THE JOURNAL OF RESEARCH REVIEW

P-ISSN: 3006-2632	E-ISSN: 3006-2640
Vol. 1. No. 04 (Oct-Dec) 2024	Page 414-425

Sustainable Progress: From Vulnerability to Resilience in Pakistan's Industry

Khurram Shahzad	PhD Economics Scholar, Department of Economics, Division of Management & Administrative Science, University of Education, Lahore, Pakistan; This research article is derived from the doctoral thesis titled "Impact of Climate Resilience and Vulnerability on Structural Sectors of Pakistan," authored by Khurram Shahzad sayadbukhari.eco@gmail.com
Ghulam Rasool Madni	Assistant Professor, Department of Economics, Division of Management & Administrative Science, University of Education, Lahore, Pakistan ghulam.rasool@ue.edu.pk

Abstract: *Climate vulnerability and resilience critically shape the industrial sector, a key driver of economic growth and employment. Climate vulnerability disrupts industrial productivity through resource scarcity, infrastructure damage, and supply chain interruptions, increasing costs and operational inefficiencies. In contrast, resilience enhances the sector's capacity to absorb shocks, recover from disruptions, and sustain long-term growth. This study investigates the effects of climate vulnerability and resilience on Pakistan's industrial sector using time series data from 1995 to 2023 sourced from the World Development Indicators (WDI) and ND-GAIN index. Applying the ARDL methodology, the analysis reveals that vulnerability significantly reduces industrial output by disrupting energy supply, increasing production costs, and weakening infrastructure. Resilience, however, mitigates these effects by supporting adaptive measures, improving recovery processes, and ensuring operational continuity. The findings highlight the need for policy interventions to enhance industrial resilience. Recommended measures include adopting green technologies, strengthening climate-resilient infrastructure, and ensuring consistent access to resources like water and energy. Regional cooperation for knowledge transfer and coordinated climate strategies can further amplify resilience outcomes. This study provides valuable insights for policymakers and researchers to address climate risks and sustain industrial growth amid increasing climate challenges.*

Keywords: Climate vulnerability, Climate resilience, Industry, Climate change, Pakistan

Introduction

Climate change, environmental degradation, and global warming have emerged as critical global challenges, exerting significant pressure on economies and ecosystems worldwide. These phenomena, primarily driven by human activity, have led to an unprecedented rise in global temperatures and the frequency of extreme weather events, including floods, droughts, heat-waves, and storms (Gorus&Aslan, 2019). As these climate-related challenges intensify, their adverse effects on economic systems become more pronounced, particularly in developing economies. For nations such as Pakistan, where industries are heavily reliant on climate-sensitive resources such as water and energy, the impacts of climate change present severe risks to industrial production, infrastructure, and overall economic stability. The urgency of addressing climate change's implications for industrial sectors in these economies has become a focal point for both scholars and policymakers.

Climate vulnerability, as defined by Tonmoy et al. (2014), refers to the extent to which a system, whether a community, region, or sector, is susceptible to the harmful effects of climate change. This vulnerability is influenced by a combination of exposure to climate risks, sensitivity to climate impacts, and the capacity to adapt to these changes (Menk et al., 2022). The industrial sector in developing countries such as Pakistan is particularly vulnerable to these factors, with climate-related disruptions to temperature, water availability, and infrastructure posing significant threats to production capacity and efficiency. The industrial sector, which includes critical areas such as textiles, cement production, and energy generation, relies on stable environmental conditions and adequate infrastructure to function effectively. As climate change exacerbates the frequency and severity of extreme weather events, industries face increased operational costs, supply chain disruptions, and reduced productivity, thus undermining economic growth (Mendelsohn, 2007). These vulnerabilities not only hinder industrial performance but also contribute to broader macroeconomic instability, especially in economies that depend on industrial outputs for employment and trade.

Surprisingly, resilience offers a potential counterbalance to these adverse effects. Resilience, in this context, refers to the ability of an industrial system to absorb and recover from the shocks induced by climate change (Cutter et al., 2008a). While climate vulnerability presents significant challenges, resilience strategies can enhance industrial production by enabling industries to adapt to changing conditions and mitigate potential disruptions. Through the adoption of energy-efficient technologies, water-saving techniques, and the diversification of supply chains, industries can reduce their dependence on climate-sensitive resources and increase their capacity to maintain stable production in the face of climate-related shocks. Additionally, investments in resilient infrastructure, such as flood-resistant manufacturing facilities and renewable energy systems, further enhance the industrial sector's ability to withstand extreme weather events. This adaptive capacity not only ensures continued production but also positions industries to remain competitive in the global market, even as climate change accelerates (Lowitzsch et al., 2020).

