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# Evaluating the Impact of Climate Risk on Financial Access and Stability in G20 Countries: A Panel Data Approach (2006-2017)

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**Abstract:** The burgeoning international concern over environmental sustainability has brought to the forefront the unique challenges climate change poses to global economies and financial markets. In the light of this, the role of International Financial Institutions like the International Monetary Fund and the World Bank in transitioning towards a green economy is increasingly critical. This study aims to elucidate the influence of climate risk on financial access and stability within G20 countries, spanning from 2006 to 2017. Employing a comprehensive panel data analysis, which accounts for cross-sectional dependence and slope heterogeneity, a fixed effects model is utilized. The Global Climate Risk Index (CRI) scores, provided by Germanwatch, serve as the primary measure of climate risk, with lower scores indicating heightened risk. The investigation reveals a non-linear relationship, where enhanced financial access correlates with diminishing climate risk, underscoring the positive impact of climate change policies on financial system efficiency. However, no significant connection is found between climate risk and financial fragility, a phenomenon potentially attributed to the resilience of countries with advanced credit markets and preemptive risk insurance measures by households. These findings imply that while climate change significantly influences financial access in G20 countries, its effect on financial fragility within the studied period is negligible. The study underscores the potential for policy interventions in climate change mitigation to augment financial system efficiency. Ensuring the consistency of professional terminology, the analysis provides insights into the nuanced relationship between climate risk and financial dynamics in major economies.

**Keywords:** Climate risk; Financial access; Financial fragility; Banking; Empirical finance; G20 countries; Panel data analysis

## 1. Introduction

Climate, a term encompassing the current state of atmospheric, oceanic, and freshwater systems, is increasingly influenced by anthropogenic factors. Among these, greenhouse gas emissions are a primary contributor to detrimental climatic alterations, disrupting natural climatic functions. It has been observed that greenhouse gases accumulate in the atmosphere, enhancing global warming by impeding solar radiation from being reflected back into space. This phenomenon is so profound that a mere 1% increment in $CO_2$ emissions is analogous to the impact of an atomic bomb on the atmosphere every 2.3 seconds. Such changes in climate induce extreme weather events such as floods and hurricanes, exerting adverse effects on global economies (Hsiang & Kopp, 2018).

The economic and financial implications of climate risk are substantial. Financial markets, as a whole, are vulnerable to these risks, posing a threat to overall financial stability. The Network for Greening the Financial System (NGFS) has identified climate change as a pivotal factor driving structural transformations within financial institutions. Consequently, the NGFS advocates for the integration of climate-induced risk into the monitoring frameworks of financial stability and micro-audits (Allen et al., 2020). The nexus between climate risk and financial stability has garnered significant attention in international treaties and political discourse. The global nature of climate risk necessitates heightened vigilance from governments and businesses alike. In this context, financial auditors are increasingly emphasizing the need for financial entities to disclose risks associated with climate change. These advanced risk assessments are integral to informed investment decisions, considering the interdependence of business entities (Kling et al., 2021; Roncoroni et al., 2021).

The implications of climate change extend profoundly into the financial system, impacting individuals and firms alike. It manifests as restricted access to finance, compounded by financial losses, the challenges of countering these losses, economic insecurity, and hurdles in resource allocation and collection. These elements contribute to systemic vulnerabilities, impeding effective resource distribution and potentially compromising the functionality of the financial system. A pivotal report by the Organization for Economic Co-operation and Development OECD (2022) highlights that the G20 countries, constituting the world's 20 most developed countries, are accountable for a staggering 80% of greenhouse gas emissions. This statistic underscores the importance of comprehensively understanding the far-reaching consequences of climate change. While the relationship between financial stability and climate risk has been explored to some extent, the interplay between financial access and fragility remains less scrutinized. This paper seeks to bridge this gap by examining the impact of climate risk on financial access and fragility in G20 countries during the period from 2006 to 2017, employing a panel data methodology. This research contributes to existing literature in three significant ways: Firstly, it delves into the relatively unexplored domain of the impact of climate risk on financial vulnerability and access within G20 countries. Secondly, it aims to inform policymakers by elucidating the effects of climate risk on both financial vulnerability and access. Thirdly, the study employs advanced second-generation econometric tests that account for heterogeneity and cross-sectional dependency.

Furthermore, the United Nations Environment Programme UNEP (2001) report posits that the financial sector is susceptible to climate change, not only due to direct impacts but also through clients' altered perceptions of risk and governmental policies aimed at mitigating climate risk. Climate change, by undermining economic and social stability, escalates risks, consequently heightening exposure for investors. This increased risk landscape adversely affects the lending, investment, and insurance operations of financial institutions. In line with this report, climate change could amplify the value-at-risk for these institutions, engendering adverse outcomes.

Climate risk poses a considerable threat to financial stability by altering investor perceptions of profitability, potentially leading to market volatility through overselling. This change in investor behavior escalates market risk and concurrently diminishes borrowers' capacity to repay debts, intensifying credit risk. Financial institutions, notably banks, may encounter liquidity risks due to loan non-repayment, while physical manifestations of climate change jeopardize operational continuity, thereby increasing operational risks. Deloitte (2022) observes that losses induced by climate change not only exacerbate credit risk but also influence the pricing strategies of insurance companies, leading to higher rates for traditional risks and lower for green technology-related risks. A striking illustration of the financial implications of climate change is provided by a CDP study, which estimates that the world's 215 largest corporations are at risk of incurring approximately $1 trillion in damages over the next five years due to climate change. This starkly highlights the significant threats climate change poses to corporate entities. Moreover, the repercussions of climate-induced risks on the financial system are profound, yet it is essential to acknowledge the opportunities it presents for the financial industry. Notably, the sustainable finance sector is projected to generate up to $1.2 trillion in climate change mitigation benefits (CDP, 2019). The risks of climate change also extend to foreign investment. Yang (2008) notes that post-natural disaster scenarios often lead to foreign capital outflows, driven by uncertainties in future repayments, thereby influencing financial access and fragility.

Given these challenges, the development of robust risk management systems is imperative for mitigating the impact of climate change on financial institutions. Financial entities are encouraged to incorporate stress testing that encompasses both physical and transition risks into their risk management frameworks. However, these efforts necessitate support through national and international policy measures aimed at combating climate change (Adrian et al., 2023).

