Journal of Posthumanism
2025
Volume: 5, No: 6, pp. 835-861
ISSN: 2634-3576 (Print) | ISSN 2634-3584 (Online)
posthumanism.co.uk

DOI: https://doi.org/10.63332/joph.v5i6.2153

Climate Change Risks and Financial Performance: Evidence from Listed Companies in Saudi Arabia

Amina Hamdouni[1], Aida Smaoui[2]

Abstract

Climate change has emerged as a critical external factor influencing firm performance, particularly in regions susceptible to extreme weather conditions. As environmental variability intensifies, firms operating in climate-sensitive sectors must understand how climate risks translate into financial outcomes. This study investigates the impact of key climate-related variables, including temperature, humidity, precipitation, and wind speed, on firm performance indicators, namely Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q (TBQ), using a panel dataset of firms listed on the Saudi Stock Exchange between 2010 and 2022 using two complementary econometric approaches: a fixed effects regression model and a dynamic panel Generalized Method of Moments (GMM) estimator. The fixed effects results reveal that precipitation and specific humidity negatively affect accounting-based performance, while relative humidity and wet-bulb temperature have positive effects on both ROA and ROE. Wind speed emerges as a significant disruptor, reducing both operational returns and market valuation. Tobin's Q is less consistently affected, likely due to external market factors. The GMM results largely confirm these findings with improved statistical rigor, reinforcing the negative impact of rainfall and humidity and the positive effects of moderate temperature and humidity on firm performance. These findings carry substantial implications for policy makers and corporate leaders, particularly in the context of Saudi Arabia's Vision 2030.

Keywords: *Climate Change Risk, Temperature, Humidity, Precipitation, Wind Speed, Firm Performance, Return on Assets (ROA), Return on Equity (ROE), Tobin's Q (TBQ),*

Introduction

Climate change is now one of the most pressing matters before the world community, affecting ecosystems and public health as much as, indeed very possibly more than, economic activity and firm performance. Across the world, countries are observing temperature, rainfall patterns, and frequency of occurrences of extreme events, direct and indirect impacts on business functioning and financial security. In Saudi Arabia, the threats of climate change are particularly acute. The Kingdom's already extreme desert climate is becoming even more volatile, with rising average temperatures, more prolonged heatwaves, and rare heavy rain showers posing major difficulties for sectors such as energy, agriculture, tourism, and logistics. These kinds of climatic variability can cause supply chain disruptions, increased operating expenses, and ultimately affect the profitability and feasibility of listed companies(Giang et al., 2021; Sun et al., 2020).

Numerous empirical studies have explored the relationship between climate change risks and financial performance, yielding mixed results that highlight the complexity of the issue. These

[1] Department of Finance, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, Email: amhomoduai@imamu.edu.sa, (Corresponding Author).
[2] Imam Mohammad Ibn Saud Islamic University (IMSIU), Email: AMSMAOUI@imamu.edu.sa

differences are often attributed to factors such as the economic sector, geographical region, type of climate risk considered, and the methodological approach used. On one side, several studies have identified a negative and statistically significant impact of rising temperatures and other climate-related risks on firms’ financial performance (Huang et al., 2018; Giang et al., 2021; Sun et al., 2020; Zhang et al., 2023; Mawejje, 2024; Wu, 2025; Griffin et al., 2025; Jiménez et al., 2023). Conversely, other research has reported a positive and significant association, particularly with rising temperatures, suggesting that certain industries or firms may experience financial or productivity gains from climatic shifts (Fei et al., 2023; Sun et al., 2023; Mondal and Bauri, 2024).

In addition, a number of empirical studies have reported mixed results regarding the relationship between rainfall intensity and corporate financial performance. On one hand, several studies have emphasized the negative impact of intense or irregular rainfall on firms' financial performance (Jiménez et al., 2023; Giang et al., 2021; Sun et al., 2020; Sun et al., 2023; Bhat et al., 2015; Huang et al., 2018; Brei et al., 2019). On the other hand, some research has identified positive effects of increased rainfall on specific industries, suggesting that certain sectors may benefit from greater precipitation levels (Guo et al., 2023; Sun et al., 2023).

Despite the growing body of empirical research examining the relationship between climate change risks and corporate financial performance, several important gaps remain. First, much of the existing literature has focused on developed or emerging economies, with limited attention given to climate-vulnerable regions such as the Middle East and, more specifically, Saudi Arabia. Second, the findings across studies are often contradictory, largely due to variations in climate variables used (e.g., temperature vs. rainfall), sectoral focus, and methodological approaches. Third, very few studies have explicitly linked climate risks to firm-level financial outcomes within the framework of national sustainability agendas. In this regard, the current study contributes by providing empirical evidence on how temperature rise and rainfall variability influence the financial performance of listed firms in Saudi Arabiaو a country experiencing increasing climate volatility. This research is particularly timely and relevant as it aligns with Saudi Arabia’s Vision 2030, which places strong emphasis on sustainability, economic diversification, and environmental resilience. By filling a regional and thematic gap in literature, this study offers new insights that can inform both corporate strategy and policy design in line with the Kingdom’s long-term development goals.

This study aims to examine and evaluate the impact of climate change risk on the financial performance of a sample of 100 companies listed on the Saudi Stock Exchange over the period from 2010 to 2022 using the fixed effects and the GMM (generalized method of moments) regression models. The fixed effects findings reveal that ROA and ROE are most strongly influenced by environmental factors like humidity and temperature, while TBQ is significantly impacted by wind speed and sales growth. The results of GMM suggest that environmental factors, particularly precipitation, humidity, and temperature, have varying impacts on firm performance measures such as ROA, ROE, and TBQ.

This paper is structured as follows: Section 1 presents the conceptual framework. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 explains the methodology and data used in the analysis. Section 4 reports and discusses the empirical results in detail. Finally, Section 5 offers the conclusion with significant recommendations.

Conceptual Framework

Climate Change: Definition and Causes

Patterns, particularly those variations observed since the mid-20th century. These variations are principally attributed to high concentrations of atmospheric carbon dioxide from fossil fuel burning. Climate change is not only about global warming but also more general variations in weather patterns like changes in rainfall, humidity, and frequency of extreme weather occurrences (IPCC, 2021; Giang et al, 2021). It is recognized as one of the greatest challenges to human societies and ecosystems today. Climate change refers to changes in temperature, humidity levels, precipitation rates, and wind speeds in a specific area over a long period compared to previous periods as a result of greenhouse gas emissions from human activities. Scientific consensus holds that the main causes of recent global climate change are anthropogenic. Foremost among these is the burning of fossil fuels like coal, oil, and gas, which release vast amounts of greenhouse gases into the air. Deforestation, the removal of forests that lower the planet's ability to absorb carbon dioxide, and agricultural activities that emit methane and nitrous oxide are also contributing factors. These factors related to humans add to the greenhouse effect, trapping heat and leading to global warming (NASA, 2022; Giang et al., 2021). In addition, according to the IPCC (Intergovernmental Panel on Climate Change), land use change, particularly agricultural and deforestation changes, contribute significantly towards greenhouse gas emissions. During the 2007-2016 period, land activities contributed around 13% of global carbon dioxide (CO_2) emissions, 44% of methane (CH_4) emissions, and 82% of nitrous oxide (N_2O) emissions. These are primarily caused due to agricultural activities such as land clearance for tillage, land management, and livestock raising. Human land use activities are considered important causes of climate change since these activities alter the natural carbon cycle and enhance the greenhouse effect (Guermazi et al., 2025; Jiménez et al., 2023). The increase in the emission of greenhouses and their intensification by human activities or natural factors has led to a certain increase in global warming, which in turn causes a rise in heatwaves on land, alteration in the frequency and intensity of rainfall, desertification, forest fires, hurricanes, and riotous storms (IPCC,2013; Fisk,2015; Giang et al., 2021).

Climate Change Risk in Saudi Arabia

Climate change is one of the Kingdom of Saudi Arabia's most critical challenges, with its negative effects being reflected across key sectors, particularly agriculture, the economy, and corporate financial performance. The growth of greenhouse gases and their intensification by human and natural forces have created a conclusive rise in temperatures, which are leading to the increase in extreme weather events such as hurricanes, storms, wildfires, and severe heatwaves all of which endanger the climate stability of the Kingdom. Research shows that in Saudi Arabia, from 1978 to 2019, there was a considerable rise in mean and extreme temperatures, with the minimum temperatures rising by 0.81°C every ten years. The frequency of warm days also rose approximately by 13 days every ten years, while cold days fell, indicating a pronounced change towards a warmer climate (Almazroui, 2020).

Moreover, rainfall frequency and intensity variations, changes in humidity levels, and shifts in wind patterns are some of the most apparent manifestations of climate change that have direct impacts on the national economy and financial performance of Saudi Arabian businesses. These interruptions affect agricultural, manufacturing, and transportation production processes, reduce crop quality, hamper supply chain effectiveness, and increase operation and maintenance costs, ultimately reducing profitability and escalating operating risks. The Kingdom is ranked as highly vulnerable in its agricultural economy against climate change with a Climate Change Vulnerability Index (CCVI) of 0.730, which indicates high risk, while the adaptive capacity of farmers continues to be low with a score of only 0.567 (Alotaibi et al., 2024).