Despite the growing recognition of climate vulnerability and resilience in the context of environmental studies, there remains a notable gap in the literature regarding their specific impact on industrial production, particularly within the context of developing countries like Pakistan. While, much research has been dedicated to understanding the effects of climate change on agriculture and the environment studies focusing on the industrial sector are scarce, especially, in the context of climate vulnerability and resilience. Furthermore, while resilience has been explored in sectors such as agriculture and infrastructure, its application to industrial production and its ability to mitigate climate impacts in countries like Pakistan have not been adequately addressed. This research aims to bridge this gap by examining the effects of climate vulnerability and resilience on Pakistan's industrial sector, with a particular focus on key industries such as textiles, cement, and power generation.

The significance of this study lies in its potential to inform climate adaptation policies for the industrial sector in Pakistan. As climate change continues to reshape global production systems, it is essential for developing economies to adopt strategies that enhance the resilience of their industries. By investigating the role of climate vulnerability and resilience in industrial production, this study contributes to the ongoing discourse on climate adaptation, sustainable industrial development, and economic resilience in the face of climate change.

Therefore, the primary objective of this study is to examine the impact of climate vulnerability on the industrial sector of Pakistan, focusing on how exposure to climate risks, sensitivity to environmental changes, and limited adaptive capacities affect industrial production. Additionally, this research aims to explore the role of climate resilience in mitigating these adverse effects by identifying strategies that enhance the capacity of industries to adapt to climate-related challenges. By analyzing the interplay between vulnerability and resilience, the study seeks to provide insights into how industrial production can be sustained and improved amidst escalating climate pressures, thereby contributing to long-term sectoral sustainability and economic stability.

1. Literature review

Chen and Yang (2019) found in their research that changes in temperature leads to change the industrial output in China. They used firm-level data for their findings explored that there exist a significant negative relation between temperatures and industrial production. They also found that their findings are more accurate in heat-sensitive sectors of industry. They have found the theoretical linkages about extreme temperatures and production as the increase in temperature reduces the efficiency of the worker that leads to more demand for the energy for cooling like air conditions, fans etc; that eventually becomes a cause of increasing production costs, that will lead to lower the output. They also explored that the small firms which are more labor intensive are more vulnerable to the temperature increase as they heavily depend on labor. They further dug out that a change in temperature that ranges in between 21–24°C is more vulnerable for the firms and decrease the industrial production very significantly. Lastly they have suggested that mitigation policies are needed especially in the smaller industries for the better health of the worker and increased production level also.

Zhang et al. (2018) has explored that temperature can effect industry in many ways by affecting industrial output, total factor productivity , and input use in Chinese manufacturing firms. They have taken a time series data from 1998 to 2007 for this purpose and found that temperature effects the production and total factor productivity in a complex nonlinear way. Contrary to this the effect of temperature is very low on the input use. They also explored that industrial output decreases drastically if the temperature increases above the level of 32°C, identifying a critical temperature threshold. Their research remains helpful for policy makers to adopt mitigation measures whenever the temperature goes beyond the threshold level. Their enhanced methods have significant the findings and enhanced their relevance.

Similarly, Lundgren et al. (2013) has analyzed the effect of rising temperatures due to climate change on workers globally, particularly in labor-intensive sectors. They further highlighted the growing concern over heat stress as a significant occupational health risk, especially for outdoor workers and those in hot environments, as global temperatures continue to rise. The area they pointed out was agricultural laborers, construction workers, and those in manufacturing industries as these professions are particularly vulnerable to heat stress because they often perform physical tasks in hot or outdoor environments. They have found that with the increase of global temperatures, the number of extreme heat days will increase that leads to more frequent and intense heat stress events. And finally it will significantly reduce worker productivity, which will also leads to lesser industrial production.

