward-looking capital market data can provide evidence of climate change risks and the declining equity valuations and wealth. Their finding also implies that physical risks arising from climate change are present in the capital markets. In another study, Bansal et al. (2019) confirm the presence of positive risk premium associated with temperature risks in the stock markets. Their finding also suggests that asset prices can provide information on the cost of climate change. The study by Kumar et al. (2019) suggests that stock markets misprice stocks which have highest climate sensitivity measured using abnormal temperature change and stock prices.

Bolton and Kacperczyk (2021) use stock returns data and carbon emissions for the USA and define a significant relationship between the firm's emission and returns concluding institutional investors are demanding a premium for carbon risks implying investors are considering the climate risks in investment decisions. Another study by Bolton and Kacperczyk (2020) on 77 countries also identifies carbon premium across the world confirming the linkage between stock returns and a firm's direct emissions. Furthermore, they also argue that stock returns are also linked with the indirect emissions due to firm's supply chain network. Huang et al. (2018) use the climate risk index to examine the relationship between climate risks and a firm's financial performance and financing choice. They argue a loss likelihood due to climate catastrophes results in lower earnings and higher earnings volatility. Their findings reveal that a firm's decision-making is affected due to climate risks and managers often make decisions taking it into account. They label firms in climate-vulnerable regions to have a higher cash buffer and higher reliance on long-term credit.

From the literature, the impact of climate risk is evident on the equity market returns and the firm's performance. The literature focusing on climate vulnerability as a risk factor is limited. In this study, we focus on the aggregate impact of climate vulnerability on the stock market returns. For Macroeconomic control, we use GDP, Industrial productivity, unemployment, interest rates, population growth. Further to evaluate the impact on the equity returns (market risk) we use the stock market returns represented by MSCI, VIX is used to gauge the market volatility and banking crisis variable explains the domestic banking health.

2.3 Theoretical Background

2.3.1 Theoretical Channel: Climate Change and Macroeconomy

In a top-down approach, the impact of climate risk flows via the macroeconomic channel to the financial markets and hence it is first important to study the linkage between climate risks and macroeconomy before discussing the linkage between climate risks and stock market returns.

The climate change risk affects the global economy through shocks and these shocks are visible primarily in form of demand-side and supply-side shocks. The demand side shocks affect the consumption pattern of households, the aggregate demand whereas on the supply side – the production capacity - physical capital, technology, and labor are affected. The impact of rising temperature affects the production capacity of the global economy, this is observed through multiple channels. To model the impact, the general starting point is via a Cobb-Douglas form production function describing the relationship between aggregate output and production factors (Batten, 2018).

$$Y_t = A_t \prod_{j=1}^{J} K_{jt}^{\alpha j} \tag{1}$$

Y_t is the total production (output) at a given time *t*. A_t is the total factor productivity and *K* represents various inputs which can be in form of labor, types of capital – natural, human, infrastructure, etc. αj are the parameters measuring the output elasticities of various capital factors. With climate change, these input factors are affected negatively and hence the total production. In our research, this effect is captured incorporating the ND-GAIN's climate vulnerability and readiness index. In the further subsections, we discuss the empirical research conducted to quantify the damaging effect.

Figure 2: Physical Risks and Macroeconomy – A Theoretical Channel

Type of shock		From gradual global warming	From extreme weather events
Demand	Investment	Uncertainty about future demand and climate risks	Uncertainty about climate risks
	Consumption	Changes in consumption patterns, e.g. more savings for hard times	Increased risk of flooding to residential property
	Trade	Changes in trade patterns due to changes in transport systems and economic activity	Disruption to import/export flows due to extreme weather events
Supply	Labour supply	Loss of hours worked due to extreme heat. Labour supply shock from migration	Loss of hours worked due to natural disasters, or mortality in an extreme case. Labour supply shock from migration
	Energy, food and other inputs	Decrease in agricultural productivity	Food and other input shortages
	Capital stock	Diversion of resources from productive investment to adaptation capital	Damage due to extreme weather
	Technology	Diversion of resources from innovation to adaptation capital	Diversion of resources from innovation to reconstruction and replacement

Source: (Batten, 2018; NGFS, 2020b)

2.3.2 Theoretical Channel: Climate Change, Macroeconomy and Stock Market Returns

To study how climate risks affect equity returns, it is crucial to understand the relationship between the macroeconomy and equity returns and the theoretical linkage between them. The relationship between macroeconomy and equity returns isn't always straight forward and hence, this relationship is one of the most discussed topics under financial economics. Dividend Discount Model (DDM) and the Modern Portfolio Theory (MPT) by Harry Markowitz (1952) is primarily the starting of the asset pricing theory. The MPT describes the risk-return framework based on the portfolio choice between risky and risk-free assets. The capital asset pricing model (CAPM) by Sharpe (1964), Lintner (1965), and Mossin (1966) build further on Markowitz's MPT and uses a single factor - the market portfolio to explain the returns. Ross (1976) proposes multifactor Arbitrage Pricing Theory (APT) as an alternative to CAPM where returns are expressed as a linear function of multiple risk factors. If no arbitrage opportunities arise due to the equilibrium prices, then the expected returns are a linear function of the factor loads represented as factor betas.

The multivariate factor model is described below.

$$r_i = \beta_{i,0} + \beta_{i,1} f_1 + \beta_{i,2} f_2 + e_i \tag{2}$$

The expected returns of a securities portfolio r_i is expressed as a function of systematic common risk factors f_n that affects the assets (i.e., macroeconomic factors), whereas $\beta_{i,n}$ are the factor loadings or the risk exposure of the security for the n^{th} factor, e_i captures the idiosyncratic risk of the asset *i*. Using the arbitrage pricing theory, the macroeconomic factor model can be developed and adequately capture the macroeconomic risk sensitivity relative to the securities portfolio.

Top-down climate finance literature widely uses the arbitrage pricing linear factor model (Balvers et al., 2017) to study the effects of climate risks and employ a portfolio-based cross-section than an individual stock (Venturini, 2022). In line with this, we use the country-specific MSCI index as a stock portfolio and incorporate macroeconomic and climate variables as factors explaining the equity market returns.

3 Methodology

3.1 Data Collection and Description

For our research questions, we have a panel dataset of 45 countries[1] over 80 quarters from 2001Q1 to 2020Q4 for 17 variables. Since most of our independent variables are macroeconomic indicators, the optimal highest frequency that can be selected for a large sample of countries is the quarterly frequency. Hence, we have quarterly as the frequency of our data. Data is collected from several institutional databases such as OECD, IMF, World Bank, Federal Reserve Bank (FRED), and professional sources such as Refinitiv, Thompson Reuters, Investing.com, etc.

3.1.1 Data Transformation

Since quarterly temperature, rainfall, and GDP variables pose seasonal components in the data, we take a quarter-to-previous year the same quarter differencing strategy to eliminate the seasonality problem in the data. To be consistent with our approach, we keep the same strategy for all the variables even if they do not contain a seasonal component. Our time-series plots and panel unit root tests results show that our time series are not stationary at raw data level but are stationary at the transformed (standardized and differenced) values[2].

Due to the cross-sectional dependence in the data, the first-generation unit root tests fail to capture the stationarity in the data, hence we use the second-generation panel unit root tests (Pesaran CIPS) to appropriately define if there is a unit root in the series. To avoid biased and inconsistent estimators, we transform the data into standardized and cross-sectionally corrected variables. If series are non-stationary, the regression results are spurious. We take differencing strategy to get rid of non-stationarity in the data. For variable selection, we rely on the theory and recent literature. We attempt to incorporate both demand and supply-side factors. Table 1 provides detailed information on the variables.

[1] A detailed list of countries is available in "Appendix A.1.1 List of Countries in the Full Panel Set".

[2] All the time-series plots and unit root (stationarity) test results are available in "Appendix A.2.1 Time-Series Plots" and " A.2.2 Second Generation Panel Unit Root Tests".

3.1.2 Climate Risk Variables

This thesis aims to study the correlation between climate change risks and stock markets. Our main variables of interest are *climate vulnerability* and *climate readiness* index which are prepared by the Notre Dame Global Adaptation Initiative (ND-GAIN) at the University of Notre Dame. The *vulnerability index* that comprises 36 indicators from six critical sectors (food, water, health, ecosystem services, human habitat, and infrastructure) is designed to capture a country's vulnerability to climate disruptions; whereas the *readiness index* that consists of three components (economic readiness, governance readiness, and social readiness) is designed to capture the preparedness of a country towards the climate change risks. Hence, we think that both indexes are well-constructed proxy variables to be used in examining the climate risk impacts on equity returns.

3.1.3 Dealing with Endogeneity Issue

However, given that there are economic components, especially in the vulnerability index, one should have a concern about the endogeneity issue. It is important to disentangle the climate risk measures and the economic risk measures to eliminate the endogeneity problem. To overcome this, Kling et al. (2018) incorporate sophisticated modeling techniques and identify the relationship between climate vulnerability and macroeconomic variables. They further categorize the indicators as low, medium, and high relation to economic variables. For our research, we reconstruct the vulnerability index from the raw data by removing the highly related variables as defined by Kling et al. (2018).

Table 1: List of Variables

Variable	Notation	Description	Motivation	References	Source
Stock Market Index Returns	MSCI	It is the stock market indexes provided by the MSCI for different types of stock portfolios [such as small-cap, mid-cap, or large-cap, and growth or value stock indexes] as price in USD. The base year is 2000 (=100) for all countries throughout all indexes. We use the log difference of this variable.	Stock market indexes are measures calculated through the aggregation of stock performances in an exchange. Besides that, as per the efficient market hypothesis, we expect that any information is immediately reflected in the stock prices leaving a very tiny room for arbitrage.	(Chen et al., 1986)	MSCI, Capital IQ
GDP Growth	GDP	It is quarterly USD-based GDP in current values. We use the log difference of this variable.	The individual growth of stocks is one of the key factors in stock valuations. At the index level, we assume GDP growth to play the same role. We expect this variable to be positively related to stock market returns.	(Beirne et al., 2020; Kahn et al., 2019)	WB
GDP Per Capita Growth	GDPPC	It is quarterly USD based on current GDP divided by the quarterly population. Given that quarterly population data is not available for all countries, we assume a linear growth during the year and convert yearly data into quarterly data using linear interpolation. We use the log difference of this variable.	GDP per capita is an indicator showing per capita economic output over a specific period. It is calculated as the GDP divided by the country's population. It is also defined as a productivity indicator. We expect GDP per capita growth to be positively correlated to stock market returns.	(Beirne et al., 2020; Kahn et al., 2019)	WB
Inflation	CPI	It is an index representing inflation with the base year of 2015 (=100). We use the log difference of this variable.	Inflation is an increase in general price levels. If there is inflation in an economy one would expect that nominal GDP to increase. Hence, we expect that inflation would be positively correlated with stock market returns.	(Chen et al., 1986; Patro et al., 2002)	FAOSTAT
Industrial Production	IP	It is an index representing industrial production with the base year of 2015 (=100). We use the log difference of this variable.	Industrial production is an indicator that shows how well is the performance of an economy. Hence, for industrial production, we expect a positive relationship with stock market returns.	(Chen et al., 1986)	OECD, WB
Unemployment Rate	UNEM	It is annualized quarterly average unemployment rate. We use the difference of this variable.	Unemployment rate is an indicator signaling the well-being of an economy. As lower unemployment is better for the economy, we expect a negative relationship with stock market returns.	(Kandoussi & Langot, 2020)	WB, IMF, ECB
Exchange Rates	FX	It is the rate of national currencies over USD, except USD, which is compared to EUR. We use the log difference of this variable.	An increase in the exchange rate of a country means that there is a decrease in the value of the local currency. It is mostly determined by the capital outflows from the country. Hence, for exchange rates, we expect a negative relationship with stock market returns.	(Gjerde & Sættem, 1999; Mookerjee & Yu, 1997)	IMF
Short-Term Interest Rates	STIR	It is the 3-month treasury bills rate. Given that in periods it may	Interest rates are substitute products of equities for		

		become negative, we use the difference of this variable.	investors. Hence, we expect a negative relationship between interest rates and stock market returns.	(Chen et al., 1986)	IMF, WB, FRED, OECD, Investing
Long-Term Interest Rates	LTIR	It is the 10-year government bond rate. Given that in periods it may become negative, we use the difference of this variable.			
Recession Dummy	REC	It is a dummy variable that takes the value of 1 if the term spread is negative and 0 otherwise. We use the level of this variable.	As per the yield curve theories, term spread is an indicator of the well-being of an economy whereas a negative term spread is associated with a potential recession or crisis. Hence, we expect a negative relationship between the recession dummy and stock market returns.	(Chen et al., 1986)	Derived by the authors.
MSCI World	MSCIW	It is a stock market index constructed by MSCI to represent the world as price in USD. The base year is 2000 (=100). We use the log difference of this variable.	It is a variable which we use as a global control. We expect a positive relationship between this variable and stock market returns.	(Harvey, 2000)	MSCI
Volatility Index	VIX	It is an index prepared by the Chicago Board Options Exchange as an indicator of fear in the market. We use the log difference of this variable.	It is a variable which we use as a global control. Since it measures the fear in the market globally, we expect a negative relationship between this variable and stock market returns.	(Beirne et al., 2020)	CBOE
Banking Crisis Dummy	BC	It is a dummy variable getting the value of 1 if there has been a banking crisis in that individual country and otherwise 0. We use the data of (Laeven & Valencia, 2018). We use the level of this variable.	As it represents the banking crisis in a country, we expect a negative relationship with stock market returns for this variable.	(Beirne et al., 2020)	(Laeven and Valencia, 2020)
Vulnerability Index	VUL	It is an index prepared by the Notre Dame Global Adaptation Initiative at the University of Notre Dame (ND-GAIN). The index value increases as the vulnerability risk of a country increases. We use the log difference of this variable.	Given that a lower index value is better for the climate vulnerability risk, we expect a negative relationship between this variable and stock market returns.	(Beirne et al., 2020; Kling et al., 2021)	ND-GAIN
Readiness Index	READ	It is another index prepared by ND-GAIN which shows the readiness of the countries to climate change using several economic, social, and governance factors. We use the log difference of this variable.	Given that a higher index value is better for the climate readiness risk, we expect a positive relationship between this variable and stock market returns.	(Beirne et al., 2020; Kling et al., 2021)	ND-GAIN
Average Temperature	TEMP	It is the quarterly average temperature measured on the surface of each country calculated by averaging the monthly mean temperatures over the quarter.	We expect a negative correlation between temperature and stock market returns.	(Bansal et al., 2016)	WB
Average Rainfall	RAIN	It is the quarterly average rainfall measured on the surface of each country calculated by averaging the monthly mean rainfall over the quarter.	We expect a positive correlation between rainfall and stock market returns.	(Damania, Desbureaux, & Zaveri, 2020)	WB