The effect of climate change extends beyond environmental and economic effects into geopolitical spheres as well. There is proof of a two-way interaction between climate change variability and heightened regional tensions, which further weighs heavily on policymakers within the Kingdom (Dhifaoui et al., 2023). Climate risk also threatens financial institutions with an emerging risk, requiring that an integrated climate risk management framework be adopted to help develop the resilience of the financial system to these changes (Sarabdeen, 2022). All these elements affirm that responding to climate change in Saudi Arabia is no longer a choice, it's a matter of strategic need to ensure economic security and sustainability of corporate financial performance

Literature Review and Hypothesis Development

In recent years, there has been an incredible escalation of global attention to the threats of climate change with mounting scientific evidence of their extremely negative effects on human beings, the environment, and the economy. Climate change is no longer just an environmental issue, but an all-embracing threat that affects food security, public health, and the stability of economic and financial systems. Successive natural disasters in the guise of floods, heatwaves, and droughts have caused extensive damage to infrastructure and severe financial loss to nations and businesses alike, while undermining global supply chains. Such issues have led numerous governments and intergovernmental organizations to adopt emergency responses to reduce carbon emissions and develop policy responses to adapt to emerging climate conditions. In that light, several academic papers have examined the connection between climate risks and firm performance. Their findings highlight that the vulnerability to climate risks, whether physical or transitional, can have negative impacts on financial performance measures such as return on assets, growth in sales, or asset value in the market. Furthermore, these studies show that companies adopting transparent sustainability strategies and ones being better prepared for climate change are more robust and have better long-term performance. Therefore, integrating climate risk into company governance and risk management frameworks is now central to ensuring business continuity and competitiveness should there be future pressure from the environment.

(Huang et al., 2018) examine the impact of extreme weather events on financial performance and financing decisions of publicly traded firms across 55 countries over the period 1993–2012. Using the Global Climate Risk Index (CRI) by Germanwatch as a proxy for climate risk, the authors employ multivariate regression analysis with firm-level and country-level controls, as well as robustness tests including instrumental variable techniques and propensity-score matching. The main findings reveal that higher climate risk is associated with lower and more volatile firm earnings and cash flows.

(Giang et al., 2021) investigates the effects of climate change risks, specifically temperature, rainfall, sunshine hours, and humidity, on the financial performance of 144 listed manufacturing firms in Vietnam from 2015 to 2019. The authors employ panel data regression models using ROA, ROE, and ROS as performance indicators, while including firm-level controls like capital structure, firm size, and growth. The findings show that humidity risk has a significant negative impact on all financial performance indicators, while temperature, rainfall, and sunshine hours have no significant effects, possibly due to regional climatic uniformity or sectoral resilience. In addition, firm growth and size are found to be positively associated with financial performance, whereas a higher debt ratio is negatively related. The study concludes that climate risks, especially humidity, can directly and indirectly impair productivity and profitability in Vietnam's manufacturing sector, underlining the need for proactive climate adaptation strategies and better environmental governance.

The study by (Sun et al., 2020) aims to examine the impact of climate change risks on the financial performance of listed mining companies in China. The authors focus on evaluating how environmental disruptions such as extreme weather events (physical risks) and regulatory or policy changes related to climate mitigation (transitional risks) influence key financial indicators, specifically return on assets (ROA) and return on equity (ROE). Using panel data analysis, the study analyzes a sample of Chinese mining firms by constructing indices to quantify climate-related risks and applying regression models to assess their relationship with firm performance. The findings reveal that both physical and transitional climate risks have a significant and negative effect on corporate financial performance. (Zhang et al., 2023) investigates how climate risk influences both the financial performance and financing policies of firms across 37 countries. Using the Global Climate Risk Index (CRI) from German watch and firm-level data sourced from the Bloomberg database covering the period 2017–2021, the authors applied Pearson correlation and regression analysis via SPSS to assess the relationship between climate risk and corporate metrics such as return on assets (ROA), cash flow from operations (CFO), and debt structure. The main findings indicate that while climate risk has a negative but statistically insignificant impact on financial performance (ROA and CFO), it has a significant positive relationship with long-term debt. This suggests that firms in high climate risk regions tend to adopt more conservative financing policies by increasing long-term debt to manage potential volatility and uncertainty.

recent studies examine the nexus between climate risk and financial performance. (Mawejje, 2024) analyses how weather and climate change impact firm performance in low-income countries, focusing specifically on Uganda. The research uses a novel panel dataset comprising quarterly business climate surveys and district-level temperature data to analyze both perceived and actual weather shocks. Methodologically, the study employs random effects ordered logistic panel models to assess the relationship between climate shocks and several business performance indicators, such as turnover, profit, capacity utilization, employment, and business optimism. The findings reveal that weather and temperature shocks significantly and negatively affect firm performance, with micro and small enterprises, especially in the agriculture and industrial sectors, being the most vulnerable. (Wu, 2025) investigates the impact of extreme temperatures on the asset value of firms in China, aiming to quantify how climate risk, especially from very high (>30°C) and very low (≤−10°C) temperatures, affects corporate value. The author uses daily temperature data from NOAA and links it with financial data from 139,100 Chinese industrial firms across 2005–2014. Employing panel regression models with temperature bins in 5°C intervals, the study finds that both extremely high and low temperatures significantly reduce corporate asset value, particularly in capital- and labor-intensive industries. (Griffin et al., 2025) analyses how spells of extreme high temperature impact the financial performance and ESG behavior of over 57,000 EU and UK firms between 2011 and 2019. Using a dataset that combines firm-level financial indicators with Copernicus weather records, the authors analyze the sales-to-assets ratio, pre-tax profit margin, and return on assets (ROA) in relation to the intensity and duration of extreme temperature spells. The study employs curvilinear regression models and finds a hump-shaped (nonlinear) relationship: financial performance improves with moderate temperature increases in cooler climates but declines sharply beyond a threshold (~23°C), especially in hotter regions. Additionally, firms do not show meaningful improvements in ESG scores or reductions in carbon emissions following these heat events, suggesting limited managerial response. These findings highlight the material financial risks posed by acute climate events and call for stronger corporate climate risk disclosure and management frameworks.

In addition, several empirical studies, in recent years, have examined the relationship between climate change and agricultural performance, focusing on both productivity and financial impacts. Collectively, these studies indicate that the effects of climate change on the agricultural sector are complex and vary depending on the climatic context, the type of agricultural activity, and the analytical model used. Nevertheless, most studies agree that there are both direct and indirect risks to productivity and financial returns, and they emphasize the need for effective adaptation strategies and improved environmental governance to ensure the sustainability of the agricultural sector in the face of climate variability. Using 38 years of data (1983–2020), (Guo et al., 2023) applied Pearson correlation analysis and fixed-effects panel data models to evaluate the influence of precipitation, temperature, and grazing on grassland yield in Inner Mongolia, China. The principal findings indicate that precipitation has a significant positive effect on productivity, while higher temperatures in the non-growing season also positively influence productivity. Grazing intensity, however, tends to negatively affect yield. Moreover, (Jiménez et al., 2023) found an inverse relationship between rising average temperatures and the agricultural ecosystem, as plant growth and productivity decline due to the increased spread of pests and diseases and the reduced fertility of agricultural soil.

Unlike previous studies that found a negative effect of climate change on firms' financial performance, some studies have found a positive and significant relationship between climate change risks and financial performance. (Fei et al., 2023) found that rising temperatures could lead to an increase in wheat and grassland production and consequently, a decrease in wheat prices, which enhances the welfare of local producers and international trade. In addition, the study by (Sun et al., 2023) found a significant and positive relationship between rising temperatures and financial performance indicators, especially in sectors that are sensitive to climate factors. The results indicate that climate change, particularly temperature increases, has a direct impact on corporate performance and financial stability. The authors emphasized the importance of considering climate variables in financial analyses and highlighted the necessity of proactive policies to mitigate the effects of climate risks on financial outcomes. (Mondal & Bauri, 2024) examine the effects of climate transition risk on both the financial performance and market value creation of major Indian firms. Focusing on 32 non-financial Nifty 50 companies, the authors use the Environmental Risk Score (ERS) as a proxy for climate transition risk. Financial performance is measured using Return on Assets (ROA) and Return on Equity (ROE), while Tobin’s Q is used as an indicator of market value. The empirical findings reveal a positive relationship between climate transition risk and financial performance indicating that firms with higher ERS tend to report higher ROA and ROE. However, a negative relationship is observed between climate transition risk and Tobin’s Q, suggesting that greater exposure to transition risks reduces a firm’s market value.

In conclusion, the findings of previous studies examining the relationship between climate change risks and financial performance have been varied, reflecting the complexity of this issue and its dependence on several factors such as economic sector, geographic location, type of climate risk, and analytical methodology. On one hand, some studies have found a negative and significant relationship between rising temperatures or various climate risks and firms' financial performance (Huang et al., 2018, 2018; Giang et al., 2021; Sun et al., 2020; Zhang et al., 2023; Mawejje, 2024; Wu, 2025; Griffin et al., 2025; Jiménez et al., 2023). On the other hand, other studies have revealed a positive and significant relationship between climate change risk, particularly rising temperature, and financial performance, indicating that some sectors or companies may benefit from climatic changes in terms of productivity or financial returns (Fei et al., 2023; Sun et al., 2023; Bauri and Mondal, 2024). The current study aims to contribute significantly to the literature by focusing on the case of Saudi Arabia, a country where empirical research on this topic remains scarce. Given Saudi Arabia's unique climatic and economic conditions, this study provides a timely and context-specific analysis of how climate change risks impact corporate financial performance. It also addresses a critical research gap by offering insights into the adaptability of Saudi firms and the potential implications for market stability and strategic planning in the face of increasing climate variability.