Colmer (2021) found the relationship between temperature changes, labor distribution, and industrial output, using India as a case study. As India, a predominantly agricultural economy was increasingly moving towards industrialization and also examined how rising temperatures became a result of climate change and are affecting economic activities, especially the labor shifts across sectors and industrial production. He founded that timely contribution to understanding how climate change affected developing economies like India in which agriculture was highly vulnerable to temperature changes, may be affected. He further found that rising temperature influenced labor mobility, with extreme heat causing workers to leave agriculture in search of less physically demanding industrial jobs. However, while labor moved to industrial sectors, industrial production did not always increase. In fact, he suggested that higher temperatures disrupted industrial productivity, particularly in sectors which based on outdoor labor or those vulnerable to energy shortages caused by increased cooling demands.

Fu et al. (2021) had explored how air pollution affects productivity, often focusing on small groups of workers in specific jobs or companies. To provide more significant insights useful for national policy, they had examine the impacts on a broad effect of manufacturing firms from 1998 and 2007, considering all possible ways pollution can affect productivity. To estimate the causal relationship between pollution and productivity, they used thermal inversions as an instrumental variable. Their findings showed that a 1 μg/m³ reduction in PM2.5 leads to a 0.82% lead to increase in productivity, with an elasticity of -0.44. Companies respond by hiring more workers, which softens the elasticity to -0.17. By leveraging the differing impacts of China's WTO accession on coastal versus inland regions, they have estimated the relation between output and pollution (with an elasticity of 1.43) and simulate the broader effects of PM2.5 on the economy, which results in an elasticity of -0.28. A 1% reduction in PM2.5 nationwide would increase annual productivity by CNY 35.9 thousand per firm, contributing CNY 5.7 billion, or 0.039%, to China's GDP.

2. Methodology

2.1. Data

This study investigates the impact of climate vulnerability and climate resilience on the industrial sectors in Pakistan. The analysis is based on time series data from 1995 to 2023, sourced from the World Development Indicators (WDI) and the ND-GAIN Index (Country Notre Dame Global Adaptation Initiative). The dependent variables in this study are industrial value-added, which represents industrial production.The independent variable is the climate risk index, which serves as a proxy for climate vulnerability and climate resilience index, which serves as a proxy of climate resilience. The ND-GAIN framework divides climate vulnerability into three components: exposure, sensitivity, and adaptive capacity. These components are further assessed through six key indicators: food, water, health, ecosystem, human habitat, and infrastructure. Table 1 presents a summary of the variables used in the analysis, along with their corresponding symbols and definition.

Table 1: Description of Variables

Variable Name	Symbol	Definition
Industrial Production	IP	Industrial output or productivity
Climate Vulnerability	CV	Exposure to climate risks
Climate Resilience	CR	Ability to maintain stability
Employment	EMP	Reflects labor market conditions
Foreign Direct Investment	FDI	Foreign investments that bring capital& technology
GDP Per Capita	GDPPC	Economic wealth per person
CO_2 Emissions	CO2	Emission of greenhouse gas
Trade	TR	Market openness and access to foreign
Exchange Rate	ER	Currency stability and competitiveness
Gross Fixed Capital Formation	GFCF	Additions to the fixed assets of the economy

2.2. Theoretical Framework

PAR Model and Climate Vulnerability-Resilience: The Pressure and Release Model (Blaikie et al. 2004) is a pioneer model for the understanding of the relation between climate vulnerability and resilience as it tells how these both the variables interact with each other to get an economy out of any climate event. Vulnerability: Is created by the pressure of structural inequalities (e.g., poverty, lack of access to resources) and dynamic pressures (e.g., environmental degradation, poor urban planning, or inadequate risk governance). It also means that vulnerable people are those ones who use to live in a unsafe locality that directly exposed to the weather events like floods, storms, and droughts. Vulnerability is the pressure part of the model as it shows higher the vulnerability higher will be the pressure of extreme weather event .Whereas; Resilience is the release part of the model that releases the pressure of climate from the industrial sector of the economy. As, it is the ability to cop up with the climate changes which also reduce the unsafe conditions that expose people to climate risks.The resilience can be increases by good governance, sustainable resource management, and social equity.

