The Economics and Finance Letters
2026 Vol. 13, No. 4, pp. 175-193
ISSN(e): 2312-430X
ISSN(p): 2312-6310
DOI: 10.18488/29.v13i4.5308
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The impact of climate change risk on financial sector stability in selected EMEA countries

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Article History
Received: 20 January 2026
Revised: 10 July 2026
Accepted: 3 August 2026
Published: 23 October 2026

Keywords
Climate change risk
EMEA
Financial sector stability
PMG-ARDL
World Bank 4x2 framework.

JEL Classification:
C33; E44; G20; Q54.

ABSTRACT

The study examines the impacts of climate change risk on financial sector stability in selected European, Middle Eastern, and African countries. Specifically, the study aimed to examine the short- and long-term effects of climate change risk on the stability of financial markets and institutions. Furthermore, the paper compared the impacts of climate change risk on financial sector stability across the three regions, namely Africa, Europe, and the Middle East. Panel annual data for the period from 1990 to 2023, collected from 55 countries, were collected and analysed using the Pooled-Mean-Group-Autoregressive-Distributed-Lag (PMG-ARDL) estimator. The study revealed insignificant impacts of climate change risk on financial markets' stability both in the short and long term, whilst for financial institutions' stability, significant positive long-term effects and insignificant short-term impacts were found. The comparative analysis also revealed significant long-term negative and positive impacts of climate change risk in Africa and the Middle East, respectively. For Europe, climate change risk was found to have insignificant impacts in both the short and long term. The results led to the conclusion that the impacts of climate change risk on financial sector stability are heterogeneous across the three regions and financial sector stability dimensions. The results underscore the necessity for forward-looking, adaptive financial regulation that incorporates scenario analysis, climate stress testing, and dynamic climate-change risk modelling.

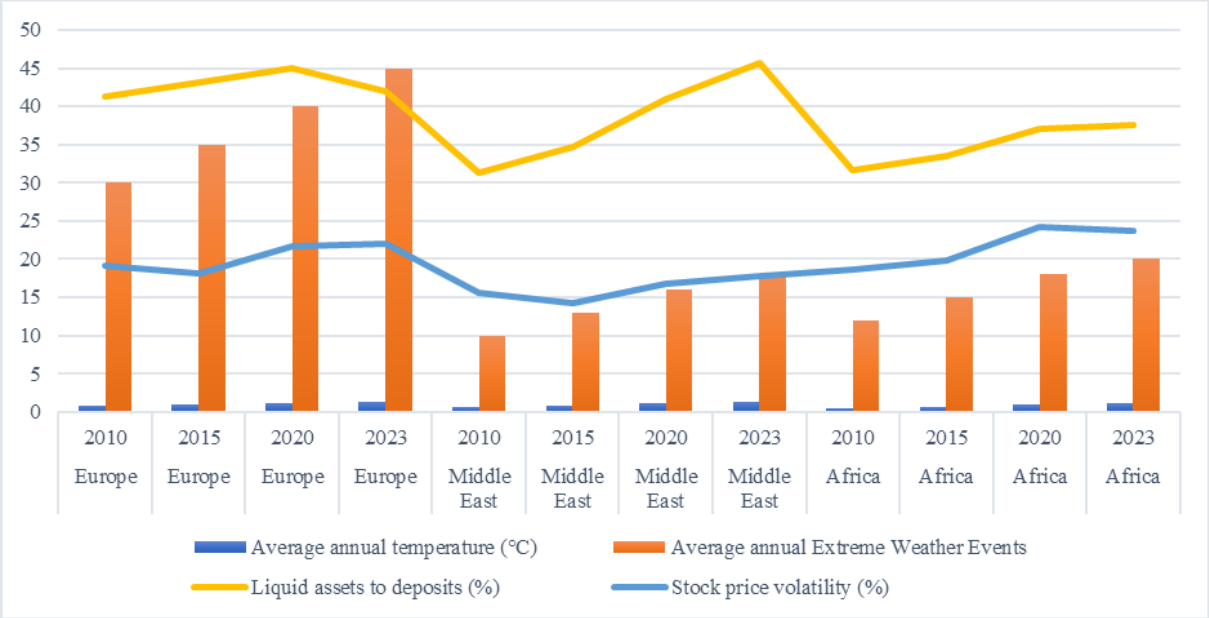
Contribution/Originality: The paper contributes to existing literature by examining the short-run and long-run impacts of climate-change risk on financial-sector stability, adopting the World Bank's 4x2 framework for measuring financial-sector development. Furthermore, it offers cross-regional empirical evidence on the impacts across three regions at different levels of economic development.

1. INTRODUCTION

Climate change represents the greatest challenge of the 21st century; it is not a future problem but is already impacting life across all regions on Earth (Barkanov et al., 2024). Climate change is emerging as a systemic risk, posing significant challenges and risks to numerous sectors, including the financial sector. The Grippa, Schmittmann, and Suntheim (2019) report showed that investors and policymakers are increasingly recognising the implications of climate change on financial stability. Climate change-related costs and economic losses are anticipated to increase in the near future (World Bank, 2022). Battiston, Dafermos, and Monasterolo (2021) assert that climate change has been recognised as one of the new sources of risks threatening financial system stability. Hence, the European Commission (2024) states that multiple efforts are underway at the global level to measure, counter and monitor the negative impacts of climate change risk (CCR) on financial stability.

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Fu, Lu, and Pirabi (2023) highlight that climate change risks threaten financial stability through physical risks, such as direct damage to infrastructure and assets, and transition risks, which arise from shifts toward a low-carbon economy. Grippa et al. (2019) further support this, stating that climate change risk affects financial system stability through two main channels, namely transition risks and physical risks. Through the physical risks of climate change, some individuals and companies are sometimes forced to migrate, which affects access to financial systems, banking deposits, and business operations, which, in turn, causes financial sector instability (Wu, Liu, & Lin, 2023). Hence, the World Bank (2022) reported the need to explore the impacts of climate change risk on financial sector stability and development, as the financial sector is the backbone of any economy (World Bank, 2022). This study, therefore, attempts to examine the effects of climate change risk on financial sector stability (FSS), focusing on selected countries from Europe, the Middle East, and Africa (EMEA). Figure 1 presents the dynamics and trends between climate change risk indicators (average annual temperature and average annual extreme weather events) and financial sector stability indicators (stock price volatility and liquid assets to deposits) over the period from 2010 to 2023.