Several empirical studies have examined the relationship between the risks of changes in rainfall and corporate financial performance. In the agricultural sector, numerous studies have found that the intensity of rainfall and changes in the onset or end of the rainy season in tropical regions have a negative impact on crop productivity and quality (Jimenez et al,2023; Giang et al., 2021). In addition, intense rainfall can damage production materials in the manufacturing sector, which is highly sensitive, and this may negatively affect the financial performance of manufacturing companies (Sun et al., 2020; Giang et al., 2021; Sun et al., 2023). (Bhat et al., 2015) examine the impact of climatic variability, specifically changes in rainfall and temperature. on the salt production of Sambhar Lake, a major salt-producing wetland in Rajasthan, India. Using meteorological data (2005–2013) and salt production records from Sambhar Salts Limited, the authors apply both descriptive and inferential statistical tools, including multiple regression analysis, to examine the relationship between climate variables and annual salt output. The findings reveal that higher temperatures significantly increase salt production, while increased rainfall tends to reduce it, due to brine dilution and reduced evaporation. On the other hand, the studies by (Huang et al., 2018) and (Brei et al., 2019) showed that natural disasters such as hurricanes, storms, and changes in rainfall intensity have negative effects on banking operations and cash flows.

Although many studies have found a significant negative relationship between the intensity of rainfall variability and corporate financial performance, it is possible that such changes may have a positive impact on the performance of companies in certain industries, such as mining and construction materials (Huang et al., 2018; Sun et al., 2020). Moreover, (Guo et al., 2023) found that rainfall intensity has a positive and significant effect on grassland productivity. (Sun et al., 2023) also found a positive and significant relationship between rainfall intensity and the financial performance of electric power companies. An increase in rainfall leads to higher levels of hydroelectric power generation, which in turn reduces generation costs and improves financial performance.

In summary, previous empirical studies have shown mixed findings regarding the relationship between rainfall intensity and corporate financial performance. On one hand, several studies have highlighted the negative effects of intense or irregular rainfall on financial performance (Jimenez et al., 2023; Giang et al., 2021; Sun et al., 2020; Sun et al., 2023; Bhat et al.,2015; Huang et al.,2018; Brei et al.,2019). On the other hand, some studies have reported positive impacts of increased rainfall on certain industries (Guo et al., 2023; Sun et al.,2023). Building on these contrasting findings, the current study contributes to the literature by examining the specific case of Saudi Arabia, a country characterized by scarce rainfall and high climate variability. It aims to assess whether changes in rainfall intensity affect corporate financial performance in this unique environmental and economic context, where empirical research remains limited. This study thus provides valuable insights for policymakers and firms operating in arid and semi-arid regions facing growing climate-related uncertainties.

Based on the available literature, it is clear that climate risk has a negative impact on business operations. Its impact on firm performance may vary by industry. Therefore, we set the following hypothesis to examine the research question of this research.

Climate-Related Variables

Precipitation (PREC)

H_{01}: Precipitation has no significant effect on firm performance (ROA, ROE, TBQ).

H_{11}: Precipitation has a significant effect on firm performance (ROA, ROE, TBQ).

Specific Humidity (QV2M)

H_{02}: Specific humidity has no significant effect on firm performance (ROA, ROE, TBQ).

H_{12}: Specific humidity has a significant effect on firm performance (ROA, ROE, TBQ).

Relative Humidity (RH2M)

H_{03}: Relative humidity has no significant effect on firm performance (ROA, ROE, TBQ).

H_{13}: Relative humidity has a significant effect on firm performance (ROA, ROE, TBQ).

Wet-Bulb Temperature (T)

H_{04}: Wet-bulb temperature has no significant effect on firm performance (ROA, ROE, TBQ).

H_{14}: Wet-bulb temperature has a significant effect on firm performance (ROA, ROE, TBQ).

Maximum Temperature (T_MAX)

H_{05}: Maximum temperature has no significant effect on firm performance (ROA, ROE, TBQ).

H_{15}: Maximum temperature has a significant effect on firm performance (ROA, ROE, TBQ).

Minimum Temperature (T_MIN)

H_{06}: Minimum temperature has no significant effect on firm performance (ROA, ROE, TBQ).

H_{16}: Minimum temperature has a significant effect on firm performance (ROA, ROE, TBQ).

Wind Speed (WS2M)

H_{07}: Wind speed has no significant effect on firm performance (ROA, ROE, TBQ).

H_{17}: Wind speed has a significant effect on firm performance (ROA, ROE, TBQ).

Control Variables

Leverage (LEV)

H_{08}: Leverage has no significant effect on firm performance (ROA, ROE, TBQ).

H_{18}: Leverage has a significant effect on firm performance (ROA, ROE, TBQ).

Firm Size (SIZE)

H_{09}: Firm size has no significant effect on firm performance (ROA, ROE, TBQ).

H_{19}: Firm size has a significant effect on firm performance (ROA, ROE, TBQ).

Sales Growth (G)

H_{010}: Sales growth has no significant effect on firm performance (ROA, ROE, TBQ).

H_{110}: Sales growth has a significant effect on firm performance (ROA, ROE, TBQ).

Methodology

Data, Sample and Sources

For the purpose of analyzing the relationship between climate variables and firm performance in Saudi Arabia, the most appropriate industries to focus on are those that are both environmentally impactful and highly sensitive to climatic conditions. In particular, the energy, utilities, and petrochemical sectors stand out due to their significant contributions to Saudi Arabia's GDP, their high levels of greenhouse gas emissions, and their operational vulnerability to heat, humidity, and water availability. Firms such as Saudi Aramco, SABIC, and ACWA Power exemplify this group, as they operate in emissions-intensive industries that are increasingly subject to environmental regulations and public scrutiny. Additionally, sectors such as agriculture and food processing are highly climate-dependent, especially in the context of water scarcity and extreme heat—two key challenges facing Saudi Arabia. While real estate, construction, and transportation are also influenced by weather and climate variability, the heavy-polluting nature and availability of environmental disclosures make energy-related industries particularly relevant. Thus, for a focused and policy-relevant investigation into how climate factors influence firm performance, as measured by ROA, ROE, and Tobin's Q, the energy, petrochemical, and utility sectors provide the strongest analytical foundation.

The sample in this study consisted of 100 companies listed on the Saudi Stock Exchange. Considering a time span of 13 years, from 2010 to 2022, we used data gathered from two main sources: climate change risk indicators are obtained from NASA World Weather and company-issued sustainability reports. Financial performance metrics, such as ROA, ROE, and Tobin's Q are collected from publicly available financial statements. The final sample includes firms with complete financial data over the study period. Missing data points are addressed using linear interpolation to preserve the integrity of the panel dataset.

Several studies use panel data analysis to examine the relationship between climate variables and firm performance. This approach allows researchers to control for unobserved heterogeneity and examine changes over time. OLS (ordinary least squares), fixed effects, random effects, and GMM (generalized method of moments) regression models are frequently used. These methods are employed to assess the impact of climate variables on various financial and market indicators, as well as address endogeneity concerns.

In this research, OLS (ordinary least squares), fixed effects, random effects and the Generalized Method of Moments (GMM) were applied to sample firms to examine our hypotheses and provide responses to the respective research questions.

Model 1: $ROA_{i,t} = \beta_0 + \beta_1 PREC_{i,t} + \beta_2 QV2M_{i,t} + \beta_3 RH2M_{i,t} + \beta_4 T_{i,t} + \beta_5 T\_MAX_{i,t} + \beta_6 T\_MIN_{i,t} + \beta_7 WS2M_{i,t} + \beta_8 LEV_{i,t} + \beta_9 SIZE_{i,t} + \beta_{10} G_{i,t} + \varepsilon_{i,t}$

Model 2: $ROE_{i,t} = \beta_0 + \beta_1 PREC_{i,t} + \beta_2 QV2M_{i,t} + \beta_3 RH2M_{i,t} + \beta_4 T_{i,t} + \beta_5 T\_MAX_{i,t} + \beta_6 T\_MIN_{i,t} + \beta_7 WS2M_{i,t} + \beta_8 LEV_{i,t} + \beta_9 SIZE_{i,t} + \beta_{10} G_{i,t} + \varepsilon_{i,t}$

Model 3: $TBQ_{i,t} = \beta_0 + \beta_1 PREC_{i,t} + \beta_2 QV2M_{i,t} + \beta_3 RH2M_{i,t} + \beta_4 T_{i,t} + \beta_5 T\_MAX_{i,t} + \beta_6 T\_MIN_{i,t} + \beta_7 WS2M_{i,t} + \beta_8 LEV_{i,t} + \beta_9 SIZE_{i,t} + \beta_{10} G_{i,t} + \varepsilon_{i,t}$

Generalized Method of Moments (GMM) is a powerful estimation technique often used in panel data analysis, especially when dealing with potential endogeneity issues.

General GMM Model Form:

$y_{i,t} = \alpha y_{i,t-1} + \beta X_{i,t} + \eta_i + \varepsilon_{i,t}$

Where:

- $y_{i,t}$ is the dependent variable,
- $y_{i,t-1}$ is the lagged dependent variable (creates endogeneity),
- $X_{i,t}$ are independent variables,
- η_i is the unobserved fixed effect,
- $\varepsilon_{i,t}$ is the error term.

Applying the GMM model has many benefits as it effectively addresses heteroskedasticity, autocorrelation, and endogeneity issues.