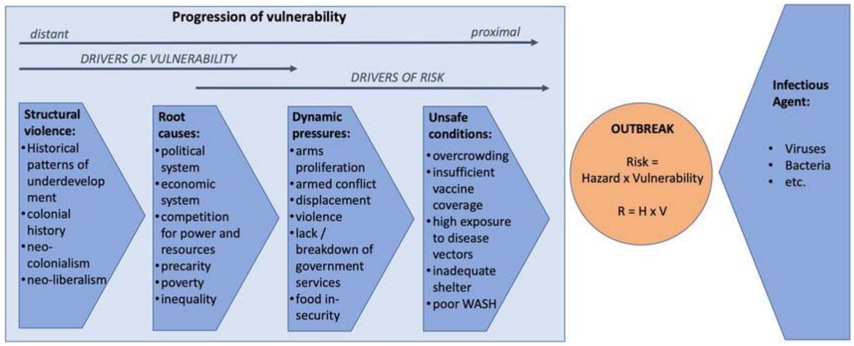

Fig. 1 Pressure and release model flowchart (Blaikie et al. 2004)

2.3. Econometrics Methodology:

2.3.1. Unit Root Test:

Testing for stationarity is a fundamental step in time series analysis to ensure the reliability of econometric models and the validity of regression results. A stationary time series is characterized by a constant mean, variance, and auto-covariance over time, whereas non-stationary series can lead to biased and spurious results, ultimately undermining the robustness of policy implications (Voumik et al., 2023). To address these concerns, this study employs the Augmented Dickey-Fuller (ADF) test, a widely recognized tool for detecting the presence of unit roots in time series data.

The ADF test builds upon the classical Dickey-Fuller framework by incorporating lagged differences of the dependent variable, thereby addressing potential issues of serial correlation in the residuals. The null hypothesis of the ADF test posits the presence of a unit root, indicating non-stationarity, while the alternative hypothesis confirms stationarity. The stationarity properties of all variables in this study i.e. climate vulnerability, climate resilience, employment in industry, foreign direct investment inflows, GDP per capita, trade, exchange rate, and gross capital formation, were examined using the ADF test at both levels and first differences.

The ADF test results guided the determination of each variable's order of integration, ensuring that no series exceeded an integration order of one. This is a critical prerequisite for applying the Autoregressive Distributed Lag (ARDL) model, which can effectively handle variables with a mix of stationarity at levels $I(0)$ and first differences $I(1)$.By employing the ADF test, this study adheres to best practices in time series econometrics, ensuring methodological rigor in the analysis of climate vulnerability and resilience impacts on Pakistan's industrial sector. The ADF test results further validate the use of the ARDL approach as an appropriate econometric tool for this investigation. ADF test is built on the estimate of the following equation.

$$\Delta Y_t = \delta_0 + \delta_1 t + \delta_2 Y_{t-1} + \sum_{k=1}^{\rho} \varphi_K \Delta Y_{t-i} + u_t \qquad (1)$$

Where δY_{t-1}shows the lagged level of Y_t. The null hypothesis is $H_0: \delta = 0$ indicates that series has a unit root and alternative hypothesis is $H_1: \delta < 0$ indicate that series is stationery.

2.3.2. ARDL Model:

This study employs the Autoregressive Distributed Lag (ARDL) model, developed by Pesaran et al. (2001), to investigate the short and long run relationships between climate vulnerability, climate resilience and the industrial sector of Pakistan. The ARDL bounds testing approach was applied to examine the existence of cointegration among the variables. This method is well-suited for models with a mix of variables integrated at levels (0) and first differences (1), providing a flexible framework for time series analysis.The ARDL approach offers several advantages. It accommodates small sample sizes and it also allows for the simultaneous estimation of short and long run relationships. The model also determines optimal lag lengths using criteria such as the Akaike Information Criterion (AIC) and

Schwarz Information Criterion (SIC), ensuring parsimonious specification.The equation for the ARDL model delivered as below.

$$\Delta LnIP_t = a_0 + \sum_{i=1}^{n} b_i\,(LnIP)_{t-i} + \sum_{j=2}^{n} c_j\,(CV)_{t-j} + \sum_{k=0}^{n} d_k\,(Z)_{t-k} + \mu_t \qquad (2)$$

$$\Delta LnIP_t = a_0 + \sum_{i=1}^{n} b_i\,(LnIP)_{t-i} + \sum_{j=2}^{n} c_j\,(CR)_{t-j} + \sum_{k=0}^{n} d_k\,(Z)_{t-k} + \mu_t \qquad (3)$$