Table 2: Descriptive Statistics for the Full Panel Dataset on Raw Data

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
MSCI	817.44	742.87	3,447.13	38.00	464.76	1.27	5.84	2,295.74	0.0000	3,780
GDP	321,491.01	101,883.60	5,436,900.00	11,464.63	668,634.91	4.67	27.39	107,419.28	0.0000	3,780
GDPPC	26,804.59	23,085.02	109,089.65	428.96	21,101.28	0.79	3.22	404.38	0.0000	3,780
CPI	88.49	91.74	197.93	12.65	18.84	-0.30	6.61	2,109.25	0.0000	3,780
IP	94.31	98.39	154.15	15.64	18.95	-0.73	4.32	613.99	0.0000	3,780
UNEM	0.07	0.06	0.34	0.01	0.05	2.27	9.73	10,389.91	0.0000	3,780
FX	399.40	7.51	15,263.59	0.50	1,669.53	6.17	43.26	279,296.21	0.0000	3,780
STIR	0.04	0.03	0.47	-0.01	0.05	3.24	22.40	65,906.70	0.0000	3,780
LTIR	0.05	0.04	0.50	-0.01	0.05	3.23	20.77	56,317.32	0.0000	3,780
REC	0.13	0.00	1.00	0.00	0.33	2.22	5.93	4,450.76	0.0000	3,780
MSCIW	1,445.31	1,347.24	2,524.92	770.15	415.85	0.52	2.46	216.25	0.0000	3,780
VIX	19.97	17.45	58.60	10.31	7.96	1.89	8.61	7,205.39	0.0000	3,780
BC	0.07	0.00	1.00	0.00	0.26	3.28	11.77	18,913.88	0.0000	3,780
TEMPAV	13.49	14.10	33.23	-23.87	10.45	-0.59	3.20	223.47	0.0000	3,780
RAINAV	86.97	65.77	420.83	0.13	71.64	1.44	4.79	1,817.54	0.0000	3,780
VUL	38.12	38.25	52.97	27.87	5.28	0.48	2.90	144.78	0.0000	3,780
READ	55.05	53.90	81.64	28.36	13.77	-0.03	1.93	180.10	0.0000	3,780

Table 3: Descriptive Statistics for the Full Panel Dataset on Transformed Data

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
LDMSCI	0.07	0.10	1.96	-2.13	0.46	-0.59	4.58	585.49	0.0000	3,600
LDGDP	0.04	0.04	0.37	-0.44	0.10	-0.49	4.23	368.44	0.0000	3,600
LDGDPPC	0.04	0.04	0.37	-0.46	0.11	-0.51	4.28	398.19	0.0000	3,600
LDCPI	0.11	0.09	2.08	-0.25	0.14	4.53	45.66	285,327.17	0.0000	3,600
LDIP	0.06	0.08	1.76	-6.64	0.31	-3.63	73.02	743,253.29	0.0000	3,600
LDUNEM	-0.00	-0.03	2.22	-1.62	0.28	1.18	9.03	6,278.61	0.0000	3,600
LDFX	0.00	-0.00	0.37	-0.16	0.05	1.18	8.85	5,960.27	0.0000	3,600
LDSTIR	-0.07	-0.01	3.13	-4.51	0.40	-1.64	20.63	48,265.15	0.0000	3,600
LDLTIR	-0.07	-0.05	2.66	-5.72	0.38	-3.15	40.68	218,936.50	0.0000	3,600
REC	0.12	0.00	1.00	0.00	0.33	2.29	6.27	4,760.77	0.0000	3,600
LDMSCIW	0.09	0.30	1.21	-2.00	0.61	-1.34	5.08	1,722.62	0.0000	3,600
LDVIX	0.03	-0.05	2.82	-2.69	1.09	0.15	3.00	12.99	0.0015	3,600
BC	0.07	0.00	1.00	0.00	0.25	3.40	12.53	20,548.53	0.0000	3,600
LDTEMP	0.00	0.00	0.64	-0.44	0.11	0.42	6.28	1,719.98	0.0000	3,600
LDRAIN	-0.00	-0.00	2.32	-2.68	0.31	0.19	9.16	5,705.16	0.0000	3,600
LDVUL	0.00	0.00	0.09	-0.08	0.02	-0.21	6.29	1,655.30	0.0000	3,600
LDREAD	0.03	0.02	0.72	-2.17	0.15	-4.13	47.35	305,315.98	0.0000	3,600

Table 2 shows the descriptive statistics of our full panel set over 17 variables on raw data. Variables in index forms and absolute values have an exponential component in trend. In that respect, taking the natural logarithm of those variables would help to convert exponential trends into linear trends. Hence, we transform the indices (*MSCI*, *CPI*, *IP*, *MSCIW*, *VIX*, *VUL*, and *READ*) and absolute value variables (*GDP* and *GDPPC*) by taking a log difference with the previous year same quarter, whereas for variables that do not possess exponentiality (*UNEM* and *RAIN*) and that have negative values in raw data (*STIR*, *LTIR*, and *TEMP*), we only take the difference of the variables with previous year same quarter. Dummy variables for banking crisis (*BC*) and recession (*REC*) are used at levels. Table 2 shows the descriptive statistics of transformed data over 17 variables and as per Jarque-Bera test statistics (Jarque & Bera, 1980), none of the variables are normally distributed.

3.2 Empirical Strategy

The relationship between climate vulnerability and readiness, macroeconomic variables, and equity market returns is a complex phenomenon. The datasets are large and require sophisticated modeling approaches. For our empirical work, we implement a fixed-effects panel regression model to study the relationship. In this section, we describe the background behind our model selection and specification, and the necessary diagnostic tests implemented to check the health of data and model specification.

3.2.1 Standardized variables

The variables in our model have different units. This makes the dependent variable (equity market returns represented by MSCI) and independent variables (climate, macroeconomic and global factor variables) difficult to compare and interpret the results. Hence, to avoid this, the literature suggests standardizing the variables. In this approach, for each series, we subtract the mean of the full panel series from the variable for each country and divide the difference by the full panel series standard deviation.

$$X_{it}^{*} = \frac{X_{it} - \bar{X}}{S_x} \tag{3}$$

where X_{it} is the original value of each observation in the series, $\bar{X}$ is the mean of the series, S_x is the standard deviation of the series, and X_{it}^{*} is the standardized value of each observation in the series. With this transformation, the mean of standardized variables is constant at 0 and the standard deviation is constant at 1. The model regression is performed on the standardized regressand and regressors.

3.2.2 Panel Data Regression Models

Stock market returns are affected by many observable and unobservable factors. Additionally, climate change is a global fact experienced differently across regions. Given these, sole time series or cross-section data analysis techniques might be inefficient to reveal the real relationship between some variables and stock market returns. Panel data is one of the widely used methods for handling complexity (Baltagi, 2021; Hsiao, 2014). Hence, we apply panel data analysis techniques which are more useful in controlling for some common observable and unobservable factors while taking the variation in the climate risk factors into account. Panel datasets structurally contain cross-sectional and time-series dimensions in data; hence, they possess several advantages and limitations compared to conventional cross-section and time-series data. Hsiao (2014) and Baltagi (2021) identify several benefits of panel data techniques as follows:

- ✓ Panel data structurally allow controlling for *individual heterogeneity* in addition to *time heterogeneity*, which is not possible with only time-series or cross-section data. They are perfect to control for the impact of omitted or unobserved variables.
- ✓ With larger data points, panel data are more informative accommodating lower collinearity among the variables, more variability, higher degrees of freedom, and higher efficiency.
- ✓ Panel data are better in *understanding the adjustments to policy changes* in macroeconomic phenomenon such as unemployment, poverty, labor mobility, or job turnover.
- ✓ Panel data are better in capturing the relationships between variables which is not simply possible to do in sole cross-section or pure time-series data.
- ✓ Panel data are better in *constructing and testing more complicated behavioral models* compared to purely cross-section or time-series data.
- ✓ A bias that can arise from aggregating over individuals or entities in solo cross-section or time-series data might be minimized or eliminated in panel data.

Whereas limitations are listed as:

- ✓ Data collection and dataset design problems

- ✓ Measurement errors
- ✓ Issues resulting from the selection process: self-selectivity, nonresponse, or attrition
- ✓ Micro-panels with a short-time span suffer from short time-series dimension
- ✓ Macro-panels with a long-time span suffer from cross-section dependence

3.2.3 One-Way Panel Regression Models

The one-way panel regression models suggest that there is either time or individual effects in the panel data affecting the dependent variable. Hence, the model is in form of either:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + v_{it} \tag{4}$$

or

$$Y_{it} = \alpha + \beta X_{it} + \lambda_t + v_{it} \tag{5}$$

whereas μ_i is denoting the time-invariant *individual effects,* λ_t is the cross-section invariant *time effects*, and v_{it} is the remaining *stochastic disturbance* (Baltagi, 2021).

By averaging the model (4) over time and the model (5) across entities, and then subtracting them from the original models will eliminate unobservable factors over time or across entities.

3.2.4 Two-Way Panel Regression Models

The two-way panel regression models suggest that there are both time and individual effects in the panel data leading the model to be in the form of:

$$Y_{it} = \alpha + \beta X_{it} + \mu_i + \lambda_t + v_{it} \qquad i = 1, \ldots, N,\ t = 1, \ldots, T \tag{6}$$

whereas μ_i denoting the unobservable time-invariant *cross-section effects,* λ_t denoting the unobservable cross-section invariant *time effects,* and v_{it} constituting the residual *stochastic disturbance* (Baltagi, 2021).

By averaging the model (6) over time and across entities at the same time, then subtracting it from the original model will eliminate the unobservable time and cross-section effects.

3.2.5 Pooled Ordinary Least Square Method

Pooled Ordinary Least Square (POLS) method is a simple linear regression approach in which different observations are pooled or combined to generate the coefficients. POLS is useful when all individuals in the panel are assumed to have the same intercept and coefficient. The POLS model for the panel data is identified as:

$$Y_{it} = \alpha + \beta X_{it} + u_{it} \tag{7}$$

where *i* corresponds to the cross-section and *t* the time dimension. In this model, it is assumed that the regression coefficients are the same for all the observations. In the context of our thesis and research questions, the coefficients are assumed to be different across countries. Hence, we do not think that the POLS is the best econometric model to apply. However, for the decision, we benefit from some tests suggested by the literature. Breusch-Pagan Lagrange Multiplier (Breusch-Pagan LM) test which is developed by Breusch and Pagan (1980) is one of the most applied tests to decide between POLS and random-effects model and to control for the cross-section dependence.

3.2.6 Random Effects Models

Random Effects Models (REM), also called Error Component Model (ECM), introduce random variables with mean intercept. In REM, the difference in the intercept is due to the randomness of the sample but not any of the entity-specific factors. The individual error components are assumed to be not correlated with each other and there is no autocorrelation between the cross-section and time-series units. In REM, we cannot use OLS but instead generalized least squares (GLS). GLS is OLS on the transformed variables (towards serial autocorrelation, heteroskedasticity, etc.) that satisfy the standard least-squares assumptions (Zellner, 1962).

3.2.7 Fixed Effects Models

To account for unobserved, heterogeneity effects which are not captured in the pooled OLS, the fixed-effect model (FEM) is used. In FEM, the intercept is different across cross-sections. This difference is due to some entity-specific factors.

There are three methods in FEM:

i. Within-group fixed effect

ii. The first difference fixed effect

iii. Least square dummy variable (LSDV)

In this study, we will be using a version of the LSDV method whose equation form is as follows (Baltagi, 2021):

$$Y_{it} = \alpha + \beta X_{it} + \gamma D_i + v_{it} \tag{8}$$

In LSDV, a dummy variable is introduced in the model to capture the fixed effects arising from a different entity. These dummy variables allow the intercepts to vary among the entities. FEM may result in several challenges arising from introducing too many dummies which can restrict the degrees of freedom for making meaningful statistical results. Further, the presence of many dummies in the model can result in multicollinearity. To decide between REM and FEM, we apply the Hausman test.

3.2.8 Estimated Baseline Equations

Given that stock market index performances are affected by many different factors across countries and climate variables are differentiating over time and across countries, we think that the fixed effects model is the best model to apply. Due to the cross-section dependence in the series, we use *seemingly unrelated regression* (SUR) adjustments in the regression model. Then, our baseline equation for the regression becomes (Baltagi, 2021):

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \chi W_{it} + \delta_i + v_{it} \tag{9}$$

whereas Y_{it} denote the equity market returns from 45 countries, X_{it} denotes all the domestic macroeconomic factors of a country (GDP, GDP per capita, inflation, industrial production, unemployment, short term interest rates, long term interest rates, exchange rates, recession, banking crisis), Z_{it} denotes climate variables (represented by ND-GAIN climate vulnerability and climate readiness index), W_{it} denotes global control factors (represented by volatility index and MSCI world index), δ_i denotes country fixed effects, and v_{it} is the error term. We employ this base model to estimate the full panel and clustering strategies results.

On the full panel level, the tested hypotheses are:

- H_0: The climate vulnerability index is negatively correlated with stock market index returns.
  H_1: Otherwise.
- H_0: The climate readiness index is positively correlated with stock market index returns.
  H_1: Otherwise.