Source: World Bank (2024).

Figure 1. Overview of financial sector stability and climate change in EMEA (2010-2023).

Figure 1 provides the dynamics and interplay between financial sector stability and CCR across the three regions. Europe's, Africa's and the Middle East's financial stability, measured by liquid assets to deposits and stock price volatility, worsened as average temperatures and average annual extreme weather events increased over the period 2010 to 2023. The evidence in Figure 1 demonstrates the significant interplay between CCR and financial sector stability. It is therefore important to investigate the effects of CCR on financial sector stability in the EMEA regions.

Although several empirical studies have attempted to examine the effects of CCR on financial stability (Adeyemi, Jempeji, Olaniran, Taliat, & Adeleke, 2025; Wu et al., 2023), there is a lack of empirical studies that comprehensively examine the impacts in relation to EMEA countries. This research therefore aims to fill the gap by contributing to the body of knowledge through showing how climate change impacts financial sector stability in selected EMEA countries, adopting the World Bank (2016) 4x2 framework for measuring financial development.

Unlike similar previous studies, the study's novelty lies in investigating how climate change risk impacts financial sector stability, specifically focusing on (i) financial institutions stability and (ii) financial markets stability as per the 4x2 framework. In addition, the paper's novelty lies in the development of indices to measure financial sector stability, namely the Financial Market Stability Index (FMSI) and the Financial Institutions Stability Index (FISI). The development of these indices helps to fill the methodological gap that exists in the measurement of financial sector

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development. This study is among the first to investigate the impact of CCR on financial sector stability in the EMEA region.

Recent literature indicates that climate change is influencing the financial systems in the EMEA region by altering asset valuations, risk assessments, and investment behaviours (Adom, 2024). Hence, understanding the effects of climate change risk on financial sector stability would help in the formulation of policies that mitigate the risks and protect EMEA countries from the disastrous damages associated with climate change. The EMEA region encompasses a spectrum of economies from advanced European financial hubs to emerging markets in Africa and resource-dependent states in the Middle East, hence offering a rich comparative landscape for analysing how climate change intersects with financial sector stability.

However, no comparative studies have been done on the impact of CCR on financial sector stability in the EMEA regions. Thus, this comparative study contributes to the body of knowledge, providing insights into how different regions at different levels of economic development are being affected by climate change risk. Furthermore, whilst existing empirical literature has examined the nexus between CCR and financial sector stability, most of the previous empirical studies were primarily country-level analyses, leading to scarce global evidence. Alternatively, it is also important to note that FSS could help realise global climate targets through aligning investments with sustainability (Monasterolo, 2020).

This guides policymakers to achieve their objectives to reduce the acceleration of CCR, as implementing climate change policies without empirical knowledge of their impacts may lead to inappropriate use of the policy instruments, leading to unintended results. The main focus of this paper is to examine the short- and long-term effects of CCR on financial-sector stability in selected EMEA countries. In this regard, the study attempts to test the following null hypotheses:

H_1: CCR has no significant impact on financial market stability in the EMEA regions.

H_2: CCR has no significant impact on financial institutions' stability in the EMEA regions.

Through testing the stated hypotheses, this paper contributes to the understanding of how CCR affects financial sector stability and provides recommendations on how to minimise the effects.

The rest of the research paper is organised and structured as follows: Section 2 reviews both empirical and theoretical literature, whilst Section 3 presents the methodology, and Section 4 focuses on the presentation and interpretation of results. Lastly, Section 5 provides the conclusions and recommendations.

2. LITERATURE REVIEW

2.1. Systemic Risk Theory

The systemic risk theory is among the emerging theories for analysing the link between climate and finance. The theory originated between 1970 and 1980 and is accredited to early economists such as Charles Kindleberger and Hyman Minsky (Mishra, 2019). From this theory, systemic risks refer to shocks that exert substantial macro-financial imbalances that adversely impact the functioning, efficiency, and stability of financial systems (Choudhury, 2021; Ojea-Ferreiro, Reboredo, & Ugolini, 2022; Sithole & Eita, 2025). In the context of this study, climate change risk represents a systemic risk that can potentially impair the stability of financial systems. Empirical studies have shown that CCR is a systemic risk that threatens the stability of financial systems (Heo, 2024; Hui-Min, Xue-Chun, Xiao-Fan, & Ye, 2021; Liu, He, Men, & Sun, 2024). Hence, the theory is relevant to this paper examining the impacts of CCR on financial sector stability.

2.2. Financial Instability Hypothesis

The paper also borrows its theoretical underpinnings from the Financial Instability Hypothesis (FIH), theorised and pioneered by Minsky (1977). The basic premise of the FIH is that financial markets are inherently unstable (Knell,

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2015; Mbotho & Zhou, 2025; Minsky, 2015; Nikolaidi, 2021). Explicitly, the FIH predicts that financial instability is mainly due to tendencies towards speculative investments in financial markets (Christophers, 2017).

In the context of this study, climate change risk can lead to financial instability by triggering speculative investments, which lead to instabilities in financial markets. Hence, the FIH offers theoretical insights for understanding the impacts of CCR on FSS.

Nevertheless, the FIH has been criticised for being too generic and descriptive, and for lacking empirical validation or modelling (Davidson, 2002; Marshall, 2021). Besides the criticisms, the FIH remains a sound theoretical framework for comprehending the effects of CCR on FSS in the EMEA regions.

2.3. Ecological Stock-Flow Consistent (E-SFC) Model

The study is also anchored on the theoretical lens of the ecological stock-flow consistent (E-SFC) model coined by Dafermos, Nikolaidi, and Galanis (2017). The model is premised on the assumption that instability or fragility of financial systems stems from carbon emissions and energy use (Dafermos et al., 2017). According to the E-SFC model, climate change risk deteriorates liquidity, solvency, and creditworthiness, leading to default (Dafermos, Nikolaidi, & Galanis, 2018). In this regard, the E-SFC model represents a sound theoretical framework for understanding the impacts of CCR on FSS as per the aim of this paper.