The dependent variable in this study is the performance of the industrial production *(IP)*, while the explanatory variables are climate vulnerability and climate resilience and other variables *(Z)* include employment, foreign direct investment, GDP per capita, CO2, trade, exchange rate, and gross capital formation. After confirming cointegration through the ARDL bounds test, the long-run coefficients were estimated to identify the sustained effects of the explanatory variables. The short run dynamics were captured through the error correction mechanism (ECM), based on the framework proposed by Engle and Granger (1987).The short-term adjustments were captured through the Error Correction Term (ECT), The ECT measures the speed at which the system returns to equilibrium after short-term deviations. The error correction model (ECM) provided insights into short-term dynamics while ensuring consistency with the long term equilibrium relationship.

$$\Delta lnIP_m = \beta_0 + \sum_{i=1}^{n} \alpha_i\,\Delta(lnIP)_{t-i} + \sum_{j=2}^{n} \Omega_j\,\Delta\,(lnCR)_{t-j} + \sum_{k=0}^{n} \omega_k\,\Delta(Z)_{t-k} + \Phi ECM_{t-1} + z_t \qquad (4)$$

$$\Delta lnIP_m = \beta_0 + \sum_{i=1}^{n} \alpha_i\,\Delta(lnIP)_{t-i} + \sum_{j=2}^{n} \Omega_j\,\Delta\,(lnCV)_{t-j} + \sum_{k=0}^{n} \omega_k\,\Delta(Z)_{t-k} + \Phi ECM_{t-1} + z_t \qquad (5)$$

The ARDL model was selected for its ability to provide robust estimates of short and long term effects, ensuring the reliability of the results. Its application in this study allows for a comprehensive analysis of the impact of climate vulnerability and resilience on Pakistan's industrial sector.

$$\Delta LnIP_t = a_0 + \sum_{i=1}^{n} b_i\,(LnIP)_{t-i} + \sum_{j=2}^{n} c_j\,(CV)_{t-j} + \sum_{k=0}^{n} d_k\,\Delta(Z)_{t-k} + \beta_0 + \beta_1(CR)_{t-1} + \beta_2(Z)_{t-1} + \mu_t \qquad (6)$$

$$\Delta LnIP_t = a_0 + \sum_{i=1}^{n} b_i\,(LnIP)_{t-i} + \sum_{j=2}^{n} c_j\,(CR)_{t-j} + \sum_{k=0}^{n} d_k\,\Delta(Z)_{t-k} + \beta_0 + \beta_1(CR)_{t-1} + \beta_2(Z)_{t-1} + \mu_t \qquad (7)$$

The ARDL bounds test was employed to examine the presence of a long-run relationship among the variables. The null hypothesis of no cointegration was tested against the alternative hypothesis of cointegration. If the calculated F-statistic exceeded the critical values of the upper and lower bounds, the null hypothesis was rejected, confirming the existence of cointegration.

2.3.3. Diagnostic Test

To ensure the reliability and robustness of the estimated results, a series of diagnostic tests were conducted. These tests assessed key econometric assumptions and the stability of the ARDL model.The Breusch-Pagan-Godfrey test (Breusch and Pagan, 1979) was used to detect heteroscedasticity in the residuals, ensuring that the variance of the errors remained constant across observations. To examine the presence of serial correlation, the Breusch-Godfrey LM test (Breusch, 1978; Godfrey, 1978) was applied, validating the assumption of error independence.The Ramsey RESET test (Ramsey, 1969) was employed to evaluate the functional form of the model and detect any specification errors, ensuring that the model was correctly specified without omitted variables or misspecifications. Furthermore, the stability of the estimated coefficients over time was assessed using the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQR) tests. These tests provided evidence on whether the model parameters remained consistent throughout the study period.

3. Empirical Findings

3.1. Unit Root Test Results

The stationarity of the variables was examined using the Augmented Dickey-Fuller (ADF) test, a critical step to ensure the suitability of the data for time series analysis. As shown in Table 2, the results indicate that none of the variables are stationary at their levels across all specifications i.e. none, intercept, and intercept plus trend. This lack of stationarity at levels suggests the presence of unit roots in the series. However, after first differencing, all variables achieve stationarity, with ADF test statistics exceeding the critical values at the 1% significance level under all configurations.The dependent variable, industrial production, along with key independent variables such as climate vulnerability and climate resilience, are non-stationary at levels but become stationary upon first differencing. Similarly, the control variables, including employment in industry, FDI inflows, GDP per capita, trade, exchange rate, and gross fixed capital formation, also exhibit stationarity only after first differencing. These results indicate that all variables are integrated of order one, I(1), and follow a stochastic trend.