3.2.9 Clustering Strategies and the Climate Effect

We determine several different clustering strategies to test if the impact of climate change discriminates among different groups of countries. To observe the impact of climate variables on stock market returns across a different cluster of countries, we introduce interaction dummy variables in the model which transform the baseline equation into the following equation:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu(Z_{it} * D_i) + \chi W_{it} + +\delta_i + v_{it} \tag{10}$$

whereas $\mu(Z_{it} * D_i)$ is the interaction dummy variable. It represents the interaction effect of climate vulnerability and climate readiness on different cluster dummies denoted by D_i. We estimate the equations for 5 clusters (emerging economies, hotter countries, countries with higher average temperature increase, countries with higher average rainfall decrease, and countries close to the equator). Our clustering strategies[3] and estimated baseline equations are as follows:

Development (Advanced vs. Emerging)**:** The climate change effect is non-linear and different across countries. Advanced economies are assumed to be better prepared given their resource availability compared to emerging economies which further face the pressure of sustainable development. In this clustering, we are inspired by the study of Beirne et al. (2020). To implement this clustering strategy, we create a dummy variable taking the value of 1 if the country is in the emerging economies group and 0 otherwise. Our baseline equation to be estimated then becomes:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_1(Z_{it} * EMERGING) + \chi W_{it} + \delta_i + v_{it} \tag{11}$$

whereas *EMERGING* is the development dummy and the estimated coefficient μ_1 are the results of the interaction effects of the climate variables on the emerging economies.

[3] List of countries in each clustering strategy is provided at "Appendix A.1.2 List of Countries in Sub-clusters".

On the cluster level, the tested hypotheses are:

- H_0: The impact of the climate vulnerability index on equity returns is different across advanced and emerging economies. (The expected correlation sign for emerging economies is negative.)
  H_1: Otherwise.
- H_0: The impact of the climate readiness index on equity returns is different across advanced and emerging economies. (The expected correlation sign for emerging economies is positive.)
  H_1: Otherwise.

Average Temperature (Above vs. Below 15C)**:** the average mean surface temperature is used to study the impact due to climate change. Burke and Tanutama (2019) observe that the aggregate productivity responds non-linearly to the temperature increase across regions. They define the range of the 15C-35C degree to be statistically significant to explain the marginal effects of one-degree change in temperature on the growth rate. Building on this, we incorporate temperature-based clustering where countries with an average temperature of 15C and above fall into the first group and the second otherwise. To implement this clustering strategy, we create a dummy variable taking the value of 1 if the country belongs to the first group and 0 otherwise. Our baseline equation to be estimated then becomes:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_2(Z_{it} * HOTTER\ COUNTRIES) + \chi W_{it} + \delta_i + v_{it} \tag{12}$$

whereas *HOTTER COUNTRIES* is the average temperature dummy and the resulting coefficient μ_2 depict the interaction effects of climate change variables in hotter countries.

On the cluster level, the tested hypotheses are:

- H_0: The impact of the climate vulnerability index on equity returns is different across hot and cold countries. (The expected correlation sign for hotter countries is negative.)
  H_1: Otherwise.
- H_0: The impact of the climate readiness index on equity returns is different across hot and cold countries. (The expected correlation sign for hotter countries is positive.)

H_1: Otherwise.

***Average Temperature Change*:** Inspired by Burke and Tanutama (2019), we further construct a binary classification variable based on a country's mean temperature change over the last 20 years compared to that of the full panel sample. As we observe divergent temperature change experiences across geographies, we think that it is interesting to see if this distinction affects stock market returns given the climate risk factors. To implement this clustering strategy, we create a dummy variable taking the value of 1 if the country is in the group that has a higher mean temperature increase compared to the full panel sample and 0 otherwise. Our baseline equation to be estimated then becomes:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_3(Z_{it} * DELTA\ TEMPERATURE) + \chi W_{it} + \delta_i + v_{it} \tag{13}$$

whereas *DELTA TEMPERATURE* is the average temperature change dummy and the estimated coefficient μ_3 are the results of the interaction effects of the climate variables on the countries experiencing higher temperature increases.

On the cluster level, the tested hypotheses are:

- H_0: The impact of the climate vulnerability index on equity returns is different across countries experiencing higher temperature increases and lower temperature increases. (The expected correlation sign for countries experiencing higher temperature increases is negative.)
  H_1: Otherwise.
- H_0: The impact of the climate readiness index on equity returns is different across countries experiencing higher temperature increases and lower temperature increases. (The expected correlation sign for countries experiencing higher temperature increases is positive.)
  H_1: Otherwise.

***Average Rainfall Change*:** We employ a similar approach for the average rainfall change as for the average temperature change. We classify the countries based on the country-wise average rainfall compared to the full panel sample average change. To implement this clustering strategy, we create a dummy variable taking the value of 1 if the country is in the group that has a higher mean rainfall decrease compared to the full panel sample and 0 otherwise. Our baseline equation to be estimated then becomes:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_4(Z_{it} * DELTA\ RAINFALL) + \chi W_{it} + \delta_i + v_{it} \quad (14)$$

whereas *DELTA RAINFALL* is the average rainfall change dummy and the estimated coefficient μ_4 are the results of the interaction effects of the climate variables on the countries experiencing higher rainfall decreases.

On the cluster level, the tested hypotheses are:

- H_0: The impact of the climate vulnerability index on equity returns is different across countries experiencing higher rainfall decreases and lower rainfall decreases. (The expected correlation sign for countries experiencing higher rainfall decrease is negative.)
  H_1: Otherwise.
- H_0: The impact of the climate readiness index on equity returns is different across countries experiencing higher rainfall decreases and lower rainfall decreases. (The expected correlation sign for countries experiencing higher rainfall decrease is positive.)
  H_1: Otherwise.

***Geography*:** The rise in temperature due to climate change will affect the countries differently based on their geographical positioning. Bansal and Ochoa (2012) show that the countries closer to the equator have a positive temperature risk premium and observe it to be decreasing as one moves further away from the equator. In their approach, the world is classified into 4 groups. Countries are grouped based on the distance from the equator and the latitude is divided by 90 to make the range between 0 and 1. The latitude selected for a country is based on the center of the country or the region with maximum population, an approach borrowed from Hall and Jones (1998). We use a similar classification approach to cluster our sample countries. Since the Czech Republic and Russia in our sample countries are missing in their groups, we add them keeping the same approach. Lastly, we combine the 4 sub-groups to form 2 groups of countries. To implement this clustering strategy, we create a dummy variable taking the value of 1 if the country is in the group that is close to the equator and 0 otherwise. Our baseline equation to be estimated becomes:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_5(Z_{it} * EQUATOR) + \chi W_{it} + \delta_i + v_{it} \quad (16)$$

whereas *EQUATOR* is the geography dummy and the estimated coefficient μ_5 are the results of the interaction effects of the climate variables on the emerging markets.

On the cluster level, the tested hypotheses are:

- H_0: The impact of the climate vulnerability index on equity returns is different across countries close to and far away from the equator. (The expected correlation sign for countries close to the equator is negative.)
  H_1: Otherwise.
- H_0: The impact of the climate readiness index on equity returns is different across countries close to and far away from the equator. (The expected correlation sign for countries close to the equator is positive.)
  H_1: Otherwise.

3.2.10 Residuals Diagnostic Checks

Before moving on to the interpretation of the results of the regressions, we do several tests to check if our results are reliable or not. Given that macro panels suffer from cross-section dependence, we first check our results for that. Breusch-Pagan LM test is applied to control for cross-section dependence in the residuals. It is calculated by the following formula (Baltagi, 2021):

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{17}$$

where $\hat{\rho}_{ij}$ is the estimated cross-correlation coefficient between the least-squares residuals $\hat{v}_{it}$.

However, when *N* is large and *T* is finite, standard tests might not be useful due to size distortions and bias (De Hoyos & Sarafidis, 2006). Therefore, to test for cross-section dependence when *N* and *T* are large, Pesaran (2004) proposes an alternative test (Pesaran CD) as follows.

$$CD_{lm} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{18}$$

Then, we also do the normality and heteroskedasticity tests for our residuals.

4 Findings and Analysis

In this section, we present the results of the model selection process, the base model on the full panel set, and the sub-clusters as described in the "*3.2.1 Clustering Strategies*" section.

4.1 Diagnostic Checks: Steps towards Model Selection

Given that the selected model affects results enormously in panel data setting, choosing the right model becomes one of the crucial steps for the research design. Hence, we pay special attention to model selection. To decide between the models available in the panel regression setting, we use several tests suggested in the literature and use some theoretical argumentations. We apply the Breusch-Pagan Lagrange Multiplier test (Breusch & Pagan, 1980) to choose between the pooled OLS and random effect models and the results suggest going with a random-effects model. The null hypothesis of the LM tests presented in Table 4 is there are no random/fixed effects in the data, and since the p-value of all tests is smaller than 0.05, we reject the null hypothesis for cross-section, time, and both together.

Table 4: Breusch-Pagan Lagrange Multiplier Test Results

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	103.48***	4902.86***	5006.34***
	(0.000)	(0.000)	(0.000)
Honda	10.17***	70.02***	56.71***
	(0.000)	(0.000)	(0.000)
King-Wu	10.17***	70.02***	50.03***
	(0.000)	(0.000)	(0.000)
Standardized Honda	10.89***	72.94***	51.54***
	(0.000)	(0.000)	(0.000)
Standardized King-Wu	10.89***	72.94***	44.82***
	(0.000)	(0.000)	(0.000)
Gourieroux, et al.	--	--	5006.34***
			(0.000)

* denotes 10%, ** denotes 5%, and *** denotes 1% significance level. In parenthesis are the p-values.

To decide between the random effects model and the fixed effects models, we apply the Hausman test. Table 5 presents the results of the Hausman test which suggests going with the random-effects model. The null hypothesis of the Hausman test is that the random effects are more efficient than fixed effects, since the p-value of all tests is greater than 0.05, we accept the null hypothesis for cross-section, period, and both together. However, even though the Hausman test indicates that the random-effects model has more efficient estimators than the fixed effects model, we cannot rely on the findings of the random effect model due to the problem of the correlated explanatory variables and cross-sectionally dependent residuals which lead to biased and inconsistent estimators.

Table 5: Hausman Test Results

Correlated Random Effects - Hausman Test
Test cross-section and period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000	14.000	1.000
Period random	0.000	12.000	1.000
Cross-section and period random	0.000	12.000	1.000

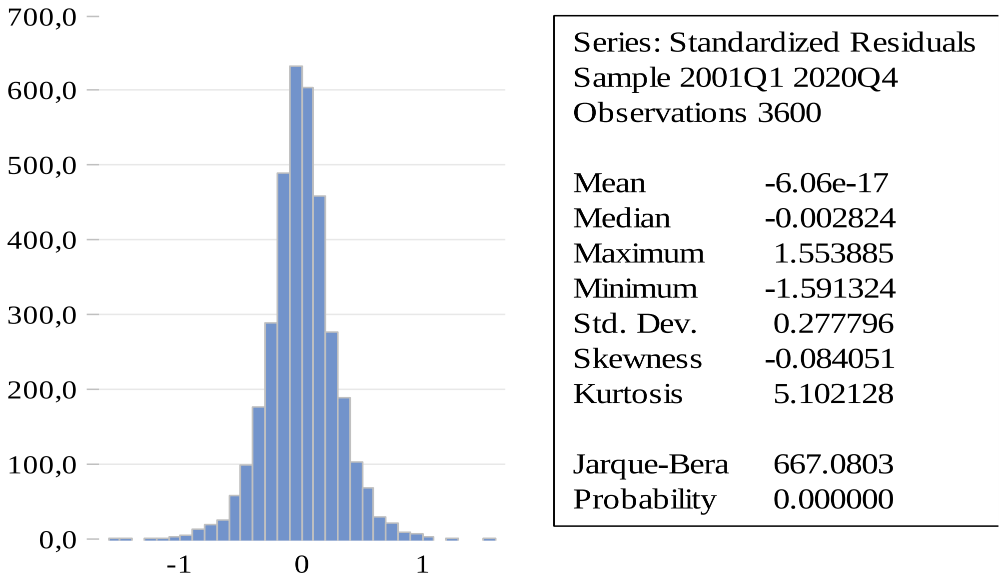
Table 6 and Figure 3 orderly exhibit the results of the cross-section dependence test and the normality test for the two-way random-effects model. given that the null hypothesis of the cross-section dependence test is there is no cross-section dependence (correlation) in residuals, the results of all cross-section dependence tests (<0.05 p-values) in Table 6 propose cross-sectionally dependent residuals. Similarly, knowing that the null hypothesis of the Jarque-Bera test is that residuals are normally distributed, one can easily observe from the p-value in Figure 3, which is smaller than 0.05, that residuals of the random effects model are not normally distributed.

Table 6: Cross-section Dependence Test for Two-way Random Effects Model

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
Periods included: 80
Cross-sections included: 45
Total panel observations: 3600
Note: non-zero cross-section means detected in data
Cross-section means were removed during the computation of correlations

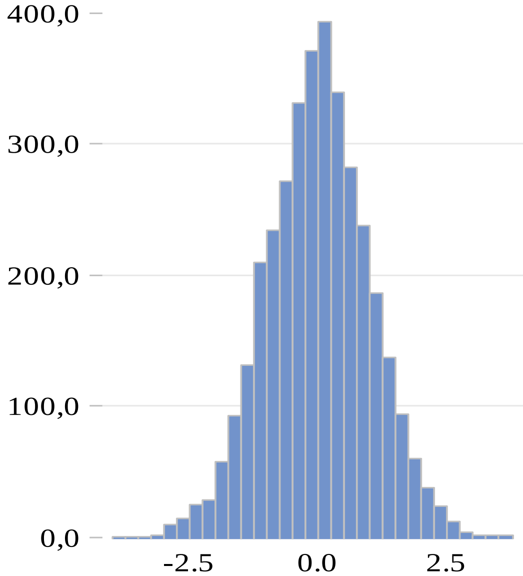
Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	12376.98	990	0.000
Pesaran scaled LM	255.90		0.000
Pesaran CD	94.17		0.000

Figure 3: Normality Test of Two-way Random Effects Model



Hence, to cope with these problems we need to use some techniques suggested by the literature. The generalized least squares (GLS) method, which is originally introduced by Aitken (1936), is one of the most applied solutions. In case N is fixed and T is large, Hsiao (2014) recommends using either the *feasible generalized least-squares* (FGLS) or *seemingly unrelated regression* (SUR) modifications to generate unbiased, consistent, efficient, and asymptotically normally distributed estimators. Given the dimensions of our panel dataset (N=45 and T=80) whereas $T > N$, we apply the seemingly unrelated regression (SUR) introduced by Zellner (1962) and white diagonal (normally distributed) standard errors. In that respect, the individual fixed and time-varying model is one of the best models that allow us to use the cross-section SUR GLS weights. After these adjustments, the cross-section dependence and non-normal residuals problems are resolved at the full panel level (See Figure 4 and Table 8 for details.).