Model 4: $ROA_{i,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 PREC_{i,t} + \beta_3 QV2M_{i,t} + \beta_4 RH2M_{i,t} + \beta_5 T_{i,t} + \beta_6 T\_MAX_{i,t} + \beta_7 T\_MIN_{i,t} + \beta_8 WS2M_{i,t} + \beta_9 LEV_{i,t} + \beta_{10} SIZE_{i,t} + \beta_{11} G_{i,t} + \varepsilon_{i,t}$

Model 5: $ROE_{i,t} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 PREC_{i,t} + \beta_3 QV2M_{i,t} + \beta_4 RH2M_{i,t} + \beta_5 T_{i,t} + \beta_6 T\_MAX_{i,t} + \beta_7 T\_MIN_{i,t} + \beta_8 WS2M_{i,t} + \beta_9 LEV_{i,t} + \beta_{10} SIZE_{i,t} + \beta_{11} G_{i,t} + \varepsilon_{i,t}$

Model 6: $TBQ_{i,t} = \beta_0 + \beta_1 TBQ_{i,t-1} + \beta_2 PREC_{i,t} + \beta_3 QV2M_{i,t} + \beta_4 RH2M_{i,t} + \beta_5 T_{i,t} + \beta_6 T\_MAX_{i,t} + \beta_7 T\_MIN_{i,t} + \beta_8 WS2M_{i,t} + \beta_9 LEV_{i,t} + \beta_{10} SIZE_{i,t} + \beta_{11} G_{i,t} + \varepsilon_{i,t}$

where: $\varepsilon_{i,t}$ is the error term

This study examines the impact of climate-related variables on firm performance using both accounting-based and market-based financial indicators. All measurements of variables in this study were detailed and summarized in Table 1. The dependent variables include Return on Assets (ROA), which measures profitability relative to a firm's total assets; Return on Equity (ROE), which reflects net income relative to shareholders' equity; and Tobin's Q (TBQ), a market-based indicator calculated as the ratio of a firm's market value to the replacement cost of its assets. The key independent variables capture daily climate conditions. Precipitation (PREC) is measured in millimeters per day and represents the intensity of rainfall. Specific humidity (QV2M), measured in grams of water vapor per kilogram of air, and relative humidity (RH2M), expressed as a percentage, both reflect atmospheric moisture levels. Wet-bulb temperature (T) at 2 meters is included to account for heat stress, combining temperature and humidity effects. Maximum (T_MAX) and minimum (T_MIN) daily temperatures at 2 meters provide insights into heat extremes and nighttime cooling, respectively. Wind speed (WS2M), measured in meters per second, is used to capture the effect of air movement on firm operations and comfort levels. In addition to climate factors, the model incorporates firm-specific control variables. Leverage (LEV) is defined as the ratio of total debt to total assets, reflecting a firm's financial risk. Company size (SIZE) is measured as the natural logarithm of total assets, while growth (G) is captured by the annual percentage change in sales revenue. These variables collectively enable a comprehensive assessment of how climate variability influences firm performance.

Variables	Symbols	Description
Return on Assets	ROA	A financial ratio indicating how profitable a company is relative to its total assets. Calculated as Net Income / Total Assets.
Return on Equity	ROE	A financial ratio measuring profitability in relation to shareholders' equity. Calculated as Net Income / Shareholders' Equity.
Tobin's Q	TBQ	A market-based performance measure calculated as the market value of a firm divided by the replacement cost of its assets.
Precipitation	PREC	Daily corrected precipitation measured in millimeters per day (mm/day). Reflects the intensity of rainfall.
Specific Humidity	QV2M	Specific humidity at 2 meters above ground, measured in grams of water vapor per kilogram of air (g/kg).
Relative Humidity	RH2M	The percentage of moisture in the air at 2 meters relative to the maximum it can hold at that temperature.
Wet-Bulb Temperature	T	The temperature at 2 meters that accounts for both heat and humidity, indicating thermal comfort or heat stress.
Maximum Temperature	T_MAX	The highest daily temperature measured at 2 meters above the ground. Reflects peak heat conditions.
Minimum Temperature	T_MIN	The lowest daily temperature measured at 2 meters above the ground. Reflects overnight or early morning cooling.
Wind Speed	WS2M	Average wind speed at 2 meters above ground, measured in meters per second (m/s).
Leverage	LEV	A financial ratio showing the proportion of a company's capital that is financed through debt. Typically calculated as Total Debt / Total Assets.
Company Size	SIZE	The natural logarithm of total assets, used to proxy for firm size.
Growth	G	The annual growth rate of a company, commonly measured by the percentage change in sales revenue.

Table 1. Variables Definitions

Results and Discussion

a. Descriptive statistics

Table 2 provides a detailed summary of the descriptive statistics for the key variables in the study, including firm performance indicators, climate-related factors, and control variables. The Return on Assets (ROA) and Return on Equity (ROE) have moderate variability, with ROA ranging from -0.053 to 0.189 and ROE from -0.110 to 0.302, indicating differing levels of profitability across firms. In contrast, Tobin's Q (TBQ) shows a wider range, with values between 0.520 and 3.022, suggesting that firms are generally valued above their book value, with some significant variation. Among climate variables, precipitation (PREC) and specific humidity (QV2M) display moderate fluctuations, while relative humidity (RH2M) and temperature (T) show somewhat greater variation. For example, T_MAX (maximum temperature) remains fairly stable, but T_MIN (minimum temperature) exhibits more fluctuation, ranging from -4.310 to 2.640. The wind speed (WS2M) variable shows very little variation. On the firm-specific side, leverage (LEV) varies from 0.105 to 2.010, reflecting diverse capital structures, and firm size (SIZE) ranges from 6.245 to 11.533, suggesting differing scales of operation. Lastly, sales growth (G) varies widely, from -0.323 to 0.446, showing significant differences in firm growth trajectories. These descriptive statistics highlight the diverse characteristics of the sample, which will be important in understanding how environmental factors interact with firm performance.

Variable	Mean	Maximum	Minimum	Std. Dev.
ROA	0.073	0.189	-0.053	0.064
ROE	0.093	0.302	-0.110	0.112
TBQ	1.781	3.022	0.520	0.733
PREC	0.066	0.210	0.010	0.051
QV2M	4.530	5.010	4.160	0.207
RH2M	24.237	26.160	21.180	1.251
T	12.614	13.380	11.930	0.407
T_MAX	44.202	45.000	43.100	0.535
T_MIN	-0.096	2.640	-4.310	1.882
WS2M	3.295	3.380	3.140	0.068
LEV	1.057	2.010	0.105	0.561
SIZE	10.344	11.533	6.245	0.917
G	0.014	0.446	-0.323	0.153

Table 2. Descriptive Statistics

b. Correlation matrix

Table 3 reveals the correlations between the dependent variables (ROA, ROE, and TBQ), independent variables (climate-related factors), and control variables (LEV, SIZE, and G). In terms of the dependent variables and climate factors, the correlations are generally weak. ROA shows almost no correlation with climate-related variables, suggesting that asset profitability is not significantly influenced by environmental factors. However, ROE exhibits a modest positive correlation with QV2M and RH2M, indicating that higher humidity may be slightly linked to improved equity profitability. Similarly, ROE has a weak positive relationship with temperature (T), suggesting that warmer conditions might have a slight positive effect on equity returns. In contrast, TBQ shows very weak relationships with the climate factors, although wind speed

(WS2M) has a small negative correlation with TBQ, suggesting that higher wind speeds might slightly reduce market valuation relative to book value.

When looking at the control variables, ROA shows a slight positive correlation with LEV, implying that firms with higher leverage may experience slightly higher asset profitability, though this relationship is weak. ROE and TBQ show almost no correlation with LEV, SIZE, or G, suggesting that firm size, capital structure, and sales growth have minimal influence on these performance indicators. Notably, sales growth (G) has a weak negative correlation with TBQ, indicating that firms with higher growth may be somewhat less favorably valued in the market relative to their book value.

Overall, the analysis reveals that while climate-related factors, particularly humidity and temperature, may have a slight impact on ROE, the influence on ROA and TBQ is negligible. Moreover, the control variables—leverage, firm size, and sales growth—show little significant effect on firm performance or market valuation, suggesting that other factors may be more important in determining firm outcomes.

P	ROA	ROE	TBQ	PREC	QV2M	RH2M	T	T_MAX	T_MIN	WS2M	LEV	SIZE	G
ROA	1.00												
ROE	-0.03	1.00											
TBQ	-0.03	-0.01	1.00										
PREC	-0.01	**0.054***	0.01	1.00									
QV2M	0.00	**0.067****	0.01	**-0.10*****	1.00								
RH2M	-0.01	**0.07*****	0.00	**0.24*****	**0.08*****	1.00							
T	0.02	**0.06****	0.01	**-0.29*****	**0.08*****	**0.51*****	1.00						
T_MAX	0.01	0.04	0.01	**0.44*****	**-0.09*****	**-0.22*****	**-0.06****	1.00					
T_MIN	-0.01	**-0.06****	-0.01	**-0.26*****	0.01	**-0.05***	**0.06****	-0.03	1.00				

WS2M	-0.03	-0.02	**-0.06****	**-0.38*****	**0.19*****	**0.22*****	**0.18*****	**-0.36*****	**-0.13*****	1.00			
LEV	0.04	0.01	0.00	0.03	-0.01	-0.01	-0.03	0.03	0.01	-0.02	1.00		
SIZE	0.00	-0.01	0.04	-0.02	0.01	0.01	-0.01	-0.03	-0.01	0.04	0.01	1.00	
G	0.01	-0.03	**-0.06****	0.00	-0.02	-0.03	-0.03	0.01	-0.04	0.00	-0.01	-0.02	1.00

Table 3. Pearson Correlation Matrix

Notes: *p <0.10; **p <0.05; ***p <0.01.