Table 2: ADF Test

Variable	Level			1st Difference		
	None	Level	Trend	None	Level	Trend
Industrial Production	-0.904	-2.112	-2.690	-9.023	-8.831	-8.671
Climate Vulnerability	-0.851	-1.778	-3.417	-5.690	-5.697	-5.584
Climate Resilience	-1.554	-1.541	-1.717	-4.996	-4.911	-4.845
Employment in Industry	1.581	0.508	-1.794	-1.451	-5.928	-7.162
FDI Inflows	-1.692	-2.758	-2.756	-3.652	-3.957	-3.512
GDP Per Capita	-1.279	-1.231	-0.427	-2.102	-3.193	-5.921
CO2	-0.114	1.245	-2.634	-2.743	-3.457	-4.568
Trade	-0.782	-2.326	-2.219	-5.301	-5.254	-5.298
Exchange Rate	0.583	1.973	1.481	2.544	-3.962	-5.703
Gross Fixed Capital Formation	-2.945	-2.931	-2.912	-5.821	-5.736	-5.648
Significance						
1%	-2.653	-3.699	-4.339	-2.653	3.699	-4.339
5%	-1.953	-2.976	-3.587	-1.195	-2.976	-3.587
10%	-1.609	-2.627	-3.229	-1.609	-2.627	-3.229

The mixed stationarity i.e. non-stationarity at levels but stationarity at first difference, demonstrated by the variables justifies the use of the autoregressive distributed Lag (ARDL) bounds testing approach. The ARDL framework is particularly robust for investigating long-run and short-run relationships in models comprising variables with a mix of I(0) and I(1) properties. This methodological choice ensures the integrity and reliability of the econometric analysis and its conclusions.

3.2. ARDL Bound Test Results

The ARDL Bounds Test was employed to examine the presence of a long-run relationship between the variables in two separate models: one for climate resilience and the other for climate vulnerability. The null hypothesis tested in the bounds framework posits that no long-run relationships exist among the variables.

In Table 3, model 1, which investigates the role of climate resilience, the calculated F-statistic is 5.713, while for Model 2, focusing on climate vulnerability, the F-statistic is 6.314. In both models, the number of regressors (k) is 7. The critical value bounds for the F-statistic at various significance levelsare presented in the table 3. Comparing the F-statistic values to the critical value bounds reveals that both models exceed the upper bound (I(1)) across all significance levels, including the stringent 1% threshold. Specifically, for Model 1, the F-statistic of 5.713 is substantially higher and similarly, for

Model 2, the F-statistic of 6.314 surpasses the same critical threshold. These results provide robust evidence to reject the null hypothesis of no cointegration.

The findings confirm the existence of a long-run relationship between the industrial production and climate resilience and climate vulnerability, in both models. The significance of the long-run relationship underscores the importance of addressing climate dynamics in shaping industrial outcomes. These results set the stage for further analysis using the ARDL model to estimate both short-run and long-run dynamics.

Table No. 3: ARDL Bound Test Results

Test Statistic	**Value**	**k**
F-statistic (Model 1: Climate Resilience)	5.713	7
F-statistic (Model 2: Climate Vulnerability)	6.314	7
Critical Value Bound		
Significance	**I0 Bound**	**I1 Bound**
10%	2.03	3.13
5%	2.32	3.50
2.5%	2.60	3.84
1%	2.96	4.26

3.3. ARDL Long-run and Short-run test Results

The ARDL estimation results, reported in Table 4 and Table 5, delineate the long run and short run relationships, between industrial production and the explanatory variables, including climate resilience, climate vulnerability.