Figure 4: Normality Test of Individual Fixed & Time-Varying Model



Series: Standardized Residuals	
Sample 2001Q1 2020Q4	
Observations 3600	
Mean	-1.26e-17
Median	0.012243
Maximum	3.739627
Minimum	-3.972759
Std. Dev.	0.997802
Skewness	-0.026682
Kurtosis	3.188270
Jarque-Bera	5.744025
Probability	0.056585

Table 7: Cross-section Dependence Test for Individual Fixed & Time-Varying Model

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in weighted residuals
Periods included: 80
Cross-sections included: 45
Total panel observations: 3600
Cross-section effects were removed during estimation

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	14.80	990	1.000
Pesaran scaled LM	-21.92		0.000
Bias-corrected scaled LM	-22.20		0.000
Pesaran CD	0.04		0.971

4.2 Empirical Results

Table 8 shows the results of three models we use to decide on our base model which is the individual fixed and time-varying model with standardized variables and cross-sectionally corrected and normalized residuals. Broadly, for the full panel set, the correlation coefficients of all macroeconomic, global, and climate factors -except the constant- are statistically significant (mostly at a 1% significance level). The correlation sign of all macroeconomic -except the GDP per capita-, global and climate factors are in line with our expectations. GDP per capita takes a negative sign contrary to our initial expectation of it to be positive, which means that the growth in GDP per capita is negatively correlated with the stock market index returns. However, it is not so strange as some studies like that of Dimson et al. (2009) also find a negative relationship between GDP per capita growth and stock market returns in a sample of 21 countries ranging from 1900-2000. They attribute this anomaly to the misaligned expectation between GDP growth and the shareholders' wealth. GDP growth, GDP per capita growth, and exchange rates have the highest magnitude in explaining the stock market index returns.

As per the focus of our research, throughout the thesis, we will be mainly focusing on and discussing the results of the climate factors. In that respect, our full panel set results to indicate that the stock market index returns are negatively correlated with the ND-GAIN climate vulnerability index and positively correlated with the readiness index, orderly at 5% and 1% significance levels. The correlation signs of both variables are in line with our expectations. The magnitude of coefficients implies a 0.18% standard deviation decrease in the stock market index returns given a 1% standard deviation increase in the vulnerability risk index and a 0.23% standard deviation increase in the stock market index returns given a 1% standard deviation rise in the readiness index.

Table 8: Comparison of Three Models towards Model Selection

Variable	(1)	(2)	(3)
Climate Factors			
Climate Vulnerability	-0.037	-0.456	-0.180**
	(0.301)	(0.282)	(0.072)
Climate Readiness	0.085***	0.032	0.096***
	(0.031)	(0.029)	(0.007)
Domestic (Macroeconomic) Factors			
GDP Growth	2.863***	2.109**	3.902***
	(0.778)	(1.058)	(0.273)
GDP Per Capita	-2.338***	-1.393	-3.429***
	(0.754)	(1.013)	(0.26)
Inflation	0.163***	0.101**	0.062***
	(0.042)	(0.045)	(0.016)
Industrial Production	0.091***	0.103***	0.084***
	(0.019)	(0.017)	(0.005)
Unemployment	-0.034*	-0.077***	-0.036***
	(0.02)	(0.018)	(0.004)
Short-term Interest Rates	-0.083***	-0.013	-0.065***
	(0.016)	(0.015)	(0.005)
Long-term Interest Rates	-0.076***	-0.11***	-0.082***
	(0.016)	(0.014)	(0.006)
Exchange Rates	-2.638***	-1.875***	-2.812***
	(0.223)	(0.221)	(0.067)
Recession	-0.018	-0.022	-0.026***
	(0.015)	(0.014)	(0.004)
Banking Crisis	-0.157***	-0.116***	-0.122***
	(0.019)	(0.02)	(0.006)
Global Factors			
MSCI World	0.317***	0.306***	0.31***
	(0.01)	(0.023)	(0.01)
VIX	-0.087***	-0.091***	-0.089***
	(0.005)	(0.013)	(0.005)
C	-0.014	-0.009	-0.005
	(0.008)	(0.017)	(0.005)
R-squared	0.648	0.356	0.814
Adjusted R-squared	0.647	0.353	0.811
No. of observations	3600	3600	3600
Fixed Effects	No	No	Yes

Notes: (1) Pooled OLS Model, (2) Two-way Random Effects Model, and (3) Individual Fixed and Time-Varying Model. In parentheses are the robust standard errors. * denotes 10%, ** denotes 5%, and *** denotes 1% significance level.

Table 9: Results from Clustering Strategies

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factors						
Climate Vulnerability	-0.180**	0.228***	0.184**	-0.786***	0.433***	0.383***
	(0.072)	(0.084)	(0.082)	(0.11)	(0.085)	(0.086)
Climate Readiness	0.096***	0.147***	0.034***	0.038***	0.176***	0.233***
	(0.007)	(0.012)	(0.01)	(0.011)	(0.012)	(0.019)
Interaction (Clustering) Variables						
Vulnerability*Emerging		-0.712***				
		(0.156)				
Vulnerability*Delta Temperature			-0.738***			
			(0.118)			
Vulnerability*Delta Rainfall				1.441***		
				(0.132)		
Vulnerability*Hotter Countries					-1.314***	
					(0.139)	
Vulnerability*Equator						-1.165***
						(0.146)
Readiness*Emerging		-0.064***				
		(0.013)				
Readiness*Delta Temperature			0.180***			
			(0.015)			
Readiness*Delta Rainfall				0.174***		
				(0.016)		
Readiness*Hotter Countries					-0.142***	
					(0.015)	
Readiness*Equator						-0.164***
						(0.022)
Total Vulnerability Effect		-0.482	-0.546	0.661	-0.877	-0.782
Total Readiness Effect		0.087	0.214	0.212	0.036	0.069
Domestic (Macroeconomic) Factors						
GDP Growth	3.902***	3.869***	3.911***	4.116***	3.912***	3.912***
	(0.273)	(0.283)	(0.277)	(0.295)	(0.284)	(0.285)
GDP Per Capita	-3.429***	-3.405***	-3.451***	-3.650***	-3.441***	-3.445***
	(0.26)	(0.269)	(0.264)	(0.281)	(0.27)	(0.271)
Inflation	0.062***	0.067***	0.056***	0.06***	0.068***	0.067***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Industrial Production	0.084***	0.085***	0.085***	0.085***	0.085***	0.084***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment	-0.036***	-0.037***	-0.033***	-0.035***	-0.038***	-0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Short-term Interest Rates	-0.065***	-0.065***	-0.060***	-0.063***	-0.064***	-0.064***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Long-term Interest Rates	-0.082***	-0.083***	-0.083***	-0.084***	-0.083***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Exchange Rates	-2.812***	-2.825***	-2.82***	-2.84***	-2.822***	-2.821***
	(0.067)	(0.068)	(0.065)	(0.067)	(0.068)	(0.068)
Recession	-0.026***	-0.028***	-0.024***	-0.027***	-0.029***	-0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Banking Crisis	-0.122***	-0.123***	-0.12***	-0.123***	-0.122***	-0.123***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Global Factors						
MSCI World	0.310***	0.311***	0.311***	0.313***	0.309***	0.310***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
VIX	-0.089***	-0.089***	-0.090***	-0.089***	-0.089***	-0.089***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
C	-0.005	-0.005	-0.005	-0.006	-0.007	-0.007
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
R-squared	0.814	0.814	0.826	0.825	0.813	0.813
Adjusted R-squared	0.811	0.811	0.823	0.822	0.810	0.810
No. of observations	3600	3600	3600	3600	3600	3600
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) full panel, (2) development cluster, (3) higher temperature increase cluster, (4) higher rainfall decrease cluster, (5) hotter countries, (6) close to the equator. In parentheses are the robust standard errors. * denotes 10%, ** denotes 5%, and *** denotes 1% significance level.

Table 9 contains the results of our base model for the clustering strategies. Overall, the results assert certain differences among the group of countries with some commonalities. Equity market returns are negatively correlated with climate vulnerability in all clusters -except rainfall (drought) clustering and positively correlated with climate readiness in two of the clusters (average temperature change and average rainfall change).

As per the *development* clustering (column 2 in Table 9), both the climate vulnerability index and climate readiness index have negative signs and are statistically significant at a 1% significance level for emerging economies. This shows the heterogeneity among the advanced and emerging economies which supports our initial expectation about development clustering. Due to the allocation of scarce resources, we expect emerging economies to be more vulnerable to climate risk and less prepared. Hence, significantly higher negative results for the vulnerability index and -contrary to full panel results- significant negative results for the readiness index are just in line with our expected effects. The negative magnitude of the interaction variable "*Vulnerability*Emerging*" propagates a 0.71% standard deviation decrease in stock market index returns, given that 1% standard deviation increase in the vulnerability index. Similarly, a 1% standard deviation increase in the "*Readiness*Emerging*" interaction variable negatively results in the stock market index returns by 0.06% standard deviation. These are the unique effects of climate vulnerability and readiness indexes in emerging economies. However, the total effect of the climate vulnerability index on the stock market index returns is a 0.48% standard deviation decrease in emerging economies, while it is a 0.09% standard deviation increase for the readiness index. The total effect is the summation of climate factors and the interaction variables. Compared to emerging economies, the interaction impact for advanced economies will be of the same magnitude with the opposite sign of the emerging economies. These results highlight the developmental impact of climate change on equity market returns.

When we group our sample of countries into two groups based on the *average change in temperature* benchmarked to the full panel average change in temperature, the unique effects are the same in sign, but higher in magnitude compared to full panel results. Our results (column 3 in Table 9) are statistically significant at a 1% significance level. In the group of countries where the average temperature change is greater than the full panel average change, the climate vulnerability index is negatively correlated with the equity returns. The coefficient of the interaction variable

"*Vulnerability*Delta Temperature*" implies a 0.74% standard deviation decrease in stock market index returns for a 1% standard deviation increase in the vulnerability index. On the other hand, the coefficient of the "*Readiness*Delta Temperature*" interaction variable proposes a 0.18% standard deviation increase in the stock market index returns as a response to a 1% standard deviation increase in the readiness index. The total effect is a 0.55% standard deviation decrease for the climate vulnerability index and a 0.21% standard deviation increase for the readiness index. These results reveal that equity market returns are more sensitive to climate risk factors in countries experiencing higher temperature rise as in line with our expectations.

Global warming and climate change manifest themselves through drought and some other extreme weather events. Hence, like in the temperature rise case, we wonder if/how equity markets are affected by the climate risk factors in countries that experience higher drought. To analyze this, we group our sample of countries into two groups based on the *average change in rainfall* over the last 20 years benchmarked to the average change in rainfall for the full panel. We use the change in rainfall as a proxy for a draught. Our results (column 4 in Table 9) are statistically significant at a 1% significance level. The correlation signs of interaction variables "*Vulnerability*Delta Rainfall*" and "*Readiness*Delta Rainfall*" evidence that equity market returns are positively correlated with climate vulnerability and readiness indexes. The magnitude of coefficients suggests a 1.44% standard deviation increase in the stock market index returns given a 1% standard deviation increase in the vulnerability index and a 0.17% standard deviation increase due to the 1% standard deviation increase in the readiness index. Although the correlation sign of the vulnerability impact is contradicting our expectations of the relationship between those variables, the magnitude of the coefficient is higher than the full panel and all other clusters coefficients which go along with our expectation of the bitterness of the impact compared full panel. The total effect is a 0.66% standard deviation increase for the climate vulnerability index and a 0.21% standard deviation increase for the readiness index. These results endorse our expectation of the equity market returns to be more sensitive -but not in the direction we anticipate- to climate risk factors in countries experiencing higher drought.

In the literature, some studies discuss how hot and cold countries are economically affected by climate change (Dell et al., 2012). Therefore, we think that it is interesting to see how equity markets react to climate risk factors in hot and cold countries. We group countries based on the average temperature in each country over the last 20 years benchmarked to 15C degrees whereas hotter countries are categorized as countries with an average temperature greater than 15C degrees. Our results (column 5 in Table 9), which are statistically significant at a 1% significance level, propose a negative correlation between the stock market index returns and both climate risk factors. The coefficients of interaction variables "*Vulnerability*Hotter Countries*" and "*Readiness*Hotter Countries*" suggest a 1.31% standard deviation decrease in the stock market index returns given 1% standard deviation increase in the vulnerability index and 0.14% standard deviation decrease due to the 1% standard deviation increase in the readiness index. The correlation sign and higher magnitude of coefficient compared to the full panel result for the vulnerability are in line with our expectations of the relationship, but not the negative sign of readiness index. The total effect of the climate vulnerability index is a 0.88% standard deviation decrease and 0.04% standard deviation increase for the readiness index. These results support our expectation of the equity market returns to be more sensitive to climate risk factors in hotter countries.

Lastly, we desire to explore if/how the geographical positioning of the countries affects the equity market returns as a response to the climate risk factors. In that respect, we divide our sample of countries into two groups following the proximity to equator strategy suggested by Bansal and Ochoa (2012). Our results (column 6 in Table 9) are statistically significant at a 1% significance level. The correlation signs of interaction variables "*Vulnerability*Equator*" and "*Readiness*Equator*" indicate that equity market returns are negatively correlated with the climate vulnerability and readiness indexes. The magnitude of coefficients suggests a 1.16% standard deviation decrease in the stock market index returns as a response to a 1% standard deviation increase in the vulnerability index and a 0.16% standard deviation decrease as a response to a 1% standard deviation increase in the readiness index. The total effect is a 0.78% standard deviation decrease due to the climate vulnerability index and a 0.07% standard deviation increase due to the readiness index. The correlation sign of the climate vulnerability index is in line with our expectations given that countries close to poles are expected to be positively affected by global warming due to factors like new land available for use, etc. These results support our expectation of the equity market returns to be negatively correlated with the climate vulnerability index and positively with the readiness index in countries close to the equator.