2.4. Climate Change Risk and Financial Market Stability

The link between CCR and financial market stability has recently gained the attention of researchers and scholars across the globe. In the context of Europe, Adeyemi et al. (2025) and Chabot and Bertrand (2023) found that climate change risk significantly hampers the stability of financial markets in the short term. Similarly, Liu, Sun, and Tang (2021) confirmed significant adverse impacts of CCR on the stability of financial markets. In the African context, Ayele and Fisseha (2024) and Mbotho and Zhou (2025) revealed that CCR significantly erodes financial market stability both in the short term and the long term. However, according to Ayele and Fisseha (2024), the long-term effects are greater than the short-term effects. Other empirical studies confirmed that CCR negatively impacts financial market stability (Liu et al., 2024; Liu et al., 2021; Ma, Cao, Wang, Vigne, & Dong, 2025; Shoaib, Rafique, Nadeem, & Huang, 2020; Zhou, Endendijk, & Botzen, 2023).

On the other hand, studies such as Yang, Huang, and Zhang (2023) and Campiglio, Daumas, Monnin, and von Jagow (2023) also argue that CCR has significant positive impacts on the stability of financial markets through initiatives such as climate-change hedging portfolios. In a nutshell, existing evidence on the impacts of CCR on financial markets tends to be mixed, a gap which this paper intends to address.

2.5. Climate Change Risk and Financial Institutions Stability

Climate change risk also poses adverse consequences for the stability of financial institutions. A significant number of prior empirical studies have confirmed significant impacts of CCR on the stability of financial institutions. Chabot and Bertrand (2023) established that climate change-related risks exert long-term negative impacts on the stability of financial institutions across Europe. Concurring with Chabot and Bertrand (2023), scholars such as Ayele and Fisseha (2024) revealed that CCR poses greater threats to the stability of financial institutions.

Fabris (2020) contended that CCR negatively impacts financial institutions' stability by adversely affecting their balance sheets (statements of financial position) of financial institutions. Equally, Ozili (2020) claims that CCR presents serious adverse consequences to the stability of financial institutions. Mbotho and Zhou (2025) and Sithole and Eita (2025) also found that CCR significantly impairs the stability of banks in South Africa.

International-level research conducted by Le, Tran, and Mishra (2023) based on a sample of 6,433 banking institutions across 109 nations confirmed that CCR significantly threatens bank stability. Noth and Schüwer (2023) provided supporting evidence that climate risk significantly weakened the financial stability of banks in the United

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States through loan defaults and higher non-performing assets. According to Zhou et al. (2023), CCR prompted bank instability.

Several other empirical studies confirmed significant adverse effects of climate change risks on the stability of banking institutions through climate-induced systemic crises, bankruptcy, asset devaluation, and default rates (Dafermos et al., 2018; Heo, 2024; Wu et al., 2023; Yaseen, Din, Shaheen, & Khan, 2024). In conclusion, the insights from existing empirical findings show that climate change risk negatively impacts the stability of financial institutions.

2.6. The Relationship Between Climate Change Risk and Financial Sector Stability

In line with the objectives, hypotheses, theoretical framework, and empirical evidence, the conceptual framework for the study is shown in Figure 2. It illustrates how climate change risk, measured by temperature, carbon emissions, and precipitation, is hypothesised to influence financial sector stability through its effects on financial market stability (FMSI) and financial institution stability (FISI), while controlling for inflation and real GDP growth.

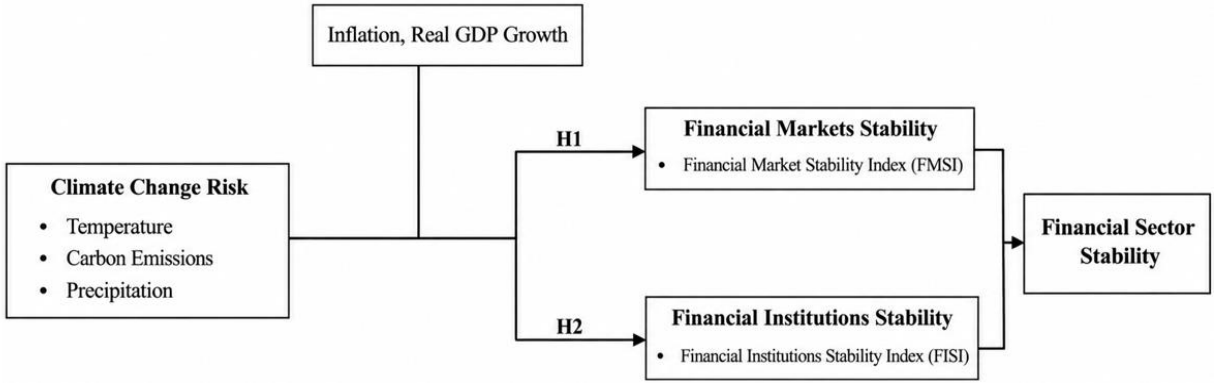


Figure 2. Conceptual framework.

3. METHODOLOGY

3.1. Data

The methodology uses a balanced panel dataset of 55 countries from the EMEA region (see Appendix 1), covering an unbroken time series from 1990 to 2023. Every country in the panel contributed consistent annual data over 34 years, yielding a sample of 1,870 country-year data points. To achieve regionally stratified comparisons, the study used geographically diverse sample sizes (55 countries across the EMEA region).

Selection of the countries was based on the availability and consistency of data in credible international databases, reflecting both regional climate and heterogeneity in the financial sector, and on the extent to which a country represents the different phases of financial market development in accordance with the global financial development 4×2 framework of the (World Bank, 2025).

This study's data draws from two main sources of quantitative data, chosen for their relevance, reliability, and international acceptance in empirical research. The first source is the World Bank's Climate Knowledge Portal, which provides annually updated, country-aggregated climate indicators such as average annual temperature, annual precipitation, and carbon dioxide emissions.