In the long run, climate resilience exhibits a statistically significant and positive impact on industrial production. This underscores the critical role of climate resilience in mitigating adverse environmental impacts and fostering industrial growth.These results are in-line with (Gupta et al 2024).Conversely, climate vulnerability demonstrates a significant negative relationship with industrial production. This indicates that heightened climate vulnerability undermines industrial productivity, likely through disruptions to infrastructure, supply chains, and labor efficiency.These results are also coincide with Nasir et al. (2022). Similarly, employment in industry positively and significantly contributes to industrial production in the both models (Dellas & Koubi 2001). Foreign direct investment (FDI) also exerts a positive and significant influence reflecting the role of capital inflows in enhancing industrial infrastructure and technological advancements (Jawaid (2017)). GDP per capita consistently yields positive impact indicating the importance of economic growth in driving industrial expansion.

Table No. 4: ARDL Long-Run Test Results

Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Climate Resilience	0.623***	0.018	-	-
Climate Vulnerability	-	-	-0.1407***	0.024
Employment in Industry	0.975**	0.034	0.309**	0.055
FDI Inflows	0.604*	0.438	0.326**	0.150
GDP Per Capita	0.026*	0.002	0.018***	0.004
CO2	-0.019**	0.039	-0.014***	0.002
TRADE	-0.017**	0.014	-0.062**	0.012
Exchange Rate	-0.047**	0.004	-0.013***	0.003
Gross Fixed Capital Formation	0.088*	0.047	0.221**	0.060
C	0.956***	0.558	0.499***	0.042

Conversely, trade and exchange rates exhibit negative and statistically significant coefficients across both models, suggesting that trade imbalances and currency volatility may constrain industrial productivity. Gross fixed capital formation positively impacts industrial production highlighting the significance of investment in physical capital.

In the short term, climate resilience maintains its positive association with industrial production. Conversely, climate vulnerability continues to exert a negative influence, emphasizing the immediate detrimental effects of climate related risks on industrial performance.These results are coincide with Kling, et al., (2021). Employment in industry demonstrates a strong positive relationship with industrial production. Similarly, FDI inflows and GDP per capita positively and significantly impact short run industrial dynamics, highlighting their role in providing immediate financial and economic support to industrial operations (Jawaid, 2016). However, trade and exchange rates remain significant but negative in the short run. These findings underscore the sensitivity of industrial output to fluctuations in external economic conditions. Gross fixed capital formation, while less pronounced, continues to positively influence industrial production. Lastly, the error correction terms for both models are highly significant (Ullah et al. (2012). These coefficients indicate speed of adjustment processes, if any shock hit to the economy and disequilibrium corrected in the subsequent period.This is also shoes the existence of a stable long run equilibrium relationship.

Table No. 5: ARDL Short-Run Test Results

Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
D(Climate Resilience)	2.046***	0.001	-	-
D(Climate Vulnerability)	-	-	-0.182***	0.066
D(Employment in industry)	2.969**	1.364	1.774***	0.045
D(FDI Inflows)	1.845	1.584	1.719***	0.041
D(GDP Per Capita)	0.044***	0.009	0.032**	0.059
D(CO2)	-0.154	0.124	-0.178	0.157
D(TRADE)	-0.739**	0.249	-0.653*	0.474
D(Exchange Rate)	0.187*	0.097	-0.013*	0.011
D(Gross Fixed Capital Formation)	0.072*	0.031	0.041**	0.022
Error Correction Term	-0.293***	0.186	-0.275***	0.090

3.4. Diagnostic test

As results shown in Table 6, the diagnostic tests confirm the robustness of the ARDL model. The LM test indicates no serial correlation, and the Ramsey RESET test confirms correct model specification. Residuals are normally distributed, and the White test shows no heteroskedasticity. These results validate the reliability of the model for analysis.

Table No. 6: ARDL Short-Run Test Results

Problems	**Applicable Test**	**F-Statistics**	**Probabilities**
Serial Correlation	Lagrange Multiplier (LM)	0.318	0.616
Functional Form	Ramsey RESET	0.493	0.952
Normality	Skewness and Kurtosis of Residual	0.841	0.656
Heteroskedasticity	White	1.163	0.142
CUSUM and CUSUM Square		Stable	