4.3 Robustness Checks

To test the robustness of our model, in addition to regressing it on several clusters, we incorporate two more approaches. In the first approach, we construct our base model with interaction variables using the lagged independent variables. In the second approach, we replace climate vulnerability and climate readiness variables with temperature and rainfall variables to test the effect. The equation of our base model including the interaction variables then becomes:

$$Y_{it} = \beta X_{it-1} + \gamma Z_{it-1} + \mu\left(Z_{it-1} * D_j\right) + \chi W_{it-1} + \delta_i + v_{it-1} \tag{19}$$

The results obtained using lagged variables in the base model are consistent with the baseline results. When we use lagged variables the statistical significance and coefficients are mostly in line with the baseline results. The control variables come with the same sign. The cluster with average temperature is not statistically significant at the panel level whereas the interaction effect of average temperature with climate vulnerability and climate readiness is still statistically significant and the coefficients are in line with that observed in the baseline model. For macroeconomic factors, the statistical significance and the nature of coefficients persist with the only exception observed in the case of inflation which becomes insignificant in the lagged model. This observation remains consistent across different clusters. A lagged model still addresses our research questions and confirms the robustness of our baseline model.

We performed a second robustness check using different climate risk variables. Due to the lack of alternative open-source climate vulnerability and readiness measures, we incorporate temperature and rainfall as alternate climate factors. Below are the equations for no-lag and lagged model of temperature and rainfall including the interaction variables:

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \mu_1\left(Temperature_{it} * D_j\right) + \mu_2\left(Rainfall_{it} * D_j\right) + \chi W_{it} + \delta_i + v_{it} \tag{20}$$

$$Y_{it} = \beta X_{it-1} + \gamma Z_{it-1} + \mu_1\left(Temperature_{it-1} * D_j\right) + \mu_2\left(Rainfall_{it-1} * D_j\right) + \chi W_{it-1} + \delta_i + v_{it-1} \tag{21}$$

Using temperature and rainfall, we observe statistical significance in the coefficients, but the observed relationship is not in line with our expectations. The relationship between temperature change and equity returns is observed to be positive implying rise in temperature positively affects stock market returns whereas, in the case of rainfall, the relationship observed is negative. This anomaly can be attributed to the nature of the temperature and rainfall variable. While temperature is a significant variable in explaining the equity market returns (Bansal et al., 2016; Bansal & Ochoa, 2012), a fixed effect panel regression may not sufficiently capture the effect.

For domestic macroeconomic variables and global variables, the statistical significance and the nature of the coefficient persist and are in line with our baseline model.

Table 10: Results of the Lagged Model with *ND-GAIN* Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factors						
Climate Vulnerability(-1)	-0.375***	0.448***	0.01	-0.779***	0.349***	0.386***
	(0.086)	(0.103)	(0.115)	(0.127)	(0.107)	(0.108)
Climate Readiness(-1)	0.138***	0.244***	0.08***	0.074***	0.227***	0.306***
	(0.012)	(0.017)	(0.015)	(0.014)	(0.019)	(0.023)
Interaction Variables						
Vulnerability*Emerging		-1.505***				
		(0.185)				
Vulnerability*Delta Temperature			-0.805***			
			(0.154)			
Vulnerability*Delta Rainfall				0.953***		
				(0.156)		
Vulnerability*Hotter Countries					-1.553***	
					(0.183)	
Vulnerability*Equator						-1.603***
						(0.187)
Readiness*Emerging		-0.132***				
		(0.014)				
Readiness*Delta Temperature			0.176***			
			(0.018)			
Readiness*Delta Rainfall				0.208***		
				(0.016)		
Readiness*Hotter Countries					-0.154***	
					(0.021)	
Readiness*Equator						-0.200***
						(0.021)
Total Vulnerability Effect		-1.052	-0.79	0.183	-1.201	-1.217
Total Readiness Effect		0.114	0.25	0.282	0.077	0.106
Domestic (Macroeconomic) Factors						
GDP Growth(-1)	1.668***	1.579***	1.688***	1.759***	1.666***	1.686***
	(0.319)	(0.328)	(0.323)	(0.335)	(0.328)	(0.326)
GDP Per Capita(-1)	-1.733***	-1.655***	-1.776***	-1.839***	-1.727***	-1.746***
	(0.306)	(0.313)	(0.309)	(0.320)	(0.313)	(0.311)
Inflation(-1)	-0.022	-0.015	-0.027	-0.017	-0.019	-0.020
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Industrial Production(-1)	0.068***	0.069***	0.07***	0.067***	0.070***	0.068***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Unemployment(-1)	0.052***	0.048***	0.054***	0.054***	0.048***	0.05***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Short-term Interest Rates(-1)	-0.103***	-0.102***	-0.099***	-0.102***	-0.103***	-0.102***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Long-term Interest Rates(-1)	-0.055***	-0.057***	-0.055***	-0.057***	-0.056***	-0.055***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Exchange Rates(-1)	-1.916***	-1.924***	-1.948***	-1.951***	-1.911***	-1.890***
	(0.083)	(0.085)	(0.081)	(0.08)	(0.083)	(0.086)
Recession(-1)	-0.092***	-0.096***	-0.093***	-0.094***	-0.096***	-0.095***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Banking Crisis(-1)	-0.192***	-0.194***	-0.193***	-0.195***	-0.194***	-0.195***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Global Factors						
MSCI World(-1)	0.176***	0.170***	0.177***	0.180***	0.171***	0.172***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
VIX(-1)	-0.057***	-0.057***	-0.058***	-0.056***	-0.059***	-0.059***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
C	0.067***	0.067***	0.068***	0.066***	0.066***	0.065***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
R-squared	0.623	0.612	0.641	0.661	0.613	0.617
Adjusted R-squared	0.617	0.605	0.635	0.655	0.606	0.61
No. of observations	3555	3555	3555	3555	3555	3555
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) full panel, (2) development, (3) higher temperature increase, (4) higher rainfall decrease, (5) hotter countries, (6) close to the equator. In parentheses are the robust standard errors. * denotes 10%, ** denotes 5%, and *** denotes 1% significance level.

Table 11: Results of the Model with *Temperature* and *Rainfall* Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factors						
Temperature	0.075***	0.082***	0.038***	0.073***	0.066***	0.085**
	(0.012)	(0.013)	(0.014)	(0.015)	(0.012)	(0.035)
Rainfall	-0.021***	-0.013***	-0.038***	-0.023***	-0.006	-0.053***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.004)	(0.007)
Interaction Variables						
Temperature*Emerging		-0.024				
		(0.027)				
Temperature*Delta Temperature			0.080***			
			(0.016)			
Temperature*Delta Rainfall				0.006		
				(0.018)		
Temperature*Hotter Countries					0.045	
					(0.036)	
Temperature*Equator						-0.018
						(0.037)
Rainfall*Emerging		-0.02***				
		(0.008)				
Rainfall*Delta Temperature			0.029***			
			(0.006)			
Rainfall*Delta Rainfall				0.004		
				(0.007)		
Rainfall*Hotter Countries					-0.029***	
					(0.007)	
Rainfall*Equator						0.054***
						(0.008)
Net Temperature Effect		0.062	0.118	0.079	0.111	0.075
Net Rainfall Effect		-0.03	-0.01	-0.016	-0.02	0.004
Domestic (Macroeconomic) Factors						
GDP Growth	3.837***	3.841***	3.825***	3.835***	3.816***	3.796***
	(0.279)	(0.279)	(0.28)	(0.28)	(0.276)	(0.272)
GDP Per Capita	-3.344***	-3.351***	-3.337***	-3.34***	-3.323***	-3.307***
	(0.266)	(0.265)	(0.267)	(0.267)	(0.263)	(0.259)
Inflation	0.065***	0.067***	0.066***	0.065***	0.065***	0.067***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Industrial Production	0.086***	0.086***	0.085***	0.086***	0.085***	0.085***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Unemployment	-0.036***	-0.037***	-0.037***	-0.036***	-0.036***	-0.037***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Short-term Interest Rates	-0.061***	-0.061***	-0.061***	-0.06***	-0.06***	-0.061***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Long-term Interest Rates	-0.087***	-0.087***	-0.088***	-0.087***	-0.088***	-0.087***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Exchange Rates	-2.788***	-2.792***	-2.793***	-2.780***	-2.800***	-2.802***
	(0.066)	(0.066)	(0.067)	(0.067)	(0.066)	(0.066)
Recession	-0.029***	-0.029***	-0.029***	-0.029***	-0.03***	-0.03***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Banking Crisis	-0.119***	-0.119***	-0.118***	-0.118***	-0.118***	-0.117***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Global Factors						
MSCI World	0.309***	0.308***	0.309***	0.309***	0.309***	0.309***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
VIX	-0.090***	-0.090***	-0.090***	-0.090***	-0.090***	-0.090***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
C	-0.004	-0.004	-0.004	-0.004	-0.004	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
R-squared	0.814	0.812	0.814	0.813	0.813	0.811
Adjusted R-squared	0.810	0.809	0.811	0.810	0.809	0.807
No. of observations	3600	3600	3600	3600	3600	3600
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) full panel, (2) development, (3) higher temperature increase, (4) higher rainfall decrease, (5) hotter countries, (6) close to the equator. In parentheses are the robust standard errors. * denotes 10%, ** denotes 5%, and *** denotes 1% significance level.

Table 12: Results of the Lagged Model with *Temperature* and *Rainfall* Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Factors						
Temperature(-1)	0.151***	0.148***	0.141***	0.174***	0.154***	0.06*
	(0.011)	(0.011)	(0.015)	(0.016)	(0.012)	(0.035)
Rainfall(-1)	-0.065***	-0.036***	-0.089***	-0.071***	-0.055***	-0.105***
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.007)
Interaction Variables						
Temperature*Emerging		0.026				
		(0.029)				
Temperature*Temperature			0.026			
			(0.019)			
Temperature*Rainfall				-0.039*		
				(0.021)		
Temperature*Hot					-0.053	
					(0.037)	
Temperature*Equator						0.094**
						(0.037)
Rainfall*Emerging		-0.082***				
		(0.008)				
Rainfall*Temperature			0.041***			
			(0.007)			
Rainfall*Rainfall				0.018**		
				(0.008)		
Rainfall*Hot					-0.024***	
					(0.008)	
Rainfall*Equator						0.061***
						(0.009)
Net Temperature Effect		0.174	0.167	0.144	0.104	0.154
Net Rainfall Effect		-0.11	-0.04	-0.052	-0.07	-0.039
Domestic (Macroeconomic) Factors						
GDP Growth(-1)	1.633***	1.584***	1.57***	1.659***	1.62***	1.591***
	(0.31)	(0.284)	(0.313)	(0.307)	(0.311)	(0.314)
GDP Per Capita(-1)	-1.651***	-1.601***	-1.601***	-1.679***	-1.637***	-1.605***
	(0.295)	(0.273)	(0.298)	(0.294)	(0.296)	(0.3)
Inflation(-1)	-0.017	-0.019	-0.007	-0.015	-0.017	-0.016
	(0.02)	(0.02)	(0.022)	(0.021)	(0.02)	(0.02)
Industrial Production(-1)	0.073***	0.072***	0.073***	0.072***	0.074***	0.073***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment(-1)	0.055***	0.058***	0.054***	0.055***	0.054***	0.055***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Short-term Interest Rates(-1)	-0.101***	-0.102***	-0.102***	-0.103***	-0.102***	-0.104***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Long-term Interest Rates(-1)	-0.062***	-0.061***	-0.062***	-0.06***	-0.061***	-0.06***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Exchange Rates(-1)	-1.854***	-1.847***	-1.861***	-1.851***	-1.856***	-1.863***
	(0.081)	(0.08)	(0.082)	(0.082)	(0.08)	(0.08)
Recession(-1)	-0.1***	-0.1***	-0.099***	-0.099***	-0.1***	-0.101***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Banking Crisis(-1)	-0.193***	-0.194***	-0.194***	-0.194***	-0.193***	-0.193***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Global Factors						
MSCI World(-1)	0.181***	0.174***	0.179***	0.181***	0.179***	0.179***
	(0.023)	(0.021)	(0.022)	(0.022)	(0.023)	(0.022)
VIX(-1)	-0.053***	-0.055***	-0.054***	-0.052***	-0.054***	-0.054***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
C	0.068***	0.069***	0.068***	0.067***	0.068***	0.068***
	(0.011)	(0.01)	(0.011)	(0.011)	(0.011)	(0.011)
R-squared	0.645	0.645	0.633	0.638	0.647	0.648
Adjusted R-squared	0.639	0.639	0.627	0.632	0.641	0.642
No. of observations	3555	3555	3555	3555	3555	3555
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) full panel, (2) development, (3) higher temperature increase, (4) higher rainfall decrease, (5) hotter countries, (6) close to the equator. In parentheses are the robust standard errors. * denotes 10%, ** denotes 5%, and *** denotes 1% significance level

5 Discussions

Our empirical results suggest that the effects arising from climate vulnerability and climate readiness are related to the equity market returns. On the full panel level, the equity market returns are negatively correlated with the increase in the physical risks of climate change and the decrease in the resilience to those risks. The relationship between climate risk factors with stock market returns is negative for climate vulnerability and positive for climate readiness, it is in line with our expectations and helps address our primary research question. The estimated negative impact on the equity returns arising from the exposure to climate vulnerability is 0.18%. This negative relationship is in line with the findings of Balvers et al. (2017) where they identified the impact of the cost of equity due to temperature change uncertainty to be 0.22%. Using a similar vulnerability measure (ND-GAIN vulnerability index), Kling et al. (2018) and Beirne et al. (2020) find a significant negative impact of climate vulnerability on the cost of capital and sovereign bond yields. In line with their findings, our results directly provide a negative relation between ND-GAIN climate vulnerability and equity market returns.