The other sources include the World Bank financial development database and The GlobalEconomy, a reliable repository of internationally valid macroeconomic and financial indicators. Table 1 presents the operationalisation and measurement of the study's variables.

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Table 1. Operationalisation, description and measurement of variables.

Variables	Variable type	Measurement/Indicators/Proxies	Variable symbol	Data Source(s)
Financial Market Stability Index (FMSI)	Dependent variable	Stock price volatility	SPV	The GlobalEconomy and the World Bank
		Stock Market Return Standard Deviation (A proxy for market volatility)	SMRS	The GlobalEconomy and the World Bank
Financial Institution Stability Index (FISI)	Dependent variable	Bank credit to bank deposits (%)	BCBD	The GlobalEconomy and the World Bank
		Liquid assets to deposits (%)	LAD	
Climate change risk index (CCRI)	Independent variable	Average Annual Temperature (°C)	TEMP	World Bank
		Annual Precipitation (mm)	PREC	
		Carbon Dioxide Emissions (million metric tonnes)	CO_2	
Economic Growth	Control Variable	Real GDP growth (%)	RGDP	World Bank Development Indicators
Inflation	Control Variable	Consumer Price Index (%)	INF	

Source: GlobalEconomy and World Bank.

3.2. Model Specification

For this study, the PMG-ARDL estimator is suitable for modelling temporal and structural heterogeneity in financial sector development across EMEA economies, while accounting for cointegration and error-correction dynamics. Recent studies in financial econometrics have demonstrated the robustness of the model when examining macro-financial linkages under different economic scenarios (Liu et al., 2024). The general PMG-ARDL models capture both short-term and long-term dynamics, specified as follows:

$$\Delta FMSI_{it} = \alpha_0 + \phi\left(FMSI_{it-j} - \beta_1 CCRI_{it-j} - \beta_2 RGDP_{it-j} - \beta_3 INF_{it-j}\right) + \gamma_1 \Delta CCRI_{it} + \gamma_2 \Delta RGDP_{it} + \gamma_3 \Delta INF_{it} + \gamma_4 \Delta FMSI_{it} + \mu i + \varepsilon_{it} \quad \text{(Model 1)}$$

$$\Delta FISI_{it} = \alpha_0 + \phi\left(FISI_{it-j} - \beta_1 CCRI_{it-j} - \beta_2 RGDP_{it-j} - \beta_3 INF_{it-j}\right) + \gamma_1 \Delta CCRI_{it} + \gamma_2 \Delta RGDP_{it} + \gamma_3 \Delta INF_{it} + \gamma_4 \Delta FISI_{it} + \mu i + \varepsilon_{it} \quad \text{(Model 2)}$$

Where:

α_0	The constant term captures country-invariant baseline effects on the dependent variable.
Φ	Error-correction coefficient demonstrating speed of adjustment toward long-term equilibrium.
Mi	Country-specific fixed effects (FE) capture unobserved heterogeneity across the panel units.
ε_{it}	Random disturbance term capturing unobserved shocks and stochastic variation.
$FMSI_{it}$	Financial Market Stability Index at time *t*.
$FISI_{it}$	Financial Institutions Stability Index at time *t*.
Subscript (it–j)	The lagged value of a variable for country ii at time *t*, with *j* representing the optimal lag length determined by model selection criteria.
I	Country index (cross-sectional unit).
T	Time index (temporal unit).
J	Optimal lag length.
γ_k	Short-run coefficients for differenced explanatory variables (where $k = 1, 2, 3, 4$).
β_k	Long-run coefficients for explanatory variables (where k = 1, 2, 3).
Δ	First-difference operator applied to the explanatory variable.

3.3. Composite Index Construction

To empirically assess the multidimensional nature of financial sector stability and climate change risk, this paper developed composite indices using the two-stage principal component analysis (PCA) technique via the Cámara and Tuesta (2014) approach. The PCA method extracted the principal components based on the Kaiser criterion and Varimax rotation. The input variables were standardised/normalised using the Min-Max normalisation method (see Appendix 2) to ensure that the composite and sub-indices were not dominated by individual indicators. For financial sector stability indices (FMSI and FISI), indicators from the World Bank's 4x2 framework were used. Indicators for FMSI construction were stock price volatility (SPV) and stock market return standard deviation (SMRS), whilst for

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FISI were bank credit to bank deposits (BCBD) and liquid assets to deposits (LAD). Climate change risk index (CCRI) was constructed using average annual precipitation (PREC), carbon emissions (CO^2), and average annual temperature (TEMP). The composite indices were estimated by principal components as linear functions of the individual indicators and estimated weights (see Appendix 2).

3.4. Model Analytical Strategy

The econometric PMG-ARDL models were estimated using STATA 18. Classical panel diagnostics tests in Table 2 were undertaken.

Table 2. Classical panel model diagnostics tests were undertaken in this study.

Test	Purpose
Pesaran CD Test	Testing cross-sectional dependence in a panel dataset
Cross-Sectionally Augmented Dickey-Fuller (CADF)	Testing for stationarity of the panel data series
Variance Inflation Factor (VIF)	Testing for multicollinearity among predictor variables
Kao (1999) panel cointegration test	Checking for the existence of a long-run association between CCR and FSS
Pesaran and Yamagata (2008) slope heterogeneity test	Testing for homogeneity in slope coefficients
Normality test using the bootstrapped panel normality test	Testing for normal distribution of regression residuals
Wooldridge test for autocorrelation in panel data	Testing the presence of serial correlation in the regression residuals
Linearity test using Augmented Component-Plus-Residual (ACPR) graphs	Checking linearity between dependent and independent variables

4. FINDINGS AND ANALYSIS

4.1. Descriptive Statistics

Table 3 presents the summary descriptive statistics for the key variables.

Table 3. Descriptive statistics for variables (n = 1870).