In the event of inadequate measures to mitigate and adapt to climate change, extreme weather events and natural disasters pose a significant threat to various economic sectors and regions, potentially leading to widespread socioeconomic consequences. To counter the gravest effects of climate change and transition towards low-carbon practices, an ambitious and timely overhaul of both developed and developing countries' economies is imperative within the next decade. Economic repercussions of climate change could adversely impact financial assets held or issued by governments and corporations (Battiston et al., 2021).

Historically, initial inquiries into climate change predominantly centered on its economic impacts, particularly those related to climatic events (e.g., Frankhauser & Tol, 1996; Mellinger et al., 1999; Schimmelpfennig, 1996). However, research focusing on the nexus between climate change and financial vulnerability remains relatively limited. Battiston et al. (2021) bifurcate the impact of climate change on financial vulnerability into two categories: climate physical risks and climate transition risks. Climate physical risks encompass potential losses in physical assets of firms, heightened credit risk in banks, and financial losses within insurance companies attributable to climate change. Conversely, climate transition risks involve financial shocks stemming from extreme asset price volatility. Klomp (2014) posits that natural disasters exacerbate liquidity risk and heighten vulnerability in the banking sector, with their impact on financial fragility varying according to a country's developmental stage. Mandel et al. (2021) highlight that climate change adversely affects the financial system, particularly in countries with more developed financial structures, thereby intensifying financial fragility in these regions. Lamperti et al. (2019) argue that climate change contributes to the financial system's fragility via the banking sector, potentially increasing the likelihood of banking crises by up to 248%. Dunz et al. (2019) suggest that while carbon taxes can effectively stimulate green loans and investments from new banks, surpassing green supports, they may also pose short-term challenges to financial stability.

The realm of research examining the impact of climate change on access to finance remains relatively underexplored. Kling et al. (2021) elucidated that climate change constrains financial access, leading to an escalation in the cost of capital. Monasterolo (2020) observed that high carbon emissions and consequent climate change adversely affect the profitability of firms. Hussain et al. (2021), in a study encompassing 26 Asian countries, revealed a bidirectional causal relationship between financial inclusion and climate change, suggesting that while financial inclusion impacts climate change, climate change reciprocally affects financial inclusion. In a subsequent study, Hussain et al. (2023) identified an N-shaped relationship between financial inclusion and $CO_2$ emissions across a sample of 102 countries.

Further inquiries into climate risk have scrutinized its impact on corporate performance (e.g., Huang et al., 2018; Kling et al., 2021). Huang et al. (2018) analyzed the relationship between climate risk and the financing preferences of publicly traded companies, noting that firms in high-risk climatic zones tend to maintain higher capital reserves to bolster corporate resilience. Kling et al. (2021) explored the interplay between climate change, corporate capital costs, and access to finance, concluding that climate fragility restricts financial access and inflates debt costs. A review of studies developing models to incorporate climate risk into financial risk assessments indicates that responsiveness to climate risk can facilitate the transition to more effective climate policies under constrained market conditions, while preserving risk equilibrium (e.g., Allen et al., 2020; Fabris, 2020; Battiston et al., 2021; Roncoroni et al. 2021).

The subsequent section of this paper presents the methodology, objectives, scope, dataset, and findings. Section 2 provides an analysis of these findings, including spearman test results, cross-section dependency tests, unit root tests, and Panel-Corrected Standard Errors (PCSE) estimation results. The data suggest that climate change significantly influences financial access in G20 countries, yet its impact on financial fragility appears negligible. The final section, Section 3, concludes the paper with a discussion of the findings derived from the analysis.

## 2. Methodology

This section delineates the study's purpose, scope, dataset, limitations, analytical methods, findings, and commentary on these findings.

### 2.1 Purpose, Scope, and Dataset

The objective of this investigation is to explore the relationship between climate risk and its impact on financial access and fragility in G20 countries, spanning the period from 2006 to 2017. This timeframe was selected based on the availability of climate risk data, which originates from 2006, and the most recent data on the dependent variables, which extends up to 2017. The analysis includes a subset of G20 countries, as detailed in Table 1. Notably, data constraints necessitate the exclusion of certain countries, including China, the United Kingdom, the United States, South Korea, and Germany.

In this study, climate risk is defined as the independent variable. The Global CRI scores, developed and released by Germanwatch, are utilized as a measure of climate risk. Since 2003, Germanwatch has been publishing the Global CRI, an analysis grounded in extreme weather events and their socioeconomic implications. This index has been widely recognized in academic research as a reliable indicator of climate risk (Masud et al., 2023; Xing & Wang, 2023). The CRI provides an objective analysis, incorporating the impact of extreme weather events alongside socioeconomic data, thus reflecting countries' vulnerability to such events and offering prognostic insights (Eckstein et al., 2019). In the CRI, while absolute figures like total deaths or total losses in US dollars might disproportionately reflect a nation's size or economic power, ratios such as deaths per 100,000 people and losses per unit of GDP emphasize the impact on smaller and less developed nations. The index prioritizes relative losses, assigning them greater weight by doubling the average ranking of all variables constituting the CRI score (Eckstein et al., 2019). Lower scores in the index correspond to higher risk levels, indicating that an increase in the index score signifies a reduction in risk (Huang et al., 2018). Table 2 presents the CRI scores of the included countries for the period 2006-2017.

In the analysis of climate risk and its financial implications, Table 1 provides a comprehensive overview of the varying risk levels across countries. It reveals that India exhibited the highest risk in multiple years (2006, 2008, 2013-2017), followed by Indonesia (2007), Saudi Arabia (2009), Russia (2010, 2012), and South Africa (2011). This study focuses on two dependent variables: financial fragility and financial access. Financial fragility is operationalized using the ratio of non-performing loans (NPL) to total bank loans, a method previously employed by researchers such as Demirgüç-Kunt & Detragiache (1998), Ghosh (2008), Toby (2014), and Pierros (2020). This metric posits that a higher ratio of NPLs indicates increased financial fragility. On the other hand, financial access is quantified as the number of bank branches per 100,000 adult inhabitants. This measure of financial access has been widely used in literature, as seen in studies by Ghosh (2008), Mbutor & Uba (2013), Setiawan (2015), Inoue & Hamori (2016), and Nguyen & Ha (2021). In this study, all variables included in the analysis are presented in their logarithmic forms to ensure uniformity and facilitate comparison. The primary data sources for this research are the databases of Germanwatch and the World Bank. While previous studies have predominantly concentrated on the economic effects of climate risk, financial stability, and firm performance (e.g., Battiston et al., 2021; Huang et al., 2018; Kling et al., 2021; Mellinger et al., 1999; Schimmelpfennig, 1996), this study endeavors to innovate by examining the bilateral impact of climate risk on financial access and financial fragility.