Given the ND-GAIN vulnerability, the index contains information on the critical sectors (food, water, health, ecosystem services, human habitat, and infrastructure) critical for sustaining life, the observed relationship between vulnerability and equity returns suggests that the stock market reacts to the changes in the critical sectors. The observed relationship between climate readiness and equity market returns is positive and in line with our expectations. ND-GAIN climate readiness index contains information around the preparedness (economic situation, governance, and social readiness), intuitively these factors should be positively related to the equity market returns.

We further determine a significant negative interaction effect of -0.71% on the equity returns for the emerging countries which can be attributed to the adverse effect arising from climate vulnerability. It also aids us to recognize the negative relation between climate risks and the economic development of a country and answers our research question. Emerging countries are more vulnerable to climate change risks and have limited resilience measures in place to combat these risks. The negative impact on equity returns for the emerging countries also supports the findings made by Kling et al. (2018), they find companies situated in developing countries are exposed to greater climate vulnerability, the cost of capital will be significantly higher, and will face more significant financial constraints. As per Dell (2012), higher temperatures arising from climate change adversely affect the economic growth in poor countries and the increasing temperature causes widespread effects reducing the outputs. From this observation made by Dell (2012) and our results, we can say that equity markets in emerging countries have negatively factored in climate risks. Our observation for the emerging countries is also in line with Beirne et al. (2020) in which they define climate vulnerability to significantly increase the cost of sovereign borrowings for the emerging countries. The results can be beneficial for the investors making long-term investments in emerging market countries where climate vulnerability may more considerably affect both equity and bond returns.

In our results for the clusters of countries where the absolute average temperature is above 15 degrees, the climate vulnerability is negatively correlated with the equity market returns with the highest coefficient. These results are in line with our expectations. It can be interpreted that apart from climate vulnerability, a country's average temperature can also play a role in explaining negative equity market returns. These results further complement the findings of Bansal (2016) where they prove temperature risk premium. Our findings are also in line with the observation made by Burke and Tanutama (2019), where they define the temperature above 15 degrees to be significant and adversely affect the economic output growth. The results from the cluster of average temperature change, where we study the change in temperature concerning the average change in the entire panel. We observe a similar relationship between climate vulnerability and equity market returns as that in the case of the average temperature cluster. It can be assumed these effects emerge from rising temperatures. Kahn et al. (2019) find persistent climate change will result in long-term negative impacts on the economy. The results further support the findings of Pankratz (2018), where they find a firm's exposure to temperature is negatively linked with financial performance. From our results and findings from Bansal (2016), Burke and Tanutama (2019), and Pankratz (2018), it can be inferred that equity markets' returns contain climate information.

In our equator-based cluster, the relationship between climate vulnerability and equity returns is observed to be negative. This observation is in line with our expectation given that countries situated closer to the equator remain generally hotter countries and as per Dell's (2012) observation, higher temperature negatively affects the economic growth holds in this case. Our results also support the findings from Bansal et al. (2012) where they identified a significant temperature risk premium for countries with greater proximity to the equator.

Whereas in the case of the average rainfall change cluster we observe that in countries where average rainfall change is below the global mean change, the interaction with climate vulnerability has resulted in positive equity market returns. This observation is not in line with our expectation as our hypothesis suggests drought-like conditions should be negatively related to equity market returns. The observed anomaly is in line with the findings of Hong et al (2019), using sophisticated drought index (PDSI) they find stock markets are inefficient in factoring in the droughts trends. They attributed this anomaly with stock markets underreaction to climate risks.

6 Conclusion

This thesis improves our understanding of the relationship between the damaging impacts of climate risk and equity returns. Using an alternative measure for climate vulnerability and readiness, we empirically investigate the relationship between climate risk and macroeconomic variables in explaining stock market returns. We further examine the impact of climate risks on different countries by clustering countries based on some commonalities such as economic development, geographical positioning, and change in weather-based factors. Using a sample of 45 advanced and emerging countries, which are exposed to climate risks differently, we find the climate vulnerability is significantly related to the equity market returns across the globe. These effects are observed to be significant for the distinct high-risk clusters of countries based on the geographical positioning, economic development, mean temperature, global temperature, and rainfall change. We find that climate risk has a significant negative relationship with the equity market returns suggesting us the damage in stock returns is arising from the climate vulnerability. For countries where the average temperature change is greater than the global average, the observed effects on equity returns are negative. Further, our results also showcase the negative relationship between climate vulnerability and equity market returns for the hotter countries (mean temperature above 15 degrees Celsius). The results for the equator-based cluster also exhibit a negative relationship suggesting countries closer to the equator have a greater climate risk exposure, the stock market returns in these regions negatively adjust with this information. The observed relationship for the average rainfall changes-based group is not in line with our expectations and could be an interesting topic for future research. These results can be beneficial for the policymakers to assess the implementation of climate risk and mitigation measures and for investors making long-term investments as climate vulnerability may significantly impact future equity returns. Our findings also suggest that the climate vulnerability variable comprehends a greater magnitude than the climate readiness magnitude indicating equity market investors factors climate vulnerability damage more than they reward climate preparedness.

7 Limitations and Future Implications

The limitation of this study primarily lies in the limited availability of climate vulnerability and readiness data. The data availability around climate risks comprises a growing segment with modern features being introduced and included as part of the climate risks. The frequency of macroeconomic variables at a global level is quarterly which makes it difficult to assess the short-term variations of equity returns. Lastly, the correlation observed between climate risks and equity returns does not imply causation. Our study utilizes a limited sample of the last 20 years, a future study with a bigger dataset could help in analyzing the impact of climate risks more broadly. Besides that, examining the impacts on different industries, or market segments would also be interesting.

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Appendix

A.1.1 List of Countries in the Full Panel Set

Advanced	Emerging
Australia	Brazil
Austria	Chile
Belgium	China
Canada	Colombia
Denmark	Czech Republic
Finland	Egypt
France	Greece
Germany	Hong Kong
Ireland	Hungary
Italy	India
Japan	Indonesia
Netherlands	Israel
New Zealand	Malaysia
Norway	Mexico
Portugal	Peru
Singapore	Philippines
Spain	Poland
Sweden	Russian Federation
Switzerland	Saudi Arabia
United Kingdom	South Africa
United States	South Korea
	Taiwan
	Thailand
	Turkey

Based on MSCI's classifications.

A.1.2 Clustering Based on 15C Temperature

Country	<15C	Country	>15C
Austria	7.45	Australia	22.01
Belgium	10.86	Brazil	25.64
Canada	-6.25	Colombia	24.85
Chile	8.73	Egypt	23.19
China	7.24	India	24.80
Czech Republic	8.98	Indonesia	26.18
Denmark	8.98	Israel	20.71
Finland	2.78	Malaysia	25.80
France	11.84	Mexico	21.41
Germany	9.84	Peru	19.69
Greece	14.48	Philippines	25.86
Hong Kong	7.24	Portugal	15.72
Hungary	11.44	Saudi Arabia	25.67
Ireland	9.70	Singapore	27.68
Italy	13.00	South Africa	18.41
Japan	11.22	Thailand	26.82
Netherlands	10.61		
New Zealand	10.23		
Norway	1.99		
Poland	9.12		
Russian Federation	-4.89		
South Korea	8.85		
Spain	14.05		
Sweden	2.82		
Switzerland	6.26		
Taiwan	7.24		
Turkey	11.91		
United Kingdom	9.17		
United States	7.79		

The sample is divided into two groups based 15C average temperature over the last 20 years.

A.1.3 Clustering Based on Average Change in Temperature

Country	<Panel Mean	Country	>Panel Mean
Austria	0.013	Australia	0.164
Canada	-0.005	Belgium	0.046
China	0.035	Brazil	0.041
Czech Republic	0.018	Chile	0.053
Denmark	0.038	Colombia	0.046
Germany	0.035	Egypt	0.042
Greece	0.030	Finland	0.043
Hong Kong	0.035	France	0.045
Hungary	0.006	Israel	0.055
India	0.004	Mexico	0.045
Indonesia	0.016	Netherlands	0.041
Ireland	0.008	Portugal	0.043
Italy	0.025	Russian Federation	0.140
Japan	0.034	South Africa	0.046
Malaysia	0.020	South Korea	0.039
New Zealand	0.018	Spain	0.041
Norway	0.029	Switzerland	0.047
Peru	0.024	Thailand	0.045
Philippines	0.025	Turkey	0.068
Poland	0.029		
Saudi Arabia	0.023		
Singapore	0.024		
Sweden	0.029		
Taiwan	0.035		
United Kingdom	0.027		
United States	0.033		

The full panel average temperature change is observed to be at 0.038. We cluster the sample countries based on if they are above or below this cut-off.

A.1.4 Clustering Based on Average Change in Rainfall

Country	<Panel Mean	Country	>Panel Mean
Austria	1.120	Germany	-1.199
Canada	-0.089	Italy	-0.481
China	0.466	Malaysia	-2.065
Czech Republic	0.874	Peru	-1.378
Denmark	-0.163	Philippines	-7.381
Greece	2.775	Singapore	-2.254
Hong Kong	0.466	Sweden	-1.815
Hungary	2.315	United Kingdom	-0.749
India	2.156	Australia	-2.011
Indonesia	1.100	Belgium	-2.443
Ireland	0.743	Brazil	-2.610
Japan	3.053	Chile	-1.720
New Zealand	0.532	Colombia	-2.329
Norway	0.399	France	-1.860
Poland	0.095	Mexico	-0.430
Saudi Arabia	0.087	Netherlands	-1.306
Taiwan	0.466	Portugal	-1.886
United States	0.546	South Africa	-2.055
Egypt	0.019	Spain	-0.441
Finland	-0.019	Switzerland	-3.408
Israel	1.038	Thailand	-2.758
Russian Federation	0.188		
South Korea	8.943		
Turkey	-0.125		

The full panel average rainfall change is observed to be at -0.347. We cluster the sample countries based on if they are above or below this cut-off.

A.1.5 Clustering Based on Proximity to the Equator

Group 1	Group 2	Group 3	Group 4	Broad 1	Broad 2
Colombia	Australia	Austria	Belgium	Australia	Austria
Indonesia	Brazil	Canada	Denmark	Brazil	Belgium
Malaysia	China	Chile	Finland	China	Canada
Mexico	Egypt	Czech Republic	Ireland	Colombia	Chile
Peru	Hong Kong	France	Netherlands	Egypt	Czech Republic
Philippines	India	Germany	Norway	Hong Kong	Denmark
Singapore	Israel	Greece	Poland	India	Finland
Thailand	Saudi Arabia	Hungary	Russian Federation	Indonesia	France
	South Africa	Italy	Sweden	Israel	Germany
	Taiwan	Japan	United Kingdom	Malaysia	Greece
		New Zealand		Mexico	Hungary
		Portugal		Peru	Ireland
		South Korea		Philippines	Italy
		Spain		Saudi Arabia	Japan
		Switzerland		Singapore	Netherlands
		Turkey		South Africa	New Zealand
		United States		Taiwan	Norway
				Thailand	Poland
					Portugal
					Russian Federation
					South Korea
					Spain
					Sweden
					Switzerland
					Turkey
					United Kingdom
					United States

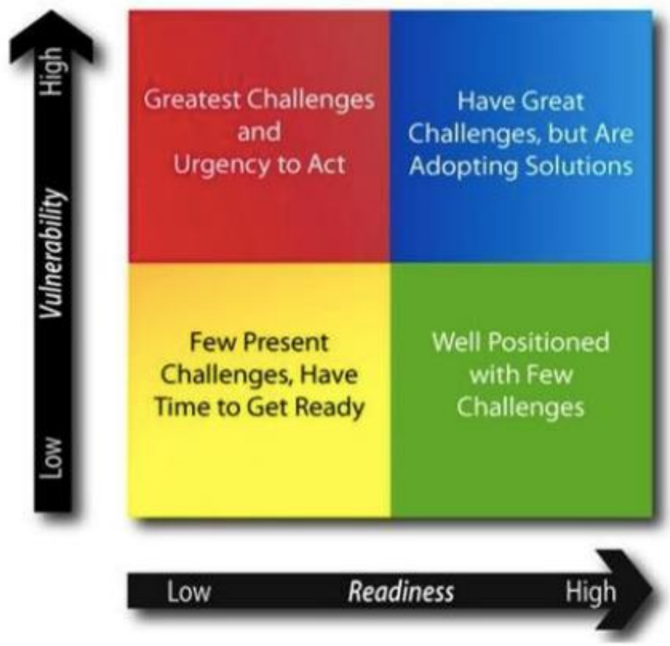
A.1.6 ND-GAIN Vulnerability Index Adjusted for Endogeneity

Sector	Indicator
Food	Projected change of cereal yields Projected population change Food import dependency
Water	Projected change of annual runoff Projected change of annual groundwater recharge Freshwater withdrawal rate Water dependency ratio
Health	Projected change of deaths from climate-induced diseases Projected change in vector-borne diseases
Ecosystem services	Projected change of biome distribution Projected change of marine biodiversity Ecological footprint Protected biome Engagement in international environmental conventions
Human habitat	Projected change of warm periods Projected change of flood hazard
Infrastructure	Projected change of hydropower generation capacity Projected change of sea-level rise impacts Dependency on imported energy Population living under 5 m above sea level