Variables	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	CD test	
							Statistic	p-value
FMSI	-1.60e-09	1.04	-1.24	31.32	15.42	444.07	53.52	0.000
FISI	-3.42e-09	1.02	-5.48	4.05	-0.28	1.31	26.16	0.000
CCRI	-5.88e-10	1.13	-1.63	7.70	2.99	14.08	22.83	0.000
RGDP	2.90	5.06	-41.01	82.81	2.04	47.98	62.74	0.000
INF	12.64	61.22	-72.73	1500.00	14.59	276.01	60.15	0.000

The descriptive statistics in Table 3 summarise the distributional features of the CCR and FSS indices generated for the EMEA region over the time series. The findings indicate that most indices are positively skewed. This is particularly apparent for FMSI, which had skewness statistics of 15.42.

The large skewness statistics highlight the possibility of existing extreme market events, such as accelerated capital flight or regulatory shocks that occurred in some selected countries. In terms of kurtosis, three indices are leptokurtic with the following kurtosis scores: FMSI (kurtosis = 444.07), FMEI (kurtosis = 60.98), and CCRI (kurtosis = 14.08).

The results show that most of the index variables are generally acceptable for macro-financial panel analysis, although the data show non-normality. Kline (2023) argues that absolute skewness values below three and kurtosis below 20 are considered acceptable and typically do not disqualify the use of parametric inference tests. On the other hand, the high kurtosis and skewness statistics for FMEI, INF, and FMSI indicate substantial non-normality and

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potential outliers that could lead to biased estimates. However, this was of less concern as the PMG-ARDL estimator is less sensitive to non-normality and outliers and produces robust and efficient estimates (Pesaran, Shin, & Smith, 1999). Furthermore, the PMG-ARDL estimator does not require variables to be normally distributed but only residuals (Kripfganz & Schneider, 2023). In addition, all variables had p-values of the CD test less than 0.05, indicating that cross-sectional dependence exists within the data in the case under study. This further justifies the suitability of the PMG-ARDL (Pesaran, 2021).

4.2. Panel Unit Root Test Results

The CADF test results presented in Table 4 confirm that most of the variables were non-stationary at level, except for RGDP and INF. The rest of the variables were stationary after first differencing.

Table 4. CADF second-generation unit root tests.

Variables	Levels		First difference	
	Constant	Constant + Trend	Constant	Constant + Trend
RGDP	-2.90***	-2.79***		
INF	-2.62***	-2.66***		
CCRI	-1.73	-2.18***	-3.90***	-3.98***
FMSI	-1.78	-2.26	-3.68***	-3.73***
FISI	-1.76	-2.32	-3.69***	-2.83***

Note: *** represents t-bar statistical significance level at 5%.

The CADF second-generation unit root test results in Table 4 indicate that RGDP and INF are stationary at levels, while CCRI, FMSI, and FISI become stationary after first differencing. These findings confirm that the variables are integrated of order I(0) and I(1), with none integrated beyond I(1), supporting their suitability for subsequent panel cointegration analysis.

4.3. Multicollinearity Test Results

The VIF statistics for multicollinearity shown in Table 5 were significantly below 10, indicating no high collinearity among the predictor variables.

Table 5. VIF Values for the Multicollinearity Test.

Variables	Model 1	Model 2
RGDP	1.05	1.05
INF	1.04	1.04
CCRI	1.02	1.02
Mean VIF	1.03	1.03

The VIF results presented in Table 5 indicate that multicollinearity is not a concern in either model. All VIF values are close to 1, with a mean VIF of 1.03, which is well below the commonly accepted threshold of 10, suggesting that the explanatory variables are not highly correlated.

4.4. Cointegration Test Results

The panel cointegration test results presented in Table 6 confirm an LR equilibrium relationship between FSS and CCR in the EMEA regions. This further justifies the use of the PMG-ARDL.

Table 6. Kao Cointegration Test Results.

Kao Co-integration test	Model 1	Model 2
t statistic	-7.40	-1.85
p-value	0.000***	0.032***

Note: *** represents the statistical significance level at 5% level.

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The Kao cointegration test results presented in Table 6 indicate that the variables are cointegrated in both models. The negative and statistically significant t-statistics, with p-values below 0.05, lead to the rejection of the null hypothesis of no cointegration. This suggests the existence of a stable long-run relationship among the variables, thereby justifying the estimation of long-run panel regression models.

4.5. Results for Slope Heterogeneity Test

The results of the Pesaran and Yamagata (2008) test for slope homogeneity in Table 7 demonstrate that the estimated models exhibit Delta-statistic p-values below 0.05, implying slope heterogeneity. This further confirms the appropriateness of the PMG-ARDL estimator.

Table 7. Slope heterogeneity test results.

Slope heterogeneity test		Model 1	Model 2
Test	Delta	9.39	16.43
	p-value	0.000***	0.000***

Note: *** depicts statistical significance at the 5% level.

The slope heterogeneity test results in Table 7 reject the null hypothesis of slope homogeneity for both models. The positive and statistically significant Delta statistics ($p < 0.05$) indicate that the slope coefficients differ across the sampled countries, suggesting the presence of heterogeneity. This justifies the use of estimation techniques that account for cross-country differences.

4.6. Results for the Normality Test

The results in Table 8 exhibit that Model 1 displayed no evidence for non-normality in residuals, given p-values greater than 0.05. Nevertheless, Model 2 with a p-value significantly less than 0.05 implies deviation from normal distribution. According to Schmidt and Finan (2018) and Galvao, Parker, and Xiao (2024), violations of the normality assumption in panel models with a large cross-sectional dimension may not significantly affect the consistency or efficiency of the estimator.

Table 8. Results for the panel normality test of residuals.

Model	Test statistic	Model 1	Model 2
Test	Chi^2 (2)	2.63	7.82
	Prob > chi^2	0.268	0.020***

Note: *** depicts statistical significance at the 5% level.

4.7. Serial Correlation in Panel Data

The results for Wooldridge's serial correlation test depicted in Table 9 provide evidence of first-order serial correlation in the panel regression residuals in Model 2, as indicated by the statistically significant F-statistics. In contrast, the model with FMSI as the dependent variable showed no serial correlation, as its p-values exceeded 0.05. Overall, these findings justify the PMG-ARDL estimator.

Table 9. Results for the autocorrelation test in panel data.