**Table 1.** Countries and used variables in the analysis

| No. | Country | |
|---|---|---|
| 1 | Australia | |
| 2 | Argentina | |
| 3 | Brazil | |
| 4 | Canada | |
| 5 | France | |
| 6 | India | |
| 7 | Indonesia | |
| 8 | Italy | |
| 9 | Japan | |
| 10 | Mexico | |
| 11 | Russia | |
| 12 | S. Arabia | |
| 13 | S. Africa | |
| 14 | Turkiye | |
| **Dependent Variables** | **Form of Calculation** | **Data Sources** |
| Financial Fragility | NPL (Non-performing loans to total bank loans) | World Bank |
| Financial Access | FA (Commercial bank branches (per 100,000 adults) | World Bank |
| **Independent Variable** | **Form of Calculation** | **Data Sources** |
| Climate Risk | CRI (Global Climate Risk Index) | Germanwatch |

**Table 2.** CRI Scores of countries included in the analysis

| Country/Year | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Australia** | 38.75 | 37.5 | 33.17 | 13.17 | 31.5 | 53.83 | 66.33 | 35.67 | 50.5 | 35.5 | 42.17 | 30.33 |
| **Argentina** | 68 | 71.33 | 39.42 | 49.83 | 69.5 | 85.5 | 47 | 20.33 | 65.67 | 63.67 | 44.67 | 55.5 |
| **Brazil** | 62.75 | 70 | 24.83 | 36.83 | 33.83 | 80.17 | 113.17 | 43.33 | 31 | 76.17 | 54.5 | 76.67 |
| **Canada** | 40.25 | 70.33 | 54.83 | 54 | 65.17 | 99.17 | 56 | 32.67 | 67.83 | 71 | 51.67 | 52.67 |
| **France** | 43 | 71.08 | 50.5 | 49 | 35.17 | 43.5 | 79.5 | 56.5 | 40.5 | 33.33 | 56.33 | 61.17 |
| **India** | 11.5 | 29.5 | 16.58 | 23.83 | 39.5 | 41.17 | 52.17 | 12.67 | 16.17 | 15.33 | 18.33 | 22.67 |
| **Indonesia** | 5.75 | 21.08 | 45 | 41.33 | 49 | 59.5 | 71.5 | 32.83 | 29.17 | 48.67 | 46.17 | 55.83 |
| **Italy** | 44.25 | 83.17 | 43.92 | 55.17 | 87.33 | 43.17 | 44.5 | 49.33 | 43.17 | 34.83 | 76.5 | 45.33 |
| **Japan** | 34.25 | 65.17 | 71.08 | 48 | 77.67 | 93 | 54.67 | 44 | 25.33 | 46.33 | 57.5 | 46.5 |
| **Mexico** | 43 | 31.08 | 39.58 | 56.67 | 27.67 | 58.5 | 65.17 | 15 | 39.83 | 56.33 | 46.67 | 64.67 |
| **Russia** | 24.75 | 87.58 | 73.67 | 62 | 11 | 44.33 | 22.17 | 60.5 | 80 | 59.5 | 60.67 | 69 |
| **S. Arabia** | 77.25 | - | 73.5 | 12.5 | 59.17 | 107.33 | 96.83 | 41.5 | 92 | 72.5 | 69.67 | 80.67 |
| **S. Africa** | 46.58 | 23.08 | 54.67 | 58.17 | 83.67 | 40 | 37.33 | 45.83 | 45.67 | 42.33 | 35.67 | 46.58 |
| **Turkiye** | 41.5 | 90.25 | 68.17 | 35.83 | 76.5 | 74.67 | 89.33 | 92.17 | 55.83 | 106 | 92.83 | 69.17 |

Source: Germanwatch.org

### 2.2 Model and Hypotheses

The regression models and hypotheses to search for the effect of climate risk on financial and financial fragility in line with research variables are reported in Figure 1.

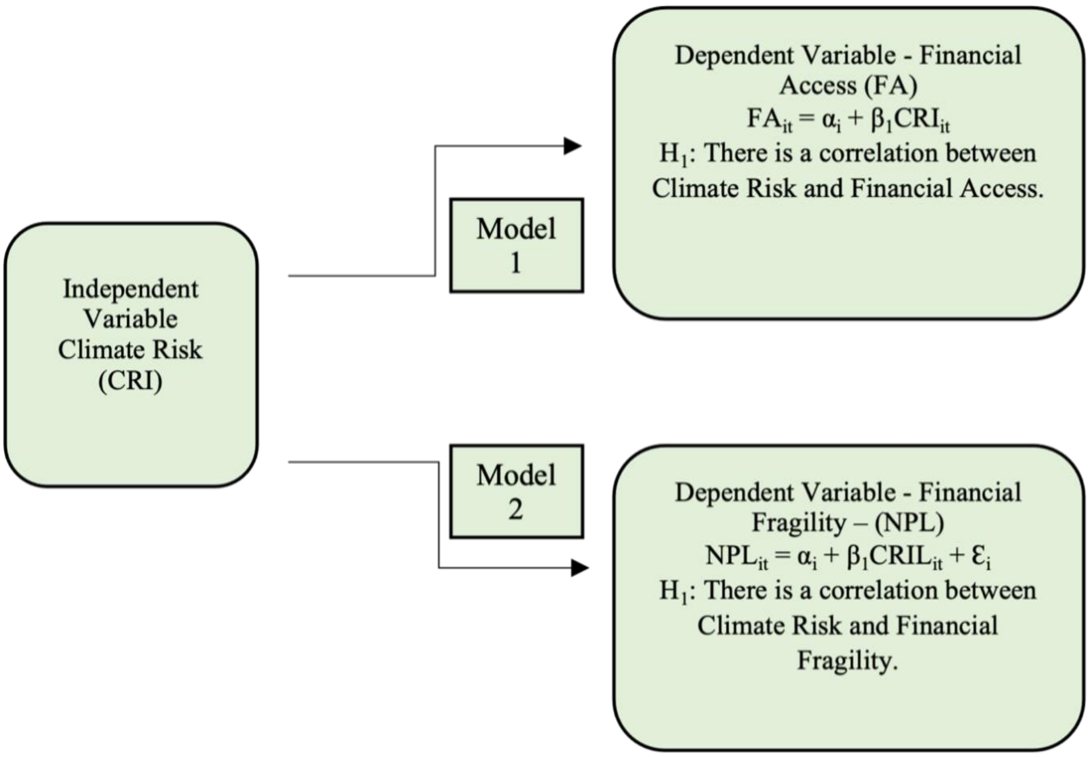


**Figure 1.** Research design
Note: Authors own interpretation

### 2.3 Research Method

The sample for this study encompasses a diverse group of G20 countries, spanning a period of 12 years. Given the temporal and spatial scope of the research, panel data analysis is selected as the most suitable methodological approach. This analysis not only accommodates the heterogeneity of the sample but also addresses cross-sectional dependence and slope heterogeneity, thereby enhancing the reliability of the findings. The research method involves a two-stage process: initially examining pertinent assumptions within the panel data analysis context, followed by the estimation of the model. This approach ensures that necessary assumptions are tested and validated before model estimation. The key assumptions addressed are as follows:

- Multicollinearity: The research first addresses the issue of multicollinearity, which refers to a high level of correlation among explanatory variables. Multicollinearity, indicating a complete or near-complete relationship between these variables, can render parameter calculations challenging and is generally undesirable in the least squares method. To ascertain the presence of multicollinearity, this study employs spearman correlation analysis, a technique widely recognized in academic literature.
- Cross-section Dependency and Slope Homogeneity Test: Neglecting the cross-sectional dependency among countries in panel data can lead to biased and inconsistent estimation results. To counter this, the study utilizes the Pesaran (2004) CDlm test, which is particularly suitable when the time dimension (T) exceeds the number of entities (N). Eq. (1) presents the mathematical formulation of this test:

$$\mathrm{CDlm} = \left(\frac{2}{N(N-1)}\right)^{1/2} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\, \hat{p}_{ij}\right) \quad \sim N(0,1) \tag{1}$$

Slope Homogeneity Test: An essential assumption in panel data analysis is the examination of slope homogeneity. This study employs the Pesaran & Yamagata (2008) homogeneity test to analyze the homogeneity of slope coefficients. Eq. (2) illustrates the mathematical formulation of this test:

$$\widetilde{\Delta}_{adj} = \sqrt{N}\, \frac{N^{-1}\ \hat{S} - E(\widetilde{Z_{it}})}{\sqrt{Var}\,(\widetilde{Z_{it}})} \sim N(0,1) \tag{2}$$

where, N denotes the number of cross-sections in the panel, S stands for the Swamy test statistic, k represents the number of explanatory variables, and Var(t, k) indicates the standard error.

- Stationarity Test: Ensuring the stationarity of series is crucial for deriving consistent and unbiased results. This study employs both primary and secondary unit root tests to ascertain stationarity, while taking into account cross-section dependency and homogeneity. The LLC (Levin et al., 2002) unit root test is applied to variables exhibiting homogeneous slope coefficients without cross-section dependence. In contrast, the IPS (Im et al., 2003) unit root test is utilized for variables with heterogeneous slope coefficients but without cross-section dependence. For variables exhibiting cross-section dependence, unit root tests including the Bootstrap (Smith et al., 2004) and Hadri & Kurozumi (2012) tests are employed. The LLC test is represented mathematically in Eq. (3):

$$\Delta \mathrm{y}_{\mathrm{i,t}} = \alpha_i + \beta_{i,t} + \theta_t + \rho y_{i,t-1} + \sum_{j=1}^{k} \emptyset_k \Delta y_{i,t-j} + \mu_{i,t} \tag{3}$$

where, Δ represents the first difference operator, m indicates the lag length, and $\mu_i$ and $\theta_t$ represent unit-specific fixed effects and time effects, respectively. The null hypothesis for the LLC test evaluates a unit root against $H_0$: $\rho$=0, with the alternative hypothesis evaluating against $H_1$: $\rho$<0. To accommodate heterogeneity in the $y_{i,t-1}$ coefficients, Im et al. (2003) extended the LLC test, proposing a procedure based on the average of individual unit root statistics. The IPS panel unit root test is based on Eq. (4):

$$\Delta \mathrm{y}_{\mathrm{i,t}} = \alpha_i + \beta_{i,t} + \theta_t + \rho y_{i,t-1} + \sum_{j=1}^{k} \emptyset_k \Delta y_{i,t-j} + \mu_{i,t} \tag{4}$$

This study incorporates the second-generation unit root test approach developed by Hadri & Kurozumi (2012), which builds upon Pesaran (2004) methodology. This advanced approach addresses cross-sectional dependence by incorporating unobserved common factors within the error term during the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) testing process. The null hypothesis, which posits stationarity, is evaluated using asymptotically normally distributed $Z_A^{SPC}$ and $Z_A^{LA}$ statistical values. The mathematical expressions for this assessment are delineated in Eqs (5) and (6):

$$Z_A^{SPC} = \frac{1}{\hat{P}_{iSPC}^2 T^2} \sum_{t=1}^{T} (S_{t=1}^{w})^2 \tag{5}$$

$$Z_A^{LA} = \frac{1}{\hat{P}_{iLA}^2 T^2} \sum_{t=1}^{T} (S_{t=1}^{w})^2 \tag{5}$$

The Bootstrap ADF test, delineated in Eqs (7) and (8), is pivotal in assessing stationarity within the panel data. In these equations, $t_i$ represents the ADF-t statistics for each cross-section, with i ranging from 1 to N, symbolizing the number of cross-sections (countries). The temporal aspect of the data is denoted by t, which spans from 1 to T. $E(t_i)$ and $Var(t_i)$ correspond to the expected value and variance of the ADF-t statistics, respectively.

$$\mathrm{t}^* = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{t_i} \tag{7}$$

$$\bar{\mathrm{t}}_{\mathrm{s}} = \frac{\sqrt{\mathrm{N}}\{\bar{\mathrm{t}} - \mathrm{E}(\mathrm{t_i})\}}{\sqrt{\mathrm{Var}(\mathrm{t_i})}} \tag{8}$$

- Selecting a Model for Estimation: The choice between pooled, fixed effects, or random effects models is determined through the application of several tests, including the F test, Breusch-Pagan LM test, and Honda test. The F test is employed to ascertain the presence of cross-section or time effects in the model, using both constrained and unconstrained models as per Topaloğlu & Korkmaz (2021). The specific formulations of these models are depicted in Eq. (9):

$$\begin{gathered} \text{Unconstrained Model: } \mathrm{Y_i} = \mathrm{X_i}\beta_{\mathrm{i}} + \mathrm{u_i} \qquad \mathrm{i} = 1,2,3,\ldots,\mathrm{N} \\ \text{Constrained Model: } \mathrm{Y_i} = \mathrm{X}\beta + \mathrm{u} \end{gathered} \tag{9}$$

The Breusch-Pagan LM test, established in 1980, is utilized to evaluate the superiority of a pooled model over a random effects model. The Honda test, a modification introduced in 1985, reformulates the two-way LM test into a more streamlined one-way test, as detailed by Baltagi (2005). The mathematical expressions for both the Breusch-Pagan LM and Honda tests are provided in Eqs (10) and (11):

$$\mathrm{LM} = (\mathrm{LM}_1 + \mathrm{LM}_2) \sim X^2 \tag{10}$$

$$\mathrm{HONDA} = \sqrt{(\mathrm{LM}_1 + \mathrm{LM}_2)} \sim N(0,1) \tag{11}$$

Given the specific nature of the study's data and the period it covers, the fixed effects model is identified as the most suitable for estimation.