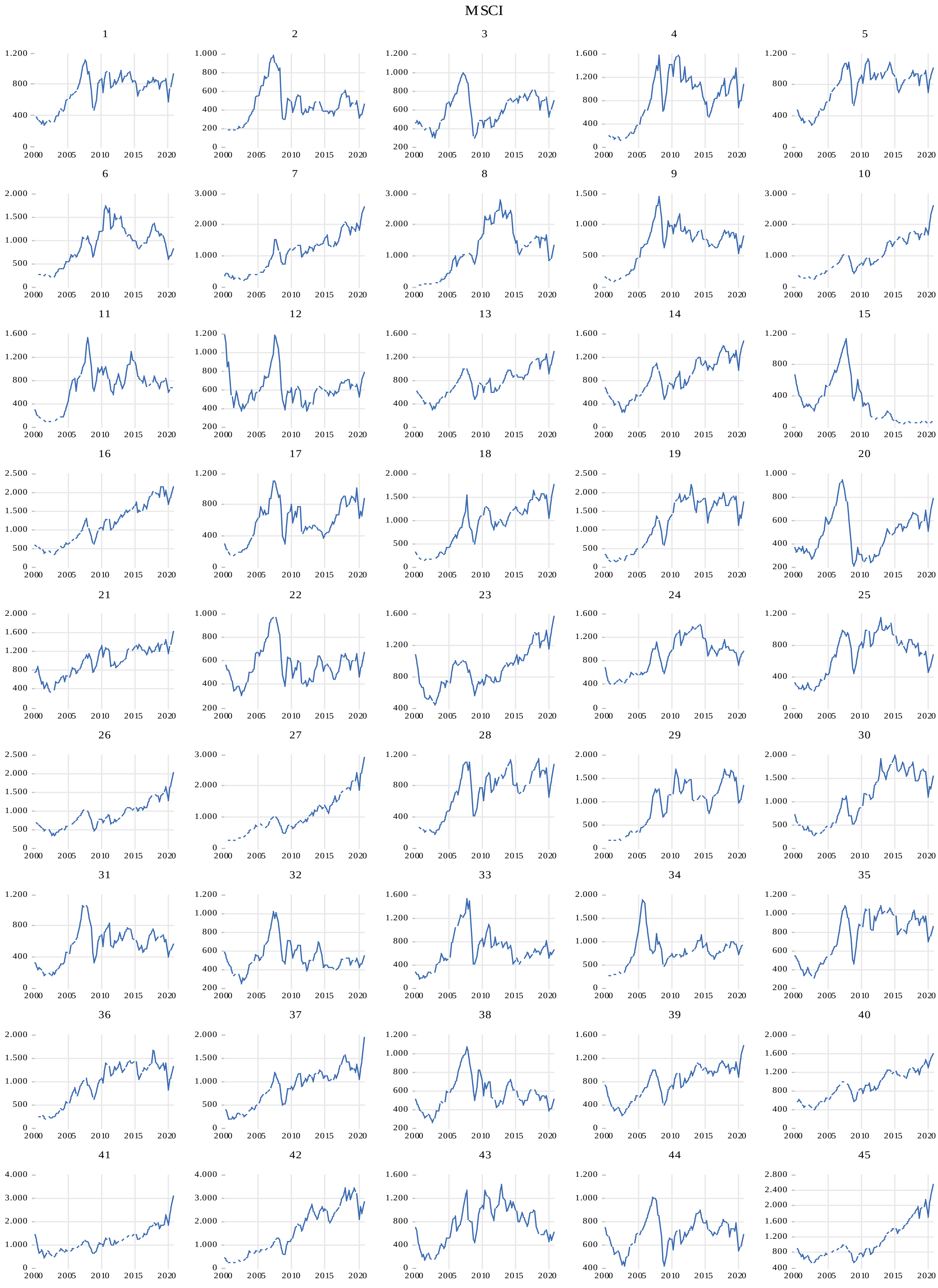
*Constructed by the authors based on Kling et al. (2018)

A.1.7 ND-GAIN Readiness Index

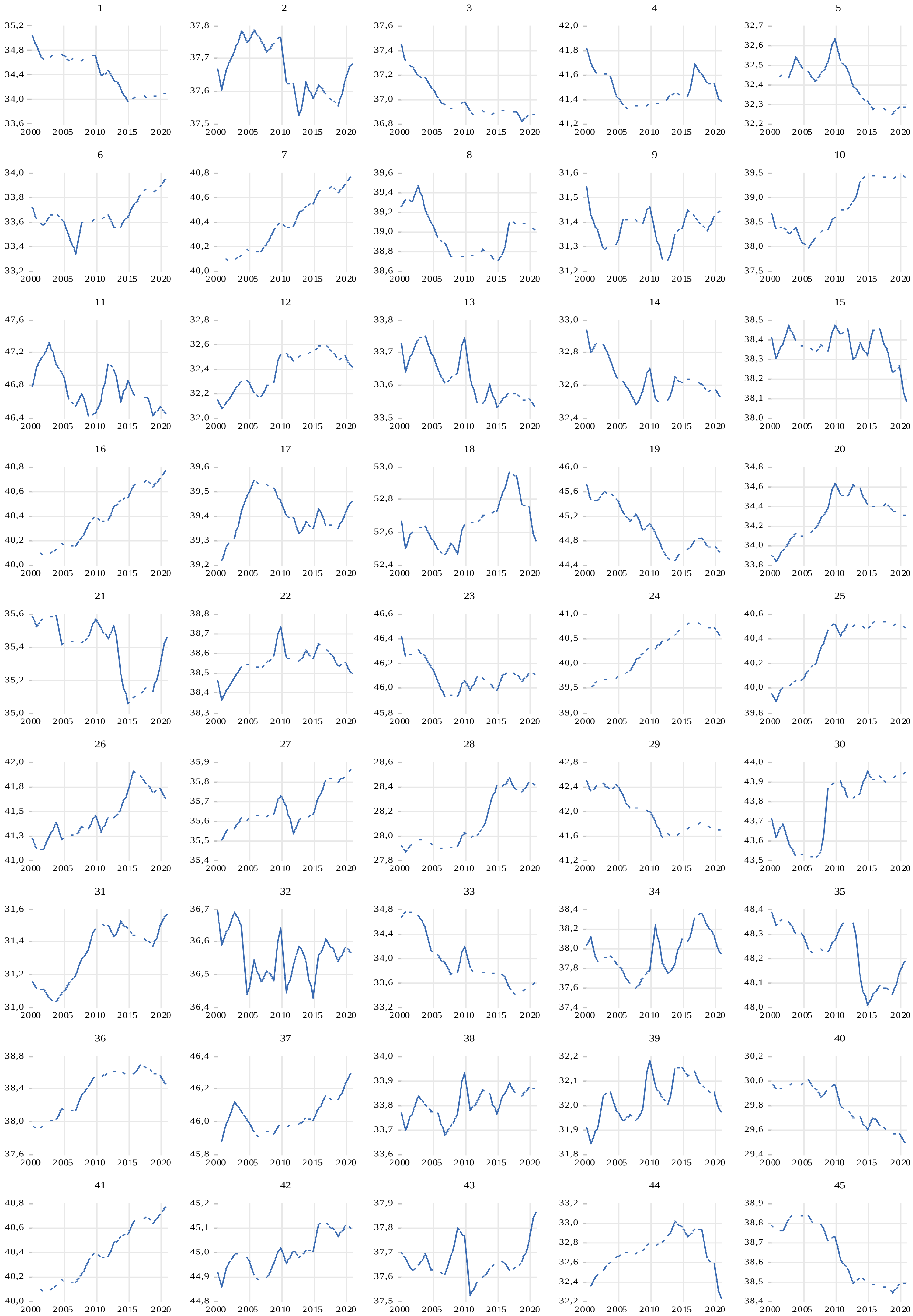
Component	Indicator
Economic readiness	Doing business
Governance readiness	Political stability and non-violence Control of corruption Rule of law Regulatory quality
Social readiness	Social inequality ICT infrastructure Education Innovation



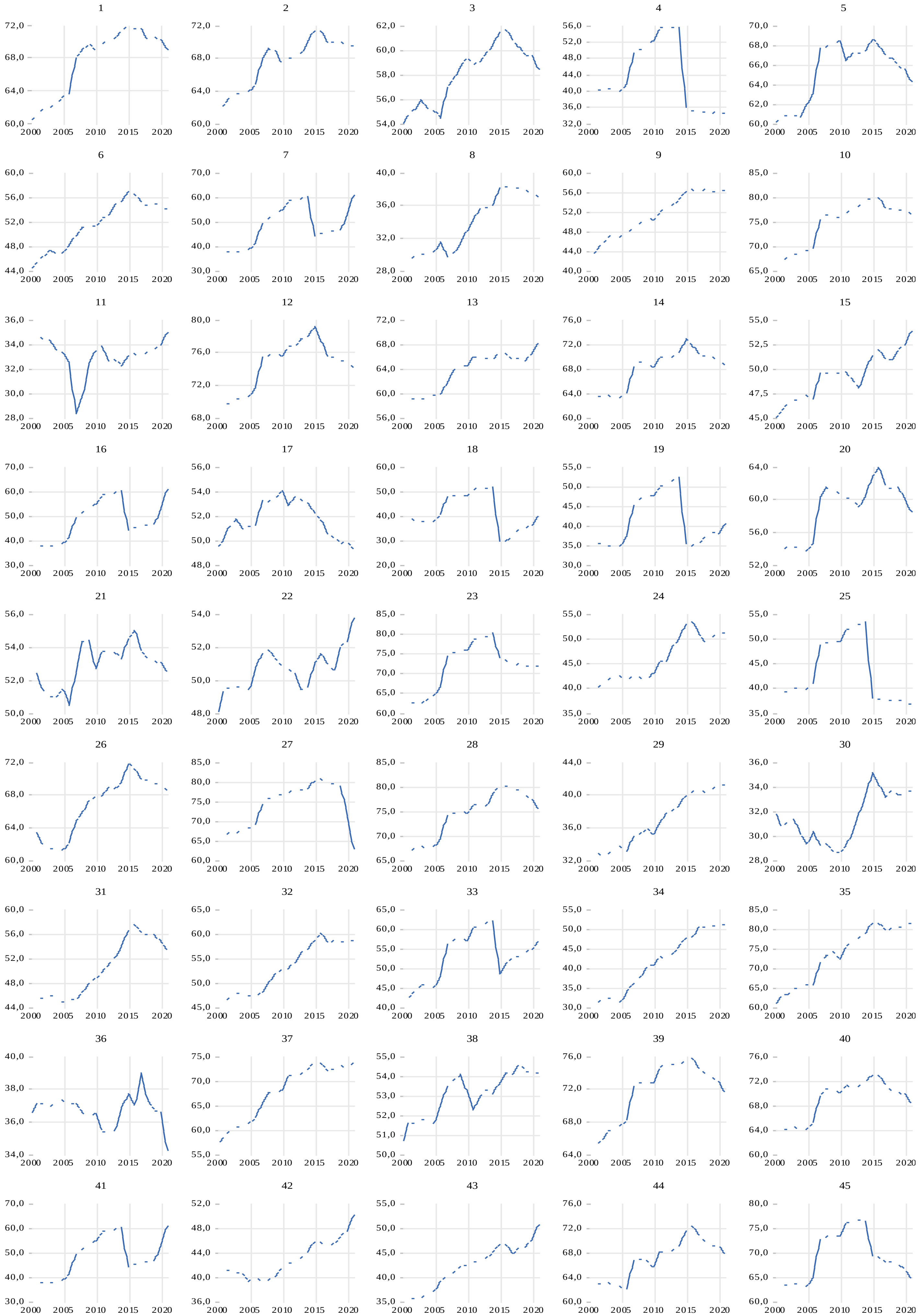
A.2.1 Time-series Plots



Climate Vulnerability



Climate Readiness



A.2.2 Second Generation Panel Unit Root Tests

Pesaran CIPS unit root test for LDMSCI
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.30268	<0.01
Truncated CIPS:	-2.30268	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDGDP
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.91208	<0.01
Truncated CIPS:	-2.91208	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDGDPPC
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.93361	<0.01
Truncated CIPS:	-2.93361	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDIP
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.51225	<0.01
Truncated CIPS:	-2.49842	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDUNEM
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.20313	<0.05
Truncated CIPS:	-2.20313	<0.05

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDCPI
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.81028	<0.01
Truncated CIPS:	-2.81028	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDFX
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-3.07466	<0.01
Truncated CIPS:	-3.07466	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDLTIR
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-3.42711	<0.01
Truncated CIPS:	-3.38627	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDSTIR
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.50757	<0.01
Truncated CIPS:	-2.50757	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDMSCIW
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	NA	>=0.10
Truncated CIPS:	0.00000	>=0.10

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDVIX
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	NA	>=0.10
Truncated CIPS:	0.00000	>=0.10

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDTEMP
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-5.56707	<0.01
Truncated CIPS:	-5.32800	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDRAIN
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-5.07112	<0.01
Truncated CIPS:	-4.74287	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDVUL
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.08630	<0.10
Truncated CIPS:	-2.08630	<0.10

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

Pesaran CIPS unit root test for LDREAD
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.77533	<0.01
Truncated CIPS:	-2.77533	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.25	-2.25
5%	-2.13	-2.13
10%	-2.06	-2.06

A.3 Model Applications and Diagnostic Tests

A.3.1 Pooled OLS

Dependent Variable: LDMSCI
Method: Panel Least Squares
Date: 11/26/21 Time: 00:06
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	-0.037	0.301	-0.124	0.901
LDREAD	0.085	0.031	2.770	0.006
LDGDP	2.863	0.778	3.678	0.000
LDGDPPC	-2.338	0.754	-3.100	0.002
LDCPI	0.163	0.042	3.853	0.000
LDIP	0.091	0.019	4.914	0.000
LDUNEM	-0.034	0.020	-1.732	0.083
LDSTIR	-0.083	0.016	-5.195	0.000
LDLTIR	-0.076	0.016	-4.695	0.000
LDFX	-2.638	0.223	-11.853	0.000
RECESSION	-0.018	0.015	-1.223	0.221
BC	-0.157	0.019	-8.053	0.000
LDMSCIW	0.317	0.010	32.242	0.000
LDVIX	-0.087	0.005	-17.071	0.000
C	-0.014	0.008	-1.617	0.106

R-squared	0.648	Mean dependent var	0.068
Adjusted R-squared	0.647	S.D. dependent var	0.464
S.E. of regression	0.276	Akaike info criterion	0.265
Sum squared resid	272.416	Schwarz criterion	0.291
Log likelihood	-461.732	Hannan-Quinn criter.	0.274
F-statistic	471.770	Durbin-Watson stat	0.676
Prob(F-statistic)	0.000		