Serial correlation test		FMSI	FISI
Test	F-statistic	1.66	656.98
	Prob > F	0.203	0.000***

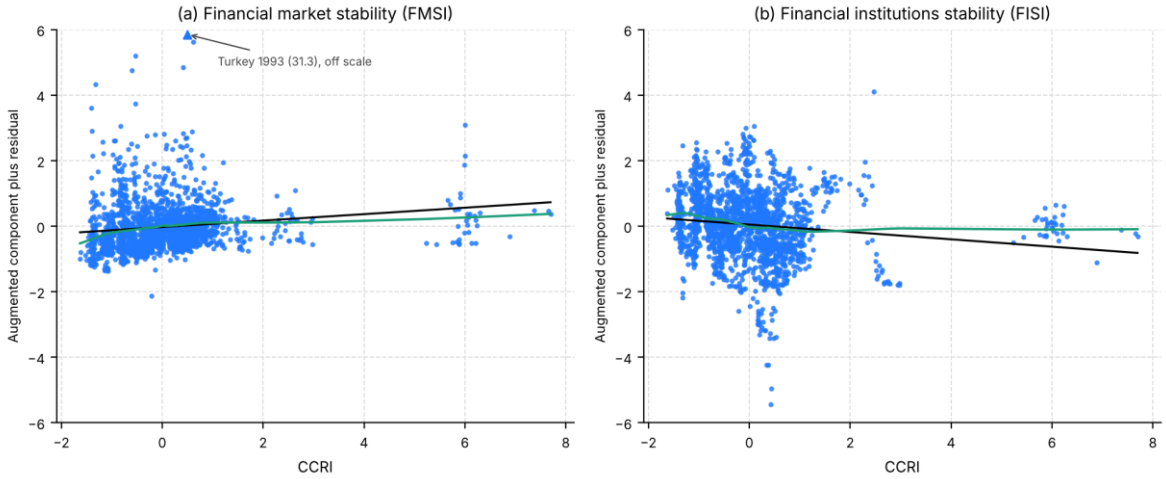
Note: *** depicts statistical significance at the 5% level.

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4.8. Test for Linearity

The study also examined linearity between FSS (the dependent variable) and CCR (the independent variable) using partial residual plots, namely ACPR plots. Figure 3 presents the ACPR plots for the two models estimated. The black solid line demonstrates the fitted linear relationship between CCR and (i) financial markets stability and (ii) financial institutions stability after controlling for other independent variables. The blue dots represent the distribution of the partial residual values around the best 'line of fit', whereas the green locally weighted scatterplot smoothing (LOWESS) curved line presents a visual assessment for potential non-linearity. The black line represents the fitted linear relationship assumed by the regression model after controlling for the other explanatory variables, while the green line is a nonparametric LOWESS curve that depicts the observed relationship between the explanatory variable (dCCRI) and the dependent variable. If the green curve closely follows the black line, the linearity assumption is considered appropriate.

The ACPR plots in Figure 3 show some degree of linearity between FSS and CCR, though the possibility of a nonlinear relationship could not be entirely ruled out. The green curve deviates from the black line, particularly at higher dCCRI values, indicating non-linearity. Nevertheless, Pesaran et al. (1999) highlight that the PMG-ARDL estimator also accommodates nonlinear relationships, as the long-run coefficients are nonlinear functions of the short-run coefficients.



Note: Blue dots show the augmented component-plus-residual values; the black line is the linear fit; the green line is the lowess smoothed fit. Both panels use the same vertical scale. One FMSI observation (Turkey, 1993; value 31.3) lies above the plotted range and is marked with a triangle; all observations are used to estimate the lines.

Figure 3. ACPR plots for financial sector stability and climate change risk: (a) FMSI; (b) FISI.

4.9. PMG-ARDL Model Empirical Results

Table 10 presents the results for the SR and LR impacts of CCR on FSS.

As depicted in Table 10 for model 1, CCRI does not have statistically significant impacts on financial market stability, in either the short-run or the long-run. Thus, H_0 cannot be rejected, suggesting no statistically significant impacts of CCR on financial market stability across the EMEA countries in this study. This finding aligns with Akpa, Olayiwola, Abuta, and Badmus (2023) in that CCR has no significant impact on the stability of financial markets, such as stock markets. The finding implies that financial markets may exhibit sector-specific resilience to climate change risk, driven by the underlying impacts of regulatory buffers and institutional integrity, as discussed by Hand Schydlowsky (2020).

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Table 10. Estimates of short- and long-term impacts on financial sector stability.

Variables	Model 1	Model 2
	Coeff. (Std. err)	Coeff. (Std. err)
Long run		
Climate change risk index	-0.289 (0.169)	1.270*** 0.262)
Real GDP	-10.195*** (1.323)	-1.370 (1.430)
Inflation	-1.297 (1.022)	-4.904*** (1.704)
Short-run		
Error correction term	-0.297*** (0.026)	-0.157*** (0.016)
Climate change risk index	0.602 (0.544)	-0.135 (0.187)
Real GDP	3.503*** (0.531)	0.754*** (0.331)
Inflation	17.643*** (6.343)	12.902*** (5.327)
Constant	1.124*** (0.109)	0.162*** (0.043)

Note: *** represents the statistical significance level at 5%.

However, the findings from model 2 illustrate that CCRI has insignificant negative impacts on financial institution stability in the short term but exerts significant positive impacts in the long term.

The findings reveal that an intensification in climate change risk by one per cent can increase financial institution stability by approximately 1.27 per cent in the long run. This means rejection of the null hypothesis that CCR has no significant impact on financial institutions' stability. Thus, in the long term, climate change can enhance the stability of financial institutions in EMEA regions. The finding is counterintuitive as it contradicts climate-finance theories such as the FIH and the majority of existing empirical evidence. The plausible explanation for the positive long-run effect could be that increased climate risk exposure can incentivise financial institutions to engage in adaptive risk pricing, enhance risk screening, strengthen capital buffers, or reallocate portfolios. Hence, in the long term, such adaptive responses can promote resilience and promote stability. In addition, the positive effect could be due to the adoption of efficient short-term climate change risk mitigation and adaptation strategies and policies in the financial sector.