- Autocorrelation and Heteroscedasticity Test: The study also considers the issues of autocorrelation and heteroscedasticity. Heteroscedasticity arises when error terms vary across different cross-sections, whereas autocorrelation occurs when these error terms exhibit significant sequential correlation. To address these issues and ensure the reliability and consistency of the results, robust estimators are employed in the models.

## 3. Results and Discuss

The relationship between climate risk, financial fragility, and financial access has been investigated using a panel data methodology. Initial results are delineated in Table 3. Subsequently, a logarithmic transformation was applied to the variables for further analysis.

**Table 3.** Descriptive statistics

| | **NPL** | **FA** | **CRI** |
|---|---|---|---|
| Mean | 77.04452 | 23.11821 | 52.12464 |
| Median | 57.48520 | 18.90500 | 49.58000 |
| Max | 210.3000 | 62.62000 | 113.1700 |
| Min | 0.000000 | 5.720000 | 0.000000 |
| Std. Dev. | 55.38047 | 13.61250 | 22.15269 |
| Skewness | 0.672614 | 0.916916 | 0.233670 |
| Kurtosis | 2.169123 | 3.144365 | 2.792323 |
| J-B | 17.49996 | 23.68645 | 1.830753 |
| Prob | 0.000158 | 0.000007 | 0.400366 |
| Obs. | 168 | 168 | 168 |
| | **LnNPL** | **LnFA** | **LnCRI** |
| Mean | 4.109966 | 2.968912 | 3.854833 |
| Median | 4.051510 | 2.939349 | 3.915295 |
| Max | 5.348535 | 4.137085 | 4.728891 |
| Min | 2.501436 | 1.743969 | 1.749200 |
| Std. Dev. | 0.746034 | 0.596049 | 0.503314 |
| Skewness | -0.191734 | -0.001487 | -1.149066 |
| Kurtosis | 2.142390 | 2.019027 | 4.847489 |
| J-B | 6.177798 | 6.736215 | 60.86235 |
| Prob | 0.045552 | 0.034455 | 0.000000 |
| Obs. | 168 | 168 | 168 |

Statistical analysis of the raw data for CRI, the study's independent variable, reveals that the average CRI score during the analysis period was 52.124, with a maximum of 113.170 and a minimum of 0.000. The standard deviation indicates relatively stable climate risk levels across different periods. This suggests that the G20 countries experienced a moderate level of climate risk during the study period. For the dependent variable, financial fragility (NPL), the average value was recorded at 77.044, with a peak at 210.300 and a trough at 0.000. The other dependent variable, financial access (FA), exhibited an average value of 23.118, reaching a maximum of 62.620 and a minimum of 5.720. The standard deviation results for both NPL and FA suggest minimal variance across periods. The Jarque-Bera probability statistics for the NPL and FA variables were found to be less than 0.05, indicating a deviation from the normal distribution and leading to the rejection of the null hypothesis for these variables. In contrast, for the CRI variable, the null hypothesis could not be rejected. Post-logarithmic transformation, the Jarque-Bera probability values for all variables were less than 0.05, signifying non-normal distribution of the series. Consequently, the Spearman correlation test, which is appropriate for non-normally distributed data, was employed to examine the multiple linear relationships between the series. The results of this correlation analysis are presented in Table 4.

**Table 4.** Spearman test results

| Correlation t-Statistic Probability | LnNPL | LnFA | LnCRI |
|---|---|---|---|
| **LnNPL** | 1.000000 | | |
| | ----- | | |
| | ----- | | |
| **LnFA** | -0.357590 | 1.000000 | |
| | -4.933433 | ----- | |
| | 0.0000 | ----- | |
| **LnCRI** | 0.190083 | 0.062479 | 1.000000 |
| | 2.494526 | 0.806566 | ----- |
| | 0.0136 | 0.4211 | ----- |

In panel data analysis, a correlation coefficient exceeding 0.75 is generally considered indicative of multicollinearity, which is undesirable (Albayrak, 2005). Analysis of the data presented in Table 1 reveals that the highest correlation coefficient, observed between NPL and FA, is (-0.35). Therefore, there is no evidence of multicollinearity or internality among the variables under study. Prior to detailed analysis, cross-sectional dependency was scrutinized for each model, with results displayed in Table 5.

**Table 5.** Cross-Section dependency test results based on model

| | **Model 1** | |
|---|---|---|
| **CD Tests** | **Stat.** | **Prob.** |
| LM | 399.511 | 0.000 |
| CDlm | 22.868 | 0.000 |
| CD | 0.507 | 0.306 |
| LMadj | 0.334 | 0.369 |
| | **Model 2** | |
| **CD Tests** | **Stat.** | **Prob.** |
| LM | 230.633 | 0.000 |
| CDlm | 10.350 | 0.000 |
| CD | 1.598 | 0.055 |
| LMadj | 1.820 | 0.034 |

To examine cross-sectional dependency, various tests are available, including the Breusch & Pagan (1980) LM test, the Pesaran (2004) CD and CDlm tests, and the Pesaran et al. (2008) LMadj test. The selection of the appropriate test depends on the relationship between the time dimension (T) and the number of cross-sections (N). The Breusch-Pagan LM test is typically employed when T is significantly greater than N. The Pesaran CDlm test is preferable when T exceeds N, while the Pesaran CD test is suitable when N surpasses T. The Pesaran et al. (2008) LMadj test, advantageous for its ability to rectify deviations observed in the Breusch-Pagan LM test and mitigate total correlation issues in the Pesaran CD test, is also employed when T exceeds N. While all test results are summarized in Table 3, the Pesaran CD test results are particularly pertinent in this study, given that N is larger than T. These results demonstrate that the probability statistics for both Model 1 and Model 2 exceed 0.05, indicating no significant concern regarding cross-sectional dependency. Table 6 details the variable-specific cross-sectional dependency results.