A.3.2 Breusch-Pagan Lagrange Multiplier Test

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one -sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	103.48	4902.86	5006.34
	(0.0000)	(0.0000)	(0.0000)
Honda	10.17	70.02	56.71
	(0.0000)	(0.0000)	(0.0000)
King-Wu	10.17	70.02	50.03
	(0.0000)	(0.0000)	(0.0000)
Standardized Honda	10.89	72.94	51.54
	(0.0000)	(0.0000)	(0.0000)
Standardized King-Wu	10.89	72.94	44.82
	(0.0000)	(0.0000)	(0.0000)
Gourieroux, et al.	--	--	5006.34
			(0.0000)

A.3.3 Two-way Random Effect Model

Dependent Variable: LDMSCI
Method: Panel EGLS (Two-way random effects)
Date: 11/26/21 Time: 00:11
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	-0.456	0.282	-1.616	0.106
LDREAD	0.032	0.029	1.130	0.259
LDGDP	2.109	1.058	1.994	0.046
LDGDPPC	-1.393	1.013	-1.375	0.169
LDCPI	0.101	0.045	2.258	0.024
LDIP	0.103	0.017	5.956	0.000
LDUNEM	-0.077	0.018	-4.188	0.000
LDSTIR	-0.013	0.015	-0.894	0.371
LDLTIR	-0.110	0.014	-7.657	0.000
LDFX	-1.875	0.221	-8.478	0.000
RECESSION	-0.022	0.014	-1.603	0.109
BC	-0.116	0.020	-5.927	0.000
LDMSCIW	0.306	0.023	13.223	0.000
LDVIX	-0.091	0.013	-7.139	0.000
C	-0.009	0.017	-0.517	0.605

Effects Specification

	S.D.	Rho
Cross-section random	0.052	0.041
Period random	0.098	0.147
Idiosyncratic random	0.231	0.812

Weighted Statistics

R-squared	0.356	Mean dependent var	0.019
Adjusted R-squared	0.353	S.D. dependent var	0.291
S.E. of regression	0.234	Sum squared resid	196.002
F-statistic	141.303	Durbin-Watson stat	0.591
Prob(F-statistic)	0.000		

Unweighted Statistics

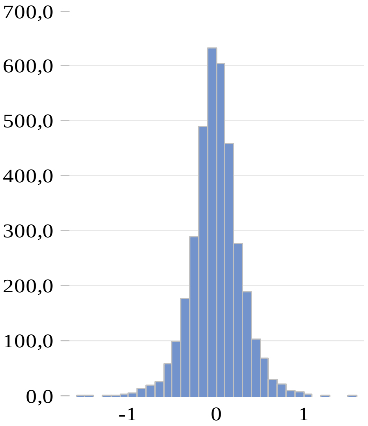
R-squared	0.641	Mean dependent var	0.068
Sum squared resid	277.736	Durbin-Watson stat	0.693

A.3.4 Hausman Test

Correlated Random Effects - Hausman Test
Equation: EQ02
Test cross-section and period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000	14.000	1.000
Period random	0.000	12.000	1.000
Cross-section and period random	0.000	12.000	1.000

A.3.5 Normality Test



Series: Standardized Residuals	
Sample 2001Q1 2020Q4	
Observations 3600	
Mean	-6.06e-17
Median	-0.002824
Maximum	1.553885
Minimum	-1.591324
Std. Dev.	0.277796
Skewness	-0.084051
Kurtosis	5.102128
Jarque-Bera	667.0803
Probability	0.000000

A.3.6 Cross-section Dependence

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in
residuals
Equation: EQ02
Periods included: 80
Cross-sections included: 45
Total panel observations: 3600
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of
correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	12376.979	990.000	0.000
Pesaran scaled LM	255.903		0.000
Pesaran CD	94.169		0.000

The residuals are not normally distributed and there is cross-section dependence in residuals.

A.3.7 Individual Fixed & Time Pooling with cross-section SUR

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 11/26/21 Time: 00:17
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	-0.180	0.072	-2.488	0.013
LDREAD	0.096	0.007	13.037	0.000
LDGDP	3.902	0.273	14.293	0.000
LDGDPPC	-3.429	0.260	-13.198	0.000
LDCPI	0.062	0.016	3.943	0.000
LDIP	0.084	0.005	15.515	0.000
LDUNEM	-0.036	0.004	-8.164	0.000
LDSTIR	-0.065	0.005	-12.230	0.000
LDLTIR	-0.082	0.006	-14.570	0.000
LDFX	-2.812	0.067	-42.155	0.000
RECESSION	-0.026	0.004	-6.896	0.000
BC	-0.122	0.006	-19.875	0.000
LDMSCIW	0.310	0.010	32.596	0.000
LDVIX	-0.089	0.005	-16.671	0.000
C	-0.005	0.005	-0.983	0.326

Effects Specification

Cross-section fixed (dummy variables)

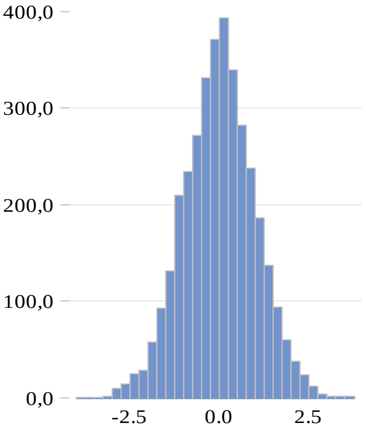
Weighted Statistics

R-squared	0.814	Mean dependent var	0.064
Adjusted R-squared	0.811	S.D. dependent var	2.341
S.E. of regression	1.006	Sum squared resid	3583.198
F-statistic	267.272	Durbin-Watson stat	1.544
Prob(F-statistic)	0.000		

Unweighted Statistics

R-squared	0.662	Mean dependent var	0.068
Sum squared resid	261.347	Durbin-Watson stat	0.689

A.3.8 Normality Test



Series: Standardized Residuals
Sample 2001Q1 2020Q4
Observations 3600

Mean	-1.26e-17
Median	0.012243
Maximum	3.739627
Minimum	-3.972759
Std. Dev.	0.997802
Skewness	-0.026682
Kurtosis	3.188270
Jarque-Bera	5.744025
Probability	0.056585

A.3.9 Cross-section Dependence

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in weighted residuals
Equation: EQ02
Periods included: 80
Cross-sections included: 45
Total panel observations: 3600
Cross-section effects were removed during estimation

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	14.800	990.000	1.000
Pesaran scaled LM	-21.916		0.000
Bias-corrected scaled LM	-22.201		0.000
Pesaran CD	0.036		0.971

Our base model is the individual fixed effect with time-varying and cross-section SUR (seemingly unrelated regression)

A.3.10 Base Model on Development Cluster

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 11/26/21 Time: 00:20
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	0.228	0.084	2.719	0.007
LDREAD	0.147	0.012	12.375	0.000
LDVUL*EM	-0.712	0.156	-4.556	0.000
LDREAD*EM	-0.064	0.013	-4.811	0.000
LDGDP	3.869	0.283	13.694	0.000
LDGDPPC	-3.405	0.269	-12.654	0.000
LDCPI	0.067	0.016	4.218	0.000
LDIP	0.085	0.005	15.674	0.000
LDUNEM	-0.037	0.004	-8.406	0.000
LDSTIR	-0.065	0.005	-12.199	0.000
LDLTIR	-0.083	0.006	-14.505	0.000
LDFX	-2.825	0.068	-41.661	0.000
RECESSION	-0.028	0.004	-7.427	0.000
BC	-0.123	0.006	-19.453	0.000
LDMSCIW	0.311	0.010	31.818	0.000
LDVIX	-0.089	0.005	-16.265	0.000
C	-0.005	0.006	-0.997	0.319

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.814	Mean dependent var	0.044
Adjusted R-squared	0.811	S.D. dependent var	2.339
S.E. of regression	1.006	Sum squared resid	3581.849
F-statistic	258.385	Durbin-Watson stat	1.547
Prob(F-statistic)	0.000		

Unweighted Statistics

R-squared	0.663	Mean dependent var	0.068
Sum squared resid	261.133	Durbin-Watson stat	0.690

A.3.11 Base Model on Mean Temperature Higher than 15C Cluster

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 11/26/21 Time: 00:24
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	0.433	0.085	5.068	0.000
LDREAD	0.176	0.012	14.421	0.000
LDVUL*HOT	-1.314	0.139	-9.469	0.000
LDREAD*HOT	-0.142	0.015	-9.430	0.000
LDGDP	3.912	0.284	13.784	0.000
LDGDPPC	-3.441	0.270	-12.757	0.000
LDCPI	0.068	0.016	4.285	0.000
LDIP	0.085	0.005	15.720	0.000
LDUNEM	-0.038	0.004	-8.582	0.000
LDSTIR	-0.064	0.005	-11.884	0.000
LDLTIR	-0.083	0.006	-14.357	0.000
LDFX	-2.822	0.068	-41.762	0.000
RECESSION	-0.029	0.004	-7.667	0.000
BC	-0.122	0.006	-19.001	0.000
LDMSCIW	0.309	0.010	31.327	0.000
LDVIX	-0.089	0.006	-16.038	0.000
C	-0.007	0.006	-1.258	0.209

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.813	Mean dependent var	0.048
Adjusted R-squared	0.810	S.D. dependent var	2.325
S.E. of regression	1.005	Sum squared resid	3578.015
F-statistic	256.152	Durbin-Watson stat	1.544
Prob(F-statistic)	0.000		

Unweighted Statistics

R-squared	0.664	Mean dependent var	0.068
Sum squared resid	260.456	Durbin-Watson stat	0.692

A.3.12 Base Model on Mean Temperature Change Cluster

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 11/26/21 Time: 00:21
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	0.184	0.082	2.251	0.024
LDREAD	0.034	0.010	3.315	0.001
LDVUL*TEMP	-0.738	0.118	-6.251	0.000
LDREAD*TEMP	0.180	0.015	12.094	0.000
LDGDP	3.911	0.277	14.135	0.000
LDGDPPC	-3.451	0.264	-13.084	0.000
LDCPI	0.056	0.016	3.523	0.000
LDIP	0.085	0.005	16.283	0.000
LDUNEM	-0.033	0.004	-7.695	0.000
LDSTIR	-0.060	0.005	-11.659	0.000
LDLTIR	-0.083	0.006	-14.893	0.000
LDFX	-2.820	0.065	-43.293	0.000
RECESSION	-0.024	0.004	-6.557	0.000
BC	-0.120	0.006	-19.619	0.000
LDMSCIW	0.311	0.009	33.937	0.000
LDVIX	-0.090	0.005	-17.376	0.000
C	-0.005	0.005	-0.897	0.370

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.826	Mean dependent var	0.056
Adjusted R-squared	0.823	S.D. dependent var	2.415
S.E. of regression	1.006	Sum squared resid	3579.093
F-statistic	279.554	Durbin-Watson stat	1.549
Prob(F-statistic)	0.000		

Unweighted Statistics

R-squared	0.663	Mean dependent var	0.068
Sum squared resid	260.835	Durbin-Watson stat	0.689

A.3.13 Base Model on Mean Rainfall Change Cluster

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 11/26/21 Time: 00:23
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	-0.786	0.110	-7.137	0.000
LDREAD	0.038	0.011	3.546	0.000
LDVUL*RAIN	1.441	0.132	10.891	0.000
LDREAD*RAIN	0.174	0.016	11.005	0.000
LDGDP	4.116	0.295	13.942	0.000
LDGDPPC	-3.650	0.281	-12.972	0.000
LDCPI	0.060	0.016	3.723	0.000
LDIP	0.085	0.005	15.514	0.000
LDUNEM	-0.035	0.004	-7.885	0.000
LDSTIR	-0.063	0.005	-12.207	0.000
LDLTIR	-0.084	0.006	-15.095	0.000
LDFX	-2.840	0.067	-42.202	0.000
RECESSION	-0.027	0.004	-7.136	0.000
BC	-0.123	0.006	-19.367	0.000
LDMSCIW	0.313	0.010	32.428	0.000
LDVIX	-0.089	0.005	-16.351	0.000
C	-0.006	0.005	-1.081	0.280

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.825	Mean dependent var	0.077
Adjusted R-squared	0.822	S.D. dependent var	2.422
S.E. of regression	1.006	Sum squared resid	3582.817
F-statistic	278.134	Durbin-Watson stat	1.543
Prob(F-statistic)	0.000		

Unweighted Statistics

R-squared	0.664	Mean dependent var	0.068
Sum squared resid	260.522	Durbin-Watson stat	0.691

A.3.14 Base Model on Proximity to Equator Cluster

Dependent Variable: LDMSCI
Method: Panel EGLS (Cross-section SUR)
Date: 12/04/21 Time: 15:31
Sample: 2001Q1 2020Q4
Periods included: 80
Cross-sections included: 45
Total panel (balanced) observations: 3600
Linear estimation after one-step weighting matrix
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDVUL	0.383346	0.086256	4.444293	0.0000
LDREAD	0.233107	0.018910	12.32743	0.0000
LDVUL*EQ	-1.165219	0.145975	-7.982315	0.0000
LDREAD*EQ	-0.163876	0.022037	-7.436234	0.0000
LDGDP	3.912030	0.285327	13.71071	0.0000
LDGDPPC	-3.445361	0.271425	-12.69361	0.0000
LDCPI	0.067160	0.016125	4.164955	0.0000
LDIP	0.084408	0.005463	15.44983	0.0000
LDUNEM	-0.036061	0.004468	-8.071007	0.0000
LDSTIR	-0.063692	0.005390	-11.81709	0.0000
LDLTIR	-0.082960	0.005799	-14.30647	0.0000
LDFX	-2.820915	0.068291	-41.30744	0.0000
RECESSION	-0.028429	0.003813	-7.456628	0.0000
BC	-0.123225	0.006326	-19.47826	0.0000
LDMSCIW	0.310134	0.009782	31.70442	0.0000
LDVIX	-0.088846	0.005497	-16.16312	0.0000
C	-0.007008	0.005557	-1.261064	0.2074

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.813299	Mean dependent var	0.033831
Adjusted R-squared	0.810134	S.D. dependent var	2.329094
S.E. of regression	1.005555	Sum squared resid	3578.430
F-statistic	256.9409	Durbin-Watson stat	1.545077
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.663420	Mean dependent var	0.067717
Sum squared resid	260.6135	Durbin-Watson stat	0.690369