However, the results align with prior studies, which show that CCR can have significant positive effects on financial market stability (Liu et al., 2021; Oguntuase, 2020; Pointner & Ritzberger-Grünwald, 2019). The results disconfirm (Minsky, 1977) FIH, which holds that exogenous shocks such as climate-related financial risks play a significant role in triggering financial instability (Nikolaidi, 2021). The results also differ from those of the research by Chabot and Bertrand (2023), which found that climate change-related risks exerted long-term negative impacts on financial stability across Europe's financial institutions.

Whilst the empirical findings reflected significant positive effects of RGDP on FMSI and FISI in the short-run, the long-run negative effect on FMSI is interesting and tends to be counterintuitive. However, the findings could reflect pro-cyclical financial risk-taking behaviours of financial institutions when periods of sustained economic growth are accompanied by asset price inflation, capital misallocation, increased leverage, and credit booms, which can weaken the stability of financial markets (Gizaw, Getachew, & Mancha, 2024; Magubane, 2025; Ullah, Zubir, & Ariff, 2024). The findings by Ullah et al. (2024) on the inverted U-shaped association between financial development and economic growth support the present empirical findings.

Furthermore, Table 11 presents the comparative empirical results on the impact of CCR on FSS among different regions.

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Table 11. Estimates for CCR and financial sector stability across EMEA regions.

Variables		Model 1	Model 2
		Coeff. (std. err)	Coeff. (std. err)
Climate change risk index	Africa	-0.288	1.271***
		(0.169)	(0.262)
	Europe	-0.195	-0.180
		(0.186)	(0.093)
	Middle East	-0.585	-0.218***
		(0.328)	(0.104)
RGDP	Africa	-4.591***	-2.548
		(1.547)	(2.309)
	Europe	-16.273***	11.359***
		(1.948)	(3.372)
	Middle East	-0.247	3.046
		(1.517)	(2.016)
Inflation	Africa	1.463	-10.649
		(2.049)	(5.911)
	Europe	-3.686***	-2.639
		(1.565)	(2.608)
	Middle East	27.783***	57.875***
		(16.379)	(16.074)
Short-run			
Error correction term	Africa	-0.297***	-0.157***
		(0.027)	(0.016)
	Europe	-0.317***	-0.157***
		(0.023)	(0.023)
	Middle East	-0.315***	-0.198***
		(0.057)	(0.045)
Climate change risk index	Africa	0.602	-0.135
		(0.544)	(0.186)
	Europe	-0.237	-0.124
		(0.189)	(0.243)
	Middle East	-0.579	0.780
		(0.461)	(0.577)
RGDP	Africa	2.813***	-0.563
		(0.820)	(0.708)
	Europe	4.956	0.406
		(0.556)	(0.555)
	Middle East	1.382	0.954***
		(1.569)	(0.419)
Inflation	Africa	-2.801	8.434
		(6.073)	(7.198)
	Europe	47.903***	11.683
		(10.751)	(9.120)
	Middle East	-13.952	-16.481***
		(10.480)	(8.399)

Note: *** represents the statistical significance level at 5%.

The results reported in Table 11 show that climate change risk has no significant long-run or short-run effects on financial market stability in all three regions. This could mean that the financial markets of nations in the region are relatively resilient to climate change shocks.

From the results in Table 11, climate change risk has insignificant positive effects on financial institution stability in the short run across all three regions. However, climate change risk has significant positive long-run impacts on financial institution stability in Africa, while having significant negative impacts in the Middle East and insignificant long-run effects in Europe. These findings indicate that a change in climate change risk by one per cent can significantly lead to a 1.27% positive change in financial institution stability in Africa and a 0.22% negative change in financial institution stability in the Middle East in the long run. The divergent results between Africa and the Middle East can be attributed to differences or gaps in regional climatic conditions and climate finance mobilisation. For

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instance, the Middle East is considered one of the most climate-vulnerable regions globally, characterised by an arid climate and chronic water scarcity challenges (Qasem & Scholz, 2025). In addition, the Middle East region has historically received relatively smaller shares of global climate finance than the African region (Saghir, 2024). These gaps sufficiently explain the divergent results. Interestingly, the results from the regional comparison in Table 11 show an LR coefficient for CCRI of 1.271 is also nearly identical to the overall coefficient for the EMEA region of 1.270 presented earlier in Table 10. These interesting results are worth explaining as they suggest that overall EMEA results were likely to be driven predominantly by the African-region sub-sample. In other words, the significant positive effect attributable to the overall EMEA region appears to reflect the strength of the association between CCR and financial-sector stability in Africa. In substantive terms, the results reflect substantial intra-region heterogeneity.

5. CONCLUSION

The study examined the impacts of CCR on financial sector stability in selected EMEA countries. Panel data for the period from 1990 to 2023 across 55 selected EMEA countries were examined using the PMG-ARDL estimator. From the empirical estimations, climate change risk has no significant short- and long-term effects on financial markets' stability. However, positive long-run impacts and insignificant short-run impacts of CCR were confirmed on financial institutions' stability. Hence, the findings pertaining to the overall impacts of CCR on financial sector stability remain heterogeneous across the EMEA regions and financial sector stability dimensions. The results further confirmed significant differences in the impacts of CCR on financial sector stability across the three regions. Overall, the results showed that the long-term impacts of CCR on financial sector stability are lower in Europe than in Africa and the Middle East. The findings align with broader evidence that developing economies are more vulnerable to climate-induced financial disruptions.

6. RECOMMENDATIONS AND POLICY IMPLICATIONS

The empirical findings highlight the need for adaptive financial regulatory measures that integrate climate stress testing, dynamic climate risk modelling, and scenario analysis. This will aid in enhancing the resilience of the financial systems both in the short term and long term, leading to sustainable financial sector stability. Based on the findings, the study recommends that policymakers and regulators in the financial sector, such as central banks, integrate and embed climate change risk into the Prudential Financial sector policies and regulations. The integration will promote effective climate change risk management to support sustainable financial sector stability across the three regions: Africa, Europe, and the Middle East. The study further recommends that financial institutions across EMEA countries undertake rigorous, structured, and regular stress testing of climate-change risks. Climate stress testing is regarded as one of the most robust and reliable interventions for enhancing the functioning and stability of financial systems. Through regular stress testing, financial institutions would be able to predict or trace the transmission channels leading to the implementation of efficient and effective mitigation or adaptation interventions.