**Table 6.** Cross-Section dependency test results based on variables

| **Variable** | **LM** | | **CDlm** | | **CD** | | **LMadj** | |
|---|---|---|---|---|---|---|---|---|
| | **Stat.** | **Prob.** | **Stat.** | **Prob.** | **Stat.** | **Prob.** | **Stat.** | **Prob.** |
| **LnCRI** | 143.995 | 0.000 | 3.928 | 0.000 | -1.312 | 0.095 | -1.076 | 0.859 |
| **LnFA** | 135.122 | 0.002 | 3.271 | 0.001 | -1.169 | 0.121 | 0.233 | 0.408 |
| **LnNPL** | 169.819 | 0.000 | 5.842 | 0.000 | -1.727 | 0.042 | 0.728 | 0.233 |

The cross-sectional dependency test results for the CRI and FA variables, as per the Pesaran CD test, reveal statistics higher than 0.05, suggesting an absence of cross-sectional dependency issues for these variables. However, for the NPL variable, the Pesaran CD test statistic falls below the critical value, indicating the presence of a cross-sectional dependency problem. Therefore, conducting homogeneity tests is essential for selecting the appropriate unit root test in the presence of cross-sectional dependency. The delta and adjusted delta statistics, as developed by Pesaran & Yamagata (2008), are presented in Table 7.

**Table 7.** Delta test results

| Variable | $\tilde{\Delta}$ | Prob. | $\tilde{\Delta}_{adj}$ | Prob. |
|---|---|---|---|---|
| **LnCRI** | -1.112 | 0.867 | -1.284 | 0.900 |
| **LnFA** | 1.908 | 0.028 | 2.203 | 0.014 |
| **LnNPL** | 1.382 | 0.083 | 1.596 | 0.055 |

The data presented in Table 7 reveal homogeneity in the slope coefficients for both the CRI and NPL variables. Conversely, for the FA variable, homogeneity is not observed, indicating heterogeneity in its slope coefficients. Following the establishment of cross-sectional dependency and homogeneity, the stationarity of the series has been evaluated. For the CRI variable, which exhibits neither cross-sectional dependency nor heterogeneity in slope coefficients, the LLC first-generation unit root test is applied. The results of this test are concisely summarized in Table 8.

**Table 8.** Unit root test results for the CRI variable

| | Constant | | Constant and Trend | |
|---|---|---|---|---|
| **Hypothesis and Testing** | **Stat.** | **p-value** | **Stat.** | **p-value** |
| LLC | -9.50712 | 0.0000 | -7.68337 | 0.0000 |
| $H_0$: has a unit root | | | | |

The LLC unit root test results for the CRI variable demonstrate that the probability statistics for both the constant model and the constant and trend models are below 0.05. This finding leads to the rejection of the null hypothesis of a unit root, confirming that the CRI series is stationary. The dependent variable, FA, is characterized by the absence of cross-sectional dependency but exhibits heterogeneity in its slope coefficient. Consequently, the stationarity of FA is examined using the IPS unit root test, a heterogeneous unit root test of the first generation tests, and the results are given in Table 9.

**Table 9.** Unit root test results for the FA variable

| | Constant | | Constant and Trend | |
|---|---|---|---|---|
| **Hypothesis and Testing** | **Stat.** | **p-value** | **Stat.** | **p-value** |
| IPS | -6.42601 | 0.0000 | -0.42973 | 0.3337 |
| $H_0$: has a unit root | | | | |

In the case of the FA variable, the results of the IPS unit root tests reveal a dichotomy. Specifically, the probability statistic for the model including only a constant term is below 0.05, indicating stationarity. In contrast, the probability statistics for the model incorporating both constant and trend terms exceed 0.05, suggesting non-stationarity. To reconcile these contradictory findings, an Ordinary Least Squares (OLS) model, encompassing both constant and trend terms, was estimated. The objective of this estimation was to ascertain the most fitting unit root test specification for the series. The results of this OLS estimation are presented in Table 10.

**Table 10.** Constant/Trend selection for FA variable unit root testing

| FA | Coef. | Std. E. | t-Stat. | Prob. |
|---|---|---|---|---|
| **C** | 2.894635 | 0.086496 | 33.46538 | 0.0000 |
| **@TREND** | 0.013505 | 0.013320 | 1.013862 | 0.3121 |

**Table 11.** Unit root test results for the NPL variable

| | | Constant | | Constant and Trend | |
|---|---|---|---|---|---|
| **Hypothesis and Testing** | | **Stat.** | **p-value** | **Stat.** | **p-value** |
| Smith et al. (2004) Bootstrap | *t-bar* | -2.507 | 0.001 | -2.028 | 0.131 |
| $H_0$: has a unit root | *WS* | -1.885 | 0.031 | -2.617 | 0.074 |
| Hadri & Kurozumi (2012) | $Z_A^{SPAC}$ | -1.1296 | 0.8707 | 1.6483 | 0.0496 |
| $H_0$: No unit root | $Z_A^{LA}$ | -1.6118 | 0.9465 | 13.2870 | 0.0000 |

The OLS estimation, conducted to identify the most suitable unit root test for the FA series, indicates significance in the model with a constant term. Consequently, the FA variable is deemed stationary based on this model specification for the unit root test. As for the NPL (Non-Performing Loans) variable, the presence of cross-sectional dependency necessitated the use of second-generation unit root tests, which accommodate cross-sectional dependencies. These tests include the Bootstrap test (Smith et al., 2004) and the Hadri & Kurozumi (2012). The results of these second-generation unit root tests for the NPL variable are summarized in Table 11.

The unit root test proposed by Smith et al. (2004) yields results for the NPL variable that differ depending on the model specifications. The test indicates that while the NPL variable possesses a unit root in the model with only a constant term, it does not exhibit a unit root in the model with both constant and trend terms. Consequently, the NPL series is considered stationary under the model with a constant term but non-stationary when both constant and trend terms are included. The Hadri & Kurozumi (2012) unit root test, which operates under a null hypothesis contrary to that of Smith et al. (2004), corroborates these findings. Under the model with just a constant term, the null hypothesis of this test cannot be rejected. However, when both constant and trend terms are included, the null hypothesis is rejected, suggesting stationarity. Thus, the results from these two tests are mutually reinforcing. Given the disparate results for the models with constant term and with both constant and trend terms, an OLS estimation incorporating both terms was conducted to determine the most appropriate unit root test specification. The outcomes of this estimation are presented in Table 12.