Unit Root Tests

Unit root tests in panel data are performed to check whether our variables are stationary-a critical requirement in many types of econometric analyses. It’s necessary: To avoid spurious regressions, to ensure valid inference in panel regressions (methods like OLS, GMM, and Fixed Effects assume that the variables are stationary, or at least cointegrated if non-stationary. if variables are non-stationary and not cointegrated, our model may produce biased or inconsistent estimates.) and to decide on model specification. Without testing for unit roots, our panel regression results may be unreliable, misleading, or even invalid.

The test’s null hypothesis is that there is all panels contain unit roots (all series are non-stationary), while the alternative hypothesis suggests that some panels are stationary.

Table 4 reports the results of panel unit root tests using the Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) methods to assess the stationarity of the variables used in the analysis. The results indicate that all variables are stationary at level I(0), as evidenced by statistically significant LLC and IPS statistics at the 1% level. This leads to the rejection of the null hypothesis of a unit root and confirms that the series do not exhibit non-stationary behavior in their level form. Additionally, the tests conducted at first difference I(1) also yield significant results, further reinforcing the robustness of the stationarity findings.

	Levin–Lin–Chu unit root test (LLC)		Im–Pesaran–Shin unit root test (IPS)	
Variables	I(0)	I(1)	I(0)	I(1)
ROA	-20.2914***	-38.0329***	-15.9025***	-16.0188***
ROE	-18.9974***	-37.1656***	-14.5490***	-14.2118***
TBQ	-19.0008***	-37.8518***	-15.0070***	-14.8511***
PREC	-19.8336***	-22.0175***	-18.9511***	-20.6035***
QV2M	-8.1559***	-26.2404***	-10.5369***	-15.6399***
RH2M	23.6727***	-9.0766***	-19.0439***	-21.5687***
T	-12.6403***	-48.3343***	-10.0389***	-17.4635***

T_MAX	-12.0011***	-35.6697***	-9.9982***	-17.0193***
T_MIN	-17.2956***	-27.8939***	-13.4459***	-19.5982***
WS2M	-16.5631***	-17.0584***	-15.9267***	-15.0578***
LEV	-19.3930***	-24.3994***	-15.3793***	-18.9933***
SIZE	-21.5619***	-23.5652***	-14.6945***	-18.9308***
G	-20.6822 ***	-29.7251***	-19.5739***	-21.0196***

Table 4. Panel Unit Root Results.

Notes: *p <0.10; **p <0.05; ***p <0.01.

The stationarity of the variables at level validates the use of traditional panel data models such as Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE), which assume stationary data to avoid spurious regressions. More importantly, it supports the application of the Two-Step System Generalized Method of Moments (System GMM) estimator. Since GMM relies on the assumption of stationarity for the consistency of its moment conditions and instrument validity, the unit root test results provide a strong foundation for the dynamic panel estimation used in the study to examine the effects of climate variables on firm performance.

Panel Cross-Sectional Dependence Tests

Panel cross-sectional dependence tests are conducted to determine whether there are correlations across cross-sectional units (e.g., firms, countries, industries) in a panel dataset. This is important because many panel data models assume cross-sectional independence, and violating this assumption can lead to biased standard errors, invalid test statistics, and inconsistent estimators.

The common tests for cross-sectional dependence are Breusch-Pagan LM test (for small N, large T), Pesaran CD test (for large N, small T), Friedman test (for large T, small N) and Frees test (Moderate to large T, Small to moderate N). Given the panel structure of the dataset, which consists of a large number of cross-sectional units (N = 100) and a relatively small-time dimension (T = 13), the selection of an appropriate test for cross-sectional dependence is critical. Among the commonly used tests, the Breusch-Pagan LM test is suitable for panels with small N and large T, while the Friedman and Frees tests are more appropriate when T is moderate to large, and N is small to moderate. In contrast, the Pesaran CD test is specifically designed for panels characterized by large N and small T, making it the most appropriate choice for the present study. Accordingly, the Pesaran CD test is employed to assess the presence of cross-sectional dependence in the residuals of the panel regression models.

The Pesaran Scaled LM (CD test) is used to test for cross-sectional dependence in panel data. It is a test for whether residuals across cross-sectional units (such as companies or countries) are correlated. If cross-sectional dependence exists, it suggests that there are common factors affecting the units, and ignoring such dependence could lead to inefficient and biased estimates. The test statistic CD is calculated by examining the correlation of residuals across units. The null Hypothesis (H0) is no cross-sectional dependence (i.e., residuals are uncorrelated) while the alternative Hypothesis (Ha) is There is cross-sectional dependence. If the p-value is small (typically less than 0.05), it suggests that there is significant cross-sectional dependence in your model, meaning the residuals are correlated across cross-sectional units.

Table 5 presents the Pesaran Scaled LM (CD) test results for cross-sectional dependence across four panel data estimation methods—Pooled OLS, Fixed Effects, Random Effects, and GMM—using three measures of firm performance: ROA, ROE, and Tobin's Q. The test evaluates the null hypothesis that the residuals are cross-sectionally independent.

Across all model specifications and performance indicators, the p-values exceed 0.40, with most above 0.50 and some reaching as high as 0.86. These high p-values indicate that the null hypothesis of no cross-sectional dependence cannot be rejected at conventional significance levels (e.g., 5%). Even for the ROA models, where test statistics range from -2.018 to -2.332, the associated p-values (from 0.5431 to 0.5536) confirm a lack of statistical significance.

The results suggest that cross-sectional dependence is not present in the residuals of any of the models tested. Consequently, standard panel estimators (such as fixed or random effects models, as well as GMM) are unlikely to be biased due to cross-sectional correlations in this dataset. Therefore, the estimation results can be interpreted with greater confidence regarding the independence assumption across firms.

	Pooled OLS Model		Fixed Effect Model		Random Effect Model		GMM Model	
Model	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value
ROA	-2.113	0.5436	-2.018	0.5536	-2.022	0.5431	-2.332	0.5531
ROE	-0.735	0.4303	-0.757	0.4492	-0.755	0.4503	-0.765	0.4102
TBQ	0.211	0.8157	0.214	0.8305	0.218	0.8277	0.215	0.8652

Table 5. The Pesaran Scaled LM (CD Test)

Slope Heterogeneity Test

The Slope Heterogeneity Test is used in panel data analysis to determine whether the relationship (slope coefficients) between independent and dependent variables differs across cross-sectional units (e.g., countries, firms, regions). The most common method is Pesaran and Yamagata (2008) Slope Homogeneity Test. To assess whether the slope coefficients are homogeneous across firms, the Pesaran and Yamagata (2008) test for slope homogeneity was conducted. The results of the test are presented in Table 6. For Return on Assets (ROA), the Delta statistic was -0.329 with a p-value of 0.742, and the Adjusted Delta statistic was -1.188 with a p-value of 0.235. Since both p-values exceed the 0.05 significance threshold, we fail to reject the null hypothesis, indicating that the slope coefficients for ROA are homogeneous across firms.

For Return on Equity (ROE), the Delta statistic was 0.495 (p-value = 0.621), and the Adjusted Delta statistic was 1.785 (p-value = 0.074). While the Adjusted Delta statistic is close to the 0.05 significance level, the p-value suggests borderline evidence of heterogeneity in the slope coefficients. However, since the result is not statistically significant at the 5% level, we fail to reject the null hypothesis of slope homogeneity, implying that the assumption of homogeneous slopes is reasonable.

For Tobin's Q (TBQ), the Delta statistic was -0.142 (p-value = 0.887), and the Adjusted Delta statistic was -0.511 (p-value = 0.609). Both p-values are much higher than the 0.05 threshold, providing no evidence of slope heterogeneity. Hence, we fail to reject the null hypothesis of homogeneity, suggesting that the slope coefficients for TBQ are also homogeneous across firms.

Overall, the results from the Pesaran and Yamagata test suggest that the slope coefficients for all three dependent variables (ROA, ROE, and TBQ) are likely homogeneous across firms.

	Delta	**p-Value**	**adj. Delta**	**p-Value**
ROA	**-0.329**	**0.742**	**-1.188**	**0.235**
ROE	**0.495**	**0.621**	**1.785**	**0.074**
TBQ	**-0.142**	**0.887**	**-0.511**	**0.609**

Table 6. Pesaran and Yamagata Test

The Pesaran and Yamagata test results suggest that the slope coefficients are homogeneous across firms for ROA, ROE, and TBQ. This implies that there is no significant variation in the relationships between independent and dependent variables across cross-sectional units.

Since Pooled OLS assumes homogeneity of the coefficients, and the test indicates no evidence against this assumption, the Pooled OLS model would be suitable for your analysis.

The Fixed Effects model is appropriate when there is unobserved heterogeneity across cross-sectional units that may affect the dependent variable. Although the test suggests homogeneous slopes, the Fixed Effects model still accounts for unobserved time-invariant heterogeneity across firms (i.e., firm-specific characteristics). Even if slopes are homogeneous, Fixed Effects could still be useful for controlling for firm-specific effects. In this case, the Fixed Effects model can still be used, but based on the slope homogeneity result, its advantages over pooled models might be less pronounced unless you suspect strong unobserved heterogeneity.

The Random Effects model assumes that the individual effects are uncorrelated with the regressors. Given the homogeneity of slopes, the Random Effects model could also be appropriate, provided that you believe the individual effects are uncorrelated with the regressors. If the assumption of no correlation between individual effects and regressors holds, then the Random Effects model would be a more efficient estimator than the Fixed Effects model.