The study further recommends that regulators and policymakers, such as central banks, implement and effectively enforce obligatory climate risk disclosure requirements by financial institutions. This will promote the implementation of tailored climate-finance policies and strategies that will drive financial sector stability.

Funding: The authors received no financial support for the research.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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Appendices.

Appendix 1. Sample and Geographical Distribution of Countries.

Region	Number of Countries	Names of countries	% Representation
Africa	15	Algeria; Botswana; Côte d'Ivoire; Egypt; Ghana; Kenya; Morocco; Eswatini; Mauritius; Tunisia; South Africa; Namibia; Zambia; Nigeria; Zimbabwe	27.3%
The Middle East	12	Bahrain; Cyprus; Iran; Israel; Kuwait; Jordan; Lebanon; Oman; Palestine; Saudi Arabia; Turkey; United Arab Emirates	21.8%
Europe	28	Austria; Croatia; Czech Republic; Belgium; Bulgaria; Denmark; Estonia; Germany; Finland; France; Hungary; Iceland; Greece; Luxembourg; Ireland; Malta; Italy; Norway; United Kingdom; Netherlands; Poland; Romania; Russia; Portugal; Spain; Slovenia; Sweden; Switzerland	50.9%
Total	55		100%

Appendix 2. Index construction.

Min-max normalisation formula:

$$Z_{it} = \frac{X_{it} - \min(X_i)}{\max(X_i) - \min(X_i)} \qquad (1)$$

Where, Z_{it} represents the value of the individual indicator i at period t following normalisation; X_{it} represents the original value of the individual indicator i at period t; min (X_i) and max (X_i) are the minimum and maximum values of indicators i across selected countries, respectively.

Following normalisation and PCA, the composite indices were determined linearly in STATA 18 using the Cámara and Tuesta (2014) approach as follows:

$$CCRI_{it} = \omega_1 CO2_{it} + \omega_2 TEMP_{it} + \omega_3 PREC_{it} \qquad (2)$$

$$FMSI_{it} = \omega_1 SPV_{it} + \omega_2 SMRS_{it} \qquad (3)$$

$$FISI_{it} = \omega_1 BCBD_{it} + \omega_2 LAD_{it} \qquad (4)$$

Where: ω_i are weights for each individual dimension estimated from PCA. Note: indicator variables were in standardised form. Table 2A presents the unrotated results from PCA for climate change risk index construction, showing the initial eigenvalues and the proportion of the variance explained by each component before Varimax rotation, as well as the cumulative variance explained by each component. Only two components (PC1 and PC2) had eigenvalues of at least 1.00. Hence, based on the Kaiser Criterion or rule (eigenvalues> 1), the two (2) components were retained (PC1 and PC2), explaining 83.06% of the total variance.

Table 2A. Unrotated PCA results for CCRI.

Component	Eigen value	% Variance	Cumulative %
PC1	1.36	45.43%	45.43%
PC2	1.13	37.63%	83.06%
PC3	0.51	16.94%	100.00%

Table 2B presents the PCA results for climate change risk index construction after Varimax rotation, showing variance, the proportion of the variance explained by each retained component, as well as the cumulative variance of the retained components. The rotated components (RC1 and RC2) explained 42.63% and 40.38% of the variance, respectively.

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Table 2B. PCA results for CCRI after Varimax rotation.

Component	Variance	% Variance	Cumulative %
RC1	1.28	42.68%	42.68%
RC2	1.21	40.38%	83.06%

Table 2C presents the PCA results for climate change risk index construction, showing the factor loadings (representing the weights) for the retained components. CO_2 and PREC had strong positive loadings of 0.8026 and 0.8460 on Component 1 and Component 2, respectively, whilst TEMP had a moderate negative loading of -0.5827 on Component 1.

Table 2C. Rotated loadings for CCRI.

Variables	Comp1	Comp2
CO_2	0.8026	-0.2186
PREC	-0.1275	0.8460
TEMP	-0.5827	-0.4862

Note: Variables were standardized.

Table 2D presents the rotated PCA results for financial market stability index construction after Varimax rotation, showing the initial eigenvalues, the proportion of the variance explained by each component, as well as the cumulative variance of the components. Rotated components (PC1 and PC2) explained 55.38% and 44.62% of the variance, respectively. Based on the Kaiser Criterion or rule (eigenvalues> 1), one (1) component was retained (PC1), explaining 55.38% of the total variance.

Table 2D. Rotated PCA results for FMSI.

Component	Eigen value	% Variance	Cumulative %
PC1	1.11	55.38%	55.38%
PC2	0.89	44.62%	100%

Table 2E presents the PCA results for FMSI construction, showing the factor loadings (representing the weights) for the retained components. The factor loadings show the contribution of each indicator to the index. Table 2E shows that the two indicators (SPV and SMRS) loaded equally onto the FMSI.

Table 2E. Loadings for FMSI.

Variables	Loading
SPV	0.7071
SMRS	0.7071

Note: Variables were standardized.

Table 2F presents the Varimax rotated PCA results for FISI construction, showing the initial eigenvalues, proportion of variance explained, and the cumulative variance explained. PC1 and PC2 had eigenvalues of 1.05 and 0.95, explaining 52.51% and 47.49% of the variance, respectively. Based on the Kaiser Criterion or rule (eigenvalues> 1), one (1) component was retained (PC1), explaining 52.51% of the total variance.

Table 2F. Rotated PCA results for FISI.

Component	Eigen value	% Variance	Cumulative %
PC1	1.05	52.51%	52.51%
PC2	0.95	47.49%	100%

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Table 2G presents factor loadings from PCA for FISI construction, showing contributions of indicators (liquid assets to deposits and back credit to bank deposits) to the index. Whilst LAD had a strong positive loading of 0.7071, BCBD had a strong negative loading of -0.7071.

Table 2G. Loadings for FISI.

Variables	Loading
BCBD	-0.7071
LAD	0.7071

Note: Variables were standardized.

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