**Table 12.** Constant/Trend selection for NPL variable unit root testing

| NPL | Coef. | Std. E. | t-Stat. | Prob. |
|---|---|---|---|---|
| C | 4.171333 | 0.108451 | 38.46295 | 0.0000 |
| @TREND | -0.011158 | 0.016701 | -0.668071 | 0.5050 |

The OLS estimations, aimed at discerning whether the model with only a constant term or the one with both constant and trend terms is more valid for the NPL variable, reveal that the constant term model is statistically significant. Therefore, this model, which indicates stationarity, is deemed appropriate for the NPL unit root test. Once the stationarity of the variables was confirmed, three distinct tests – the F-test, Breusch & Pagan (1980), and Honda (1985) – were applied to select the most fitting model from among fixed effects, random effects, and pooled options. These tests were instrumental in examining the impact of climate risk on financial fragility and access to finance. The results of these model selection tests are detailed in Table 13.

**Table 13.** Estimation model determination analysis results for Model 1 and Model 2

| Model 1 | | |
|---|---|---|
| **Test** | **Statistic** | **p-value** |
| F-group_fixed | 184.7206 | 0.000000 |
| F-time_fixed | 2.087817 | 0.024773 |
| F-two_fixed | 101.0607 | 0.000000 |
| LM-group_random | 790.7173 | 0.000000 |
| LM-time_random | 4.886378 | 0.027069 |
| LM-two_random | 795.6037 | 0.000000 |
| Honda-group_random | 28.11970 | 0.000000 |
| Honda-time_random | -2.210515 | 0.986465 |
| Honda-two_random | 18.32056 | 0.000000 |
| **Model 2** | | |
| **Test** | **Statistic** | **p-value** |
| F-group_fixed | 203.5822 | 0.000000 |
| F-time_fixed | 2.288563 | 0.013184 |
| F-two_fixed | 111.6853 | 0.000000 |
| LM-group_random | 794.5942 | 0.000000 |
| LM-time_random | 4.542130 | 0.033070 |
| LM-two_random | 799.1363 | 0.000000 |
| Honda-group_random | 28.18855 | 0.000000 |
| Honda-time_random | -2.131227 | 0.983465 |
| Honda-two_random | 18.42531 | 0.000000 |

Analysis of the F-test results, as detailed in Table 13, suggests that employing a fixed effects model is more effective than a pooled model for predicting the outcomes of the study. The Breusch & Pagan (1980) and Honda (1985) test results further reinforce this conclusion, as their probability statistics fall below the critical values, indicating that a random effects model is more efficient than the pooled model. Subsequent tests conducted to ascertain the presence of group and time effects reveal that while there is a significant time effect in the estimated model, a cross-sectional effect is not observed. Baltagi (2005) posits that model estimation using the fixed effects model yields more consistent results, particularly when the data analyzed pertains to a specific group over a defined period. In this study, the country group under examination is not randomly selected, and all data are fully integrated into the model for analysis. Consequently, the fixed effects model is chosen for estimation purposes in each of the models. The results of the heteroscedasticity and autocorrelation tests, conducted within the framework of the fixed effects model, are presented in Table 14.

**Table 14.** Heteroscedasticity and autocorrelation test results

| Model 1 | | |
|---|---|---|
| Heteroscedasticity | | |
| LMh_fixed | 407.2765 | 0.000000 |
| $H_0$: No Heteroskedasticity | | |
| Autocorrelation | | |
| LMp-stat | 105.6519 | 0.000000 |
| LMp*-stat | 133.2193 | 0.000000 |
| $H_0$: No Autocorrelation | | |
| **Model 2** | | |
| Heteroscedasticity | | |
| LMh_fixed | 186.0047 | 0.000000 |
| Autocorrelation | | |
| LMp-stat | 39.76324 | 0.000000 |
| LMp*-stat | 56.58163 | 0.000000 |

In the fixed effects estimates for both Model 1 and Model 2, the Breusch-Pagan-Godfrey LM statistics fall below the critical value. This outcome signals that there is heteroscedasticity present in the models, as indicated by non-constant residual variances across all cross sections and non-zero covariances. Heteroscedasticity can significantly impact the reliability of regression results, necessitating corrective measures. Moreover, autocorrelation tests, as per Baltagi & Li (1991) and Born & Breitung (2016), reveal autocorrelation issues in both Model 1 and Model 2. Autocorrelation, characterized by the dependence of successive error terms on each other, can also affect the validity of regression analysis. To address these issues of heteroscedasticity and autocorrelation, the Period SUR (PCSE) model, developed by Beck & Katz (1995), is a suitable corrective approach. The PCSE model is particularly effective in adjusting panel standard errors to account for these specific problems. The estimation results of applying the PCSE model to Model 1 and Model 2 are presented in Table 15.

**Table 15.** Period SUR (PCSE) Estimation results

| Variables | Model 1 | Model 2 |
|---|---|---|
| LnCRI | 0.061539** | 0.038301 |
| C | 2.731688*** | 3.962321*** |
| $R^2$ | 0.945713 | 0.950376 |
| Adj. $R^2$ | 0.936156 | 0.941639 |
| S.E. of reg. | 0.150606 | 0.180227 |
| F-stat. | 98.9500*** | 108.7804*** |

Note: ***,** and * indicates %1, %5 and %10 significance respectively

The Period SUR (PCSE) estimates provide critical insights into the relationship between climate risk and financial dynamics. The positive and significant coefficient of the independent variable (CRI) in Model 1 indicates a tangible impact of climate change on financial access. A lower score on the CRI reflects a higher risk level. Therefore, an increase in this variable signifies a decrease in climate risk. Consequently, the positive coefficient suggests that financial access improves as climate risk diminishes. Specifically, a 1% decrease in climate risk corresponds to a 6.15% increase in financial access. The independent variable accounts for 94.5% ($R^2$) of the variation in financial access, indicating that climate change significantly explains the variability in financial access. Thus, Hypothesis 1 is accepted.

In Model 2, while the F statistic confirms the model's significance and its ability to explain 95% ($R^2$) of the variability in the dependent variable, the independent variable's coefficient is positive yet not statistically significant. This finding indicates the absence of a significant relationship between CRI scores and NPL. Consequently, Hypothesis 2 is rejected, leading to the conclusion that climate risk does not notably influence financial fragility. This lack of effect may be attributable to the resilience of credit markets in developed countries or proactive risk-insurance measures by households in these markets. Additionally, the impact of climate risk on financial vulnerability might vary depending on the sample period.