The GMM model is typically used when there are potential endogeneity issues (e.g., simultaneous causality or omitted variable bias) or if the model specification requires robust estimation methods for dynamic panel data. The Pesaran and Yamagata test does not directly inform whether GMM is necessary, but if you suspect that endogeneity is an issue or if you have a dynamic model (e.g., with lagged dependent variables), then GMM would be suitable.

However, if endogeneity is not a concern and the slopes are homogeneous, GMM might be overkill, and simpler models like Pooled OLS or Fixed/Random Effects could suffice

Model Specifications Tests

For panel data, the linear regression model can be expressed in three common forms: The Pooled Ordinary Least Squares (PLS), fixed effect model (FEM) and random effect model (REM). To select the best model between pooled least squares (PLS), fixed effect model (FEM) and random effect model (REM), we use statistical tests based on the chi-square distribution. The key tests include:

-Breusch-Pagan (LM Test) (PLS vs. REM): Tests whether there is significant variance in the panel data that requires random effects. If the p-value is small (< 0.05), we prefer the random effects model.

-The F-Test (Chow Test) (PLS vs. FEM): Tests whether fixed effects are needed or if pooled

OLS is sufficient. If the p-value is small (e.g., < 0.05), we prefer the fixed effects model.

-Hausman Test (Chi-Square) (FEM vs. REM): Tests whether the random effects model produces unbiased estimates. If the p-value is small (e.g., < 0.05), we choose the fixed effects model.

Table 7 presents the results of three specification tests—Chow test, Hausman test, and Breusch-Pagan Lagrange Multiplier (LM) test—used to identify the most suitable panel data model for analyzing firm performance. The Chow test produced highly significant p-values for all three dependent variables (ROA = 0.0001, ROE = 0.0000, TBQ = 0.0001), indicating the presence of structural differences across cross-sectional units and rejecting the validity of the pooled OLS model. The Hausman test results also showed statistical significance for each model (ROA = 0.0000, ROE = 0.0065, TBQ = 0.0055), supporting the use of the fixed effects model over random effects, as the assumption of no correlation between regressors and unobserved heterogeneity is violated. In contrast, the Breusch-Pagan test yielded non-significant results (ROA = 0.8000, ROE = 1.0000, TBQ = 1.0000), suggesting that random effects are not significantly different from pooled OLS. However, given the strong evidence from both the Chow and Hausman tests, the fixed effects model is identified as the most appropriate specification for all three firm performance indicators.

	Chow Test	Hausman Test	Breusch-Pagan Test
Model	p-Value	p-Value	p-Value
ROA	0.0001***	0.0000***	0.8000
ROE	0.0000***	0.0065***	1.0000
TBQ	0.0001***	0.0055***	1.0000

Table 7. Best Model Test Results

Notes: *p <0.10; **p <0.05; ***p <0.01.

Multicollinearity test and Normality test

In table 8, the results from the Multicollinearity test and Normality test provide insights into the relationships and distribution characteristics of the variables.

The Variance Inflation Factor (VIF) values reported for the independent variables across the three models (ROA, ROE, and TBQ) reveal the extent of multicollinearity among the variables. The VIF values for most variables are relatively low, with the highest being 7.01 for T in the TBQ model, indicating that there is no severe multicollinearity present in the models, as VIF values greater than 10 are typically considered problematic. Variables such as PREC, QV2M, and RH2M exhibit higher VIF values, indicating some degree of multicollinearity, but still below the critical threshold, suggesting manageable levels of collinearity between the independent variables. In contrast, LEV, SIZE, and G have VIF values close to or just above 1, indicating minimal collinearity with other variables.

Also, Table 8 displays the normality test results by applying skewness and kurtosis. Variables with skewness values more than three and kurtosis values greater than ten should be considered to have outliers. Following these standards, none of the variables exceed the threshold. Thus, all variables in this study are normally distributed.

	Multicollinearity test			Normality test	
Variables	ROA	ROE	TBQ	Skewness	Kurtosis
ROA	-	-	-	-0.0213	1.7659
ROE	-	-	-	0.0501	1.8414
TBQ	-	-	-	-0.0842	1.8401
PREC	3.43	3.44	3.42	1.6748	13.2872
QV2M	3.68	3.58	3.66	0.6975	3.6239
RH2M	6.86	6.77	6.98	-0.8241	3.4368
T	7.01	6.96	7.09	0.1737	2.4353
T_MAX	1.96	1.94	1.92	-0.5757	2.5671
T_MIN	1.23	1.22	1.21	-0.6131	2.6735
WS2M	1.56	1.55	1.52	-0.8075	3.0559
LEV	1.00	1.04	0.98	-0.0159	1.7637
SIZE	1.01	1.11	1.08	-1.5885	3.7798
G	1.01	1.21	1.14	0.3001	2.8412

Table 8. Multicollinearity test and Normality test

Estimation Results

In Table 9, the fixed effect model results assess the relationship between firm performance indicators—Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q (TBQ)—and various climate-related variables, alongside control variables such as leverage (LEV), firm size (SIZE), and sales growth (G).

For ROA, the results show that precipitation (PREC) and specific humidity (QV2M) have significant negative impacts, with coefficients of -0.0752 and -0.0699, respectively. In contrast, relative humidity (RH2M) and wet-bulb temperature (T) exhibit positive and statistically significant effects on ROA (0.0060 and 0.0255, respectively). Wind speed (WS2M) also shows a strong negative effect on ROA (-0.0581), while minimum temperature (T_MIN) negatively influences ROA with a coefficient of -0.0013. Other climate variables, like maximum temperature (T_MAX), do not show a significant relationship with ROA. Among the control variables, leverage (LEV) has a weak positive effect (0.0071), while size (SIZE) and growth (G) do not significantly impact ROA. The model explains 47.7% of the variation in ROA (R-squared = 0.4766), with a marginal overall significance (p = 0.08).

For ROE, relative humidity (RH2M) is positively significant (0.0110) and indicates that higher humidity improves equity returns. Similarly, wet-bulb temperature (T) and maximum temperature (T_MAX) also show positive coefficients, with T significant at the 10% level (0.0245). Minimum temperature (T_MIN), however, negatively affects ROE (-0.0038), suggesting colder conditions harm equity returns. Wind speed (WS2M) and precipitation (PREC) have no significant impact on ROE, and specific humidity (QV2M) also does not significantly affect returns. Among control variables, leverage (LEV), firm size (SIZE), and sales growth (G) do not significantly influence ROE. The model explains 35.4% of the variation in ROE (R-squared = 0.3541), with a marginal p-value of 0.07, indicating that environmental factors may play a role, but other unaccounted variables likely drive ROE.

For Tobin's Q (TBQ), wind speed (WS2M) has the strongest negative relationship with market valuation (-0.9076, significant at $p < 0.01$), suggesting that adverse weather conditions significantly hurt firm value. Additionally, sales growth (G) shows a negative and statistically significant relationship with TBQ (-0.2630), indicating that slower growth may decrease a firm's market valuation. Interestingly, relative humidity (RH2M) and maximum temperature (T_MAX) have positive coefficients, though not statistically significant. Wet-bulb temperature (T) and minimum temperature (T_MIN) show negative effects, but these are not significant. Other variables, such as precipitation (PREC) and specific humidity (QV2M), also do not significantly impact TBQ. The model explains only 24.4% of the variation in TBQ (R-squared = 0.2444), and the overall significance is marginal ($p = 0.09$), suggesting that market valuation is influenced by various factors, with weather conditions being one of them.

Table 9 presents a mixed picture of how climate-related variables and control variables affect firm performance indicators. ROA and ROE are most strongly influenced by environmental factors like humidity and temperature, while TBQ is significantly impacted by wind speed and sales growth. The models exhibit varying levels of explanatory power, with ROA explaining the most variation (47.7%), followed by ROE (35.4%), and TBQ (24.4%). However, all models show marginal significance (p-values between 0.07 and 0.09), suggesting that while climate conditions do influence firm performance and valuation, other unobserved factors are likely to contribute to the outcomes.

	ROA	ROE	TBQ
Variables	Coefficient	Coefficient	Coefficient
PREC	-0.0752**	-0.0278	-0.6302
QV2M	-0.0699***	-0.0510	0.0921
RH2M	0.0060***	0.0110**	0.0107
T	0.0255***	0.0245*	-0.0430
T_MAX	0.0039	0.0112*	0.0082
T_MIN	-0.0013**	-0.0038*	-0.0122
WS2M	-0.0581***	-0.0601	-0.9076***
LEV	0.0071*	0.0014	-0.0169
SIZE	0.0010	-0.0013	0.0327
G	0.0081	-0.0176	-0.2630**
C	-0.0656	-0.5307	4.0043
R-squared	0.4766	0.3541	0.2444
Adjusted R-squared	0.4719	0.3491	0.2386
F-statistic	117.37	70.66	41.70
Prob(F-statistic)	0.08	0.07	0.09

Table 9. The Fixed Effect Model Results

Notes: *p <0.10; **p <0.05; ***p <0.01.

Robustness Check

To verify the robustness of the results obtained from the fixed effects regression, we conduct a robustness check using the Panel Generalized Method of Moments (GMM) with a Two-Stage Least Squares (2SLS) instrument weighting matrix. This method allows for more accurate estimation by addressing potential endogeneity issues that could arise due to the correlation between the independent variables and the error term. By utilizing instrument variables in the first stage, the 2SLS approach helps mitigate biases that could distort the relationships between climate-related variables, firm performance indicators, and control variables. The use of the Panel GMM method further enhances the reliability of our results by accounting for unobserved heterogeneity and potential serial correlation within the panel data structure. This robustness check ensures that our findings are not sensitive to the estimation method and that the results are reliable under alternative econometric techniques, consistent with prior empirical work that applied the Two-Step System GMM approach to similar data and context (Hamdouni, 2025a)

Table 10 presents the results of the Generalized Method of Moments (GMM) model for three dependent variables: Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q (TBQ). The table shows the estimated coefficients for various explanatory variables, as well as several diagnostic tests to assess the model's validity.

The GMM results reinforce many of the core findings from the fixed effects model but do so with greater statistical rigor by controlling for potential dynamic effects and endogeneity. This strengthens the empirical evidence that climate variables—particularly precipitation, humidity, and wind speed—exert consistent and economically meaningful effects on firm performance, especially in heavy-polluting industries that are more vulnerable to environmental disruptions.

PREC (precipitation) shows a significant negative relationship with ROA (coefficient = -0.0748, p-value < 0.05), but no significant effect on ROE and TBQ. This indicates that increased precipitation negatively impacts firm performance as measured by ROA, but not ROE or TBQ.

QV2M (specific humidity at 2 meters) has a highly significant negative effect on ROA (coefficient = -0.0688, p-value < 0.01) but no significant effect on ROE. For TBQ, it has a positive coefficient, though it is not significant.

RH2M (relative humidity at 2 meters) is positively related to both ROA (coefficient = 0.0059, p-value < 0.01) and ROE (coefficient = 0.0111, p-value < 0.05), suggesting that higher humidity improves firm performance on both metrics. The effect on TBQ is also positive but not significant.

T (wet-bulb temperature at 2 meters) shows a positive and significant effect on ROA and ROE (coefficients = 0.0250 and 0.0247, respectively, both with p-values < 0.05), indicating that higher wet-bulb temperature is beneficial for firm performance. However, it has a negative and not significant effect on TBQ (coefficient = -0.0428).

T_MAX (maximum temperature) has a positive, though non-significant, effect on ROA, and a significant positive effect on ROE (coefficient = 0.0112, p-value < 0.05), but no significant effect on TBQ.

T_MIN (minimum temperature) shows a significant negative effect on ROA (coefficient = -0.0013, p-value < 0.05) and ROE (coefficient = -0.0038, p-value < 0.05), suggesting that colder minimum temperatures can be detrimental to firm performance. For TBQ, the negative effect is not significant (coefficient = -0.0124).

WS2M (wind speed at 2 meters) has a strong negative effect on ROA (coefficient = -0.0578, p-value < 0.01) and TBQ (coefficient = -0.9061, p-value < 0.01), indicating that higher wind speeds negatively affect both firm performance measures, though its impact on ROE is not significant.

Regarding control variables, LEV (leverage), SIZE (firm size), and G (sales growth) do not show consistent or significant effects across all dependent variables, though G is negatively and significatively related to TBQ (coefficient = -0.2867, p-value < 0.05), suggesting that higher sales growth reduces firm valuation.

	ROA	ROE	TBQ
Variables	Coefficient	Coefficient	Coefficient
PREC	-0.0748**	-0.0283	-0.6339
QV2M	-0.0688***	-0.0515	0.0923
RH2M	0.0059***	0.0111**	0.0105
T	0.0250***	0.0247**	-0.0428
T_MAX	0.0039	0.0112**	0.0079
T_MIN	-0.0013**	-0.0038**	-0.0124
WS2M	-0.0578***	-0.0601	-0.9061***
LEV	0.0054	0.0031	-0.0047
SIZE	0.0006	-0.0013	0.0301
G	0.0074	-0.0195	-0.2867**
C	-0.0579	-0.5336	4.0254
Prob>chi2	0.000	0.000	0.000
AR (1) (p-value)	0.0788	0.0833	0.0941
AR (2) (p-value)	0.24	0.26	0.22
Hansen test	3.872	5.832	11.814
P-value	0.273	0.121	0.168

Table 10. The GMM Model Results

Notes: *p <0.10; **p <0.05; ***p <0.01.

The Arellano-Bond tests for autocorrelation show that AR (1) is marginally significant (p-values ranging from 0.0788 to 0.0941), which is consistent with expectations due to the first-differencing of the data. Importantly, the AR (2) tests are not statistically significant (p-values between 0.22 and 0.26), indicating the absence of second-order serial correlation in the differenced residuals. This supports the validity of the moment conditions used in the GMM estimations. Furthermore, the Hansen test for overidentifying restrictions confirms the validity of the instruments, as all p-values exceed the conventional 0.10 threshold. Hansen test is used to test the validity of the instruments used in the GMM estimation. The Hansen test results for the three models (ROA, ROE, and TBQ) indicate that the instruments used in the GMM estimation are valid, as the p-values for the Hansen test are 0.273, 0.121, and 0.168, all of which are greater than the typical significance threshold of 0.05. This suggests that the instruments do not suffer from endogeneity and are appropriately chosen.

In summary, the results suggest that environmental factors, particularly precipitation, humidity, and temperature, have varying impacts on firm performance measures such as ROA, ROE, and TBQ. The instruments used in the GMM model appear to be valid, for the three models (ROA, ROE, and TBQ.

To enhance the robustness of the findings and address potential endogeneity, the results from the fixed effects model (Table 9) are compared with those of the two-step System GMM estimation (Table 10). Overall, the GMM results largely reinforce the fixed effects findings, particularly in the ROA and ROE models. For instance, precipitation (PREC), specific humidity (QV2M), and wind speed (WS2M) consistently show negative and statistically significant effects on ROA across both models, highlighting their detrimental impact on operational efficiency. Similarly, relative humidity (RH2M) and wet-bulb temperature (T) maintain their positive and significant influence on ROA, suggesting that moderate humidity and temperature conditions can enhance productivity. The negative effect of minimum temperature (T_MIN) is also robust across both estimations. For ROE, both models identify RH2M as positively significant, while T and T_MAX also exhibit positive effects, with slightly stronger statistical significance in the GMM results. Notably, the GMM model identifies a significant negative effect of T_MIN on ROE, aligning with the fixed effects outcome. In the case of Tobin's Q (TBQ), both models consistently show that wind speed (WS2M) and sales growth (G) have strong negative effects on market valuation. While some climate variables such as PREC and QV2M remain statistically insignificant in the TBQ models, the direction of their coefficients remains generally consistent. The consistency of signs and statistical significance across the fixed effects and GMM estimations strengthens confidence in the core findings—especially the adverse impacts of precipitation, wind speed, and specific humidity, and the beneficial effects of moderate humidity and temperatures. However, the GMM model addresses two key limitations of the fixed effects model: (1) Dynamic Effects (By including lagged dependent variables, GMM captures the persistence in firm performance.) and (2) Endogeneity (GMM corrects for potential simultaneity bias or reverse causality between climate variables and firm outcomes). Importantly, the GMM model, by controlling for unobserved heterogeneity and accounting for dynamic relationships, offers a more reliable estimation framework. The validity of the GMM specification is further supported by non-significant AR (2) tests and acceptable Hansen test p-values, indicating no second-order autocorrelation and no overidentification issues. The Hansen test p-values (> 0.10) and the non-significant AR (2) test results confirm that the GMM estimators are statistically valid and well-specified.

Discussion

The results of the fixed effects and two-step system GMM regressions provide new empirical insights into the relationship between climate-related variables and firm performance in the context of Saudi Arabia's heavy-polluting industries. These findings are interpreted in light of previous empirical studies, highlighting both areas of convergence and divergence, with explanations rooted in regional, industrial, and methodological differences.

Precipitation (PREC) and specific humidity (QV2M) exhibited significant negative effects on return on assets (ROA), leading to the rejection of hypotheses H_{01} and H_{02}. These results are consistent with prior studies, such as Giang et al. (2021), who found humidity negatively impacted manufacturing productivity in Vietnam, and Sun et al. (2020), who observed rainfall disruptions in Chinese mining operations. Bhat et al. (2015) similarly documented brine dilution and productivity losses due to precipitation in India's salt industry. The convergence with these studies can be attributed to the operational disruptions caused by excessive moisture, particularly in outdoor, heat-intensive processes typical of Saudi Arabia's industrial sectors.

Conversely, relative humidity (RH2M) and wet-bulb temperature had significant positive effects on ROA and return on equity (ROE), supporting hypotheses H_{13} and H_{14}. These findings align with Griffin et al. (2025), who reported that moderate humidity levels and thermal comfort enhance labor efficiency in European firms. This convergence likely reflects physiological and productivity benefits associated with tolerable climatic conditions, especially in regions where extreme aridity is the norm.

Minimum temperature (T_MIN) demonstrated a negative and statistically significant relationship with both ROA and ROE, confirming hypothesis H_{16}. This finding mirrors those of Wu (2025), who reported that falling temperatures diminished firm productivity in China's industrial sectors. Although cold spells are infrequent in Saudi Arabia, they may interfere with energy efficiency and standard operational practices.

However, maximum temperature (T_MAX) showed a positive association with ROE but was insignificant for ROA, leading to partial rejection of hypothesis H_{05}. This result diverges from the predominantly negative temperature effects reported in studies such as Sun et al. (2023). A plausible explanation lies in sectoral adaptation: energy and petrochemical firms in Saudi Arabia may be more resilient to extreme heat due to capital-intensive infrastructure and thermal acclimatization. Additionally, higher temperatures can drive electricity demand, indirectly benefiting energy producers.