The study primarily focuses on the direct impact of climate risk on financial fragility. However, it is plausible that climate risk exerts indirect effects on financial vulnerability. The findings underscore that a reduction in climate risk enhances financial access. Consequently, policy measures aimed at mitigating climate change could bolster the efficiency of the financial system. By reducing liquidity risk in this group of countries and facilitating the mobilization of idle funds into the financial system, such policies hold the potential to significantly improve the overall financial health and stability of these economies.

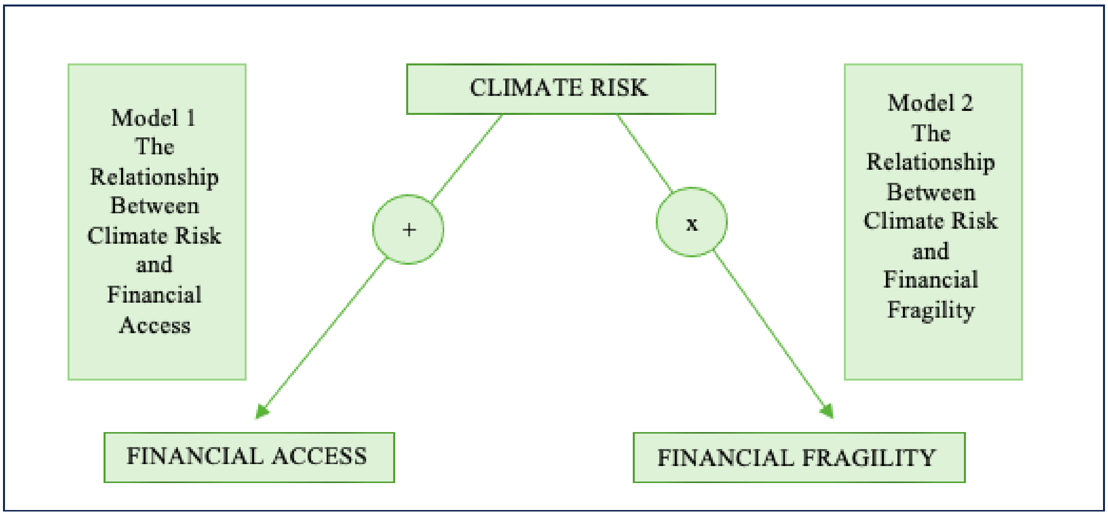


**Figure 2.** Graphical summary
Note: + & x indicate positive relationship and no relationship, respectively
Note: Authors own interpretation

The conclusions drawn from this study, encapsulated in Figure 2, demonstrate that mitigating climate risk positively influences financial access within the countries analyzed. Notably, this investigation did not uncover a significant correlation between financial fragility and climate risk. Consequently, it can be inferred that climate change, within the confines of this study's data and period, does not exert a measurable impact on financial fragility.

## 4. Conclusions

This study has rigorously examined the impact of climate risk on financial access and fragility within G20 countries during the 2006-2017 period through panel data analysis. It has been determined that climate change exerts both direct and indirect effects on the financial system. Specifically, climate change can engender increased caution among individuals, institutions, and economic managers due to heightened uncertainties. Such amplified uncertainties at a global scale may constrain consumption and investments, particularly among risk-averse individuals. This scenario could potentially diminish the efficacy of deposit channels or other investment vehicles for individual savings, thereby impeding the flow of funds into the financial system and escalating liquidity risk. Consequently, banks might face challenges in fulfilling their fundamental roles of deposit collection and loan extension.

Furthermore, expenditures aimed at mitigating environmental damages caused by climate change could intensify liquidity demands. This increase may pose challenges in access to finance for individuals, businesses, and public administrators. Additionally, the insurance sector is not immune to these threats. Environmental damages attributable to climate change may escalate costs for insurance companies, eroding their profitability. A potential outcome could be a widespread withdrawal of insurance companies from the market, disrupting reinsurance systems and elevating insurance premiums to levels beyond the affordability of many individuals. This scenario could engender fragility within the financial system, potentially triggering financial and even economic crises.

The empirical findings indicate a significant impact of climate change on financial access. A decrease of 1% in climate risk correlates with a 6.15% increase in financial access in G20 countries. Policies aimed at mitigating climate risk and curtailing its impacts are observed to enhance financial access. Thus, climate change policies can potentially augment the efficiency of the financial system. Such policies might reduce liquidity risk in financial markets, facilitate the mobilization of idle funds into the financial system, and expand credit opportunities. Policymakers may enhance the efficiency of the financial system by investing more robustly in climate change mitigation policies. Given the potential of the financial system to contribute to climate change mitigation, the incorporation of climate risk into prudential policies by central banks and financial supervisors becomes crucial. Additionally, governments should consider financial system implications in the transition to a low-carbon economy and establish mechanisms to prevent environmental degradation due to financial resource allocation.

In the analysis of the relationship between climate change and financial fragility, it is observed that climate change does not exert a significant effect on financial fragility within G20 countries. Nevertheless, governments should be vigilant in preventing negative impacts of climate risk on financial access. Although the study period did not show a significant influence of access to finance on financial fragility, existing research suggests that it could positively impact financial stability. These findings imply that implementing climate risk mitigation strategies might help contain any potential increase in financial fragility.

Limitations of this study include the latest data year being 2017, suggesting the need for subsequent analyses with more recent data. The exclusion of China, the UK, the US, South Korea, and Germany due to data unavailability necessitates replication across different country groups for comparative analysis. This study focused on the direct impacts of climate risk on financial access and vulnerability. Future research could explore the moderating role of climate risk. Additionally, the employment of the fixed effects model, due to the period limitation, leaves room for investigating long-run cointegration and causality relationships between relevant variables. Replication of the study with asymmetric tests could also yield valuable insights.

**Author Contributions**

Conceptualization, T.N.; software, T.N. and E.E.T.; formal analysis, T.N.; writing—original draft preparation, T.N. and E.E.T.; writing—review and editing, T.N., S.S., E.E.T. and I.E.; supervision, S.S. and I.E., visualization, S.S. and I.E. All authors have read and agreed to the published version of the manuscript." The relevant terms are explained at the credit taxonomy.

**Data Availability**

The data used to support the research findings are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare no conflict of interest.

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