Wind speed (WS2M) showed a negative and statistically significant effect on both ROA and Tobin's Q, supporting hypothesis H_{17}. This aligns with findings by Huang et al. (2018) and Brei et al. (2019), who reported that wind events disrupt logistics and infrastructure, reducing firm value. The convergence suggests that wind-induced operational risks are broadly applicable across geographies.

Among the control variables, leverage (LEV) exhibited a weakly positive but mostly insignificant effect on ROA. This is consistent with Zhang et al. (2023), who found that climate risk does not significantly influence short-term capital structure. Similarly, firm size (SIZE) was insignificant, supporting hypothesis H_{09}. However, this diverges from Giang et al. (2021), who reported a positive relationship between firm size and performance. The divergence may stem from institutional differences; in Saudi Arabia, larger firms may suffer from bureaucratic inefficiencies or rely more heavily on state support, diminishing scale advantages. Notably, (Hamdouni, 2025b) found contrasting evidence, indicating that firm size had a significant impact on firm performance. Unexpectedly, sales growth (G) negatively affected Tobin's Q, leading to the rejection of hypothesis H_{010}. This contradicts conventional expectations and may reflect investor concerns about the long-term viability of growth in high-emission industries, particularly amid rising global pressure for ESG compliance (Mondal & Bauri, 2024).

The two-step system GMM model—used to address endogeneity and dynamic effects—confirmed several key findings from the fixed effects model. Precipitation and specific humidity remained significantly negative, while relative humidity, wet-bulb temperature, and maximum temperature retained their positive effects. Wind speed continued to exert a significant negative influence on firm performance. These robust results affirm the presence of persistent climate-related financial risks.

Interestingly, control variables such as leverage, and size were mostly insignificant in the GMM framework. Sales growth (G) negatively affected Tobin's Q, leading to the rejection of hypothesis H_{010}. Similar findings were reported by (Hamdouni, 2025a), who observed that firms in heavy-polluting sectors face market skepticism despite financial growth, highlighting the increasing importance of ESG performance in shaping investor perceptions and firm valuation in the context of Saudi Arabia's Vision 2030.

This may reflect the fact that these firm-level characteristics evolve slowly and may not explain short-term performance variability captured in dynamic models.

These findings underscore the context-dependent nature of climate-finance linkages. While some relationships are universally observed, others are shaped by local economic structures, sectoral resilience, and investor sentiment. By focusing on Saudi Arabia's heavy-polluting sectors, this study provides novel evidence on how climate variables influence firm performance in resource-dependent and arid-region economies. The results have practical implications for corporate risk management and public policy in the face of increasing climate volatility.

Conclusion and Implications

This study investigates the impact of climate change risk on the financial performance of firms listed on the Saudi Stock Exchange, focusing on the period from 2010 to 2022. By incorporating multiple climate-related variables into firm-level performance models, the research offers empirical insights into how environmental shifts, such as changes in temperature, humidity, precipitation, and wind speed, affect corporate outcomes measured by Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q (TBQ).

The results reveal a nuanced relationship between climate indicators and firm performance. Variables such as relative humidity and wet-bulb temperature are associated with improved financial metrics, while others, particularly wind speed, minimum temperature, and specific humidity, exert adverse effects. Market valuation (Tobin's Q) appears especially sensitive to environmental volatility, though less consistently than accounting-based measures like ROA and ROE. These findings were confirmed using robust econometric techniques, including fixed-effects and GMM estimations, which address issues of endogeneity and unobserved heterogeneity.

The implications of these results are particularly relevant to Saudi Arabia's Vision 2030. First, the findings underscore the need for companies to integrate climate risk into their strategic and operational decision-making, recognizing environmental conditions as financially material. Second, they highlight the importance of incorporating climate considerations into investment and infrastructure planning, especially for sectors vulnerable to weather fluctuations. Third, the study supports the development of climate-informed financial regulations and disclosure practices, aligning with global sustainability frameworks. Lastly, the evidence provides guidance for Saudi Arabia's green transition by identifying which climate factors most affect firm value, thereby helping to align corporate behavior with national goals for sustainability, economic diversification, and environmental resilience.

Funding

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (Grant Number: IMSIU-DDRSP2502).

References

Almazroui, M. (2020). Changes in Temperature Trends and Extremes over Saudi Arabia for the Period 1978–2019. Advances in Meteorology, 2020, 1–21. https://doi.org/10.1155/2020/8828421

Alotaibi, B. A., Xu, W., Shah, A. A., & Ullah, W. (2024). Exploring Climate-Induced Agricultural Risk in Saudi Arabia: Evidence from Farming Communities of Medina Region. Sustainability, 16(10), 4245. https://doi.org/10.3390/su16104245

Bhat, A. H., Sharma, K. C., & Banday, U. J. (2015). Impact of Climatic Variability on Salt Production in

Sambhar Lake, a Ramsar Wetland of Rajasthan, India.
Brei, M., Mohan, P., & Strobl, E. (2019). The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. The Quarterly Review of Economics and Finance, 72, 232–239. https://doi.org/10.1016/j.qref.2018.12.004
Dhifaoui, Z., Ncibi, K., Gasmi, F., & Alqarni, A. A. (2023). The Nexus between Climate Change and Geopolitical Risk Index in Saudi Arabia Based on the Fourier-Domain Transfer Entropy Spectrum Method. Sustainability, 15(18), 13579. https://doi.org/10.3390/su151813579
Fei, C., Jägermeyr, J., McCarl, B., Contreras, E. M., Mutter, C., Phillips, M., Ruane, A. C., Sarofim, M. C., Schultz, P., & Vargo, A. (2023). Future climate change impacts on U.S. agricultural yields, production, and market. Anthropocene, 42, 100386. https://doi.org/10.1016/j.ancene.2023.100386
Giang, N. T. H., Hanh, T. M., Hien, P. T., Trinh, N. T., Huyen, N. T. K., & Trang, V. H. (2021). The Impacts of Climate Change Risks on Financial Performance: Evidence from Listed Manufacturing Firms in Vietnam: International Conference on Emerging Challenges: Business Transformation and Circular Economy (ICECH 2021), Hanoi, Vietnam. https://doi.org/10.2991/aebmr.k.211119.052
Griffin, P. A., Lont, D. H., & Lubberink, M. J. P. (2025). The effects of extreme high temperature spells on financial performance. The British Accounting Review, 57(2), 101383. https://doi.org/10.1016/j.bar.2024.101383
Guermazi, I., Smaoui, A., & Chabchoub, M. (2025). Analysis of factors mitigating greenhouse gas emissions (GHG) in Saudi Arabia. Society and Business Review, ahead-of-print(ahead-of-print). https://doi.org/10.1108/SBR-09-2024-0313
Guo, X., Arshad, M. U., Zhao, Y., Gong, Y., & Li, H. (2023). Effects of climate change and grazing intensity on grassland productivity—A case study of Inner Mongolia, China. Heliyon, 9(7), e17814. https://doi.org/10.1016/j.heliyon.2023.e17814
Hamdouni, A. (2025a). The impact of ESG disclosure on corporate performance: Empirical evidence from Saudi Arabia's listed heavy-polluting companies. International Journal of Innovative Research and Scientific Studies, 8(3), 1164–1174. https://doi.org/10.53894/ijirss.v8i3.6766
Hamdouni, A. (2025b). The nexus between corporate governance improvements, corporate investment and value creation: Evidence from Shariah-compliant companies. International Journal of Innovative Research and Scientific Studies, 8(2), 321–328. https://doi.org/10.53894/ijirss.v8i2.5159
Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. Journal of International Business Studies, 49(5), 633–656. https://doi.org/10.1057/s41267-017-0125-5
Jiménez, O. R., Bornemann, A. C., Medina, Y. E., Romero, K., & Bravo, J. R. (2023). Prospects of biological inputs as a measure for reducing crop losses caused by climate change effects. Journal of Agriculture and Food Research, 14, 100689. https://doi.org/10.1016/j.jafr.2023.100689
Mawejje, J. (2024). How does the weather and climate change affect firm performance in low-income countries? Evidence from Uganda. Sustainable Futures, 7, 100167. https://doi.org/10.1016/j.sftr.2024.100167
Mondal, A., & Bauri, S. (2024). The impact of climate transition risk on firms' value – evidence from select Indian-listed companies. Asian Journal of Accounting Research, 9(3), 257–274. https://doi.org/10.1108/AJAR-08-2023-0264
Sarabdeen, M. (2022). A Framework for Climate Change Risk Management Practice and Performance of Financial Institutions in Saudi Arabia. Journal of Accounting Research, Organization and Economics, 5(2), 181–190. https://doi.org/10.24815/jaroe.v5i2.28094
Sun, Y., Yang, Y., Huang, N., & Zou, X. (2020). The impacts of climate change risks on financial performance of mining industry: Evidence from listed companies in China. Resources Policy, 69,

101828. https://doi.org/10.1016/j.resourpol.2020.101828

Sun, Y., Zou, Y., Jiang, J., & Yang, Y. (2023). Climate change risks and financial performance of the electric power sector: Evidence from listed companies in China. Climate Risk Management, 39, 100474. https://doi.org/10.1016/j.crm.2022.100474

Wu, B. (2025). Climate Risk and Corporate Value: Evidence from Temperature Bins and Panel Regression (No. arXiv:2503.14233). arXiv. https://doi.org/10.48550/arXiv.2503.14233

Zhang, X., Zhang, M., & Fang, Z. (2023). Impact of Climate Risk on the Financial Performance and Financial Policies of Enterprises. Sustainability, 15(20), 14833. https://doi.org/10.3390/su152014833