4. Conclusion and Policy Recommendation

The primary objective of this study was to analyze the impact of climate vulnerability on the industrial sector of Pakistan, considering the effects of exposure, sensitivity, and adaptive capacities. Furthermore, the role of climate resilience in mitigating these adverse effects was examined. Employing ARDL methodology, the analysis revealed significant long-run and short-run relationships between industrial production and the explanatory variables.The findings indicate that climate resilience has a substantial positive impact on industrial production, reinforcing its critical role in ensuring industrial sustainability amidst climate risks. Conversely, climate vulnerability negatively affects industrial productivity, both in the short and long term, highlighting the urgent need to address exposure and sensitivity to climate-related risks. Economic indicators such as employment in industry, FDI inflows, GDP per capita, and gross fixed capital formation consistently exhibit positive contributions to industrial production. These factors underscore the importance of economic growth, investment, and labor market stability in fostering industrial development. On the other hand, trade openness and exchange rate fluctuations negatively influence industrial performance, suggesting potential vulnerabilities to external economic shocks.The results emphasize the necessity of integrating climate resilience into industrial policies and strategies to mitigate the detrimental effects of climate vulnerability. Such integration is essential to sustaining industrial production, ensuring long-term sectoral growth, and achieving economic stability in the face of escalating climate challenges.To enhance industrial resilience and sustainability amid escalating climate challenges, targeted policy interventions are imperative. Investment in adaptive infrastructure, such as climate-resilient industrial facilities and robust supply chains, is essential to mitigate climate-related disruptions. Promoting research and development in climate-smart technologies can further improve industrial efficiency and long-term viability. Strengthening institutional frameworks for disaster risk management and environmental sustainability is critical for reducing vulnerability to climate risks.

Economic policies should prioritize attracting foreign direct investment (FDI) through tax incentives, streamlined regulatory processes, and legal safeguards. Supporting GDP growth via industrial diversification and improved credit access for small and medium-sized enterprises (SMEs) can bolster industrial productivity. Strategic trade policies are needed to minimize dependence on volatile global markets and promote regional trade. Stabilizing the exchange rate through effective monetary and fiscal policies is equally crucial to mitigate adverse economic impacts on industrial performance.Capacity-building programs should equip industrial stakeholders with skills to implement climate adaptation strategies effectively, complemented by public awareness initiatives to highlight the economic and environmental benefits of resilience measures. An integrated, multi-sectoral approach across agriculture, water management, and infrastructure is essential to address overlapping vulnerabilities and foster comprehensive resilience. These recommendations underscore the need for a cohesive policy framework to ensure sustainable industrial development and economic stability.

References

Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (2004). At risk: natural hazards, people's vulnerability and disasters.Routledge.

Breusch, T.S. (1978), Testing for autocorrelation in dynamic linearmodels. Australian Economic Papers, 17(31), 334-355.

Breusch, T.S., Pagan, A.R. (1979), A simple test for heteroskedasticity and random coefficient variation.Econometrica: Journal of theEconometric Society, 45, 1287-1294.

Cannon, T., & Müller-Mahn, D. (2010). Vulnerability, resilience and development discourses in context of climate change. Natural hazards, 55, 621-635.

Chen, X., & Yang, L. (2019). Temperature and industrial output: Firm-level evidence from China. Journal of Environmental Economics and Management, 95, 257-274.

Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from India. American Economic Journal: Applied Economics, 13(4), 101-124.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008).A place-based model for understanding community resilience to natural disasters. Global environmental change, 18(4), 598-606.

Dellas, H., & Koubi, V. (2001). Industrial employment, investment equipment, and economic growth. *Economic Development and Cultural Change*, *49*(4), 867-881.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, 251-276.

Fakher, H. A., Ahmed, Z., Acheampong, A. O., & Nathaniel, S. P. (2023). Renewable energy, nonrenewable energy, and environmental quality nexus: An investigation of the N-shaped Environmental Kuznets Curve based on six environmental indicators. Energy, 263, 125660.

Francis, C. A., & Clegg, M. D. (2020).Crop rotations in sustainable production systems.In Sustainable agricultural systems (pp. 107-122).CRC Press.

Fu, S., Viard, V. B., & Zhang, P. (2021). Air pollution and manufacturing firm productivity: Nationwide estimates for China. The Economic Journal, 131(640), 3241-3273.

Galderisi, A., Ferrara, F. F., &Ceudech, A. (2010).Resilience and/or vulnerability?Relationships and roles in risk mitigation strategies. In Space is Luxury, Selected Proceedings, 24Th Aesop Annual Conference 2010 (pp. 388-405). Centre for Urban and Regional Studies Publications.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. Econometrica: Journal of the Econometric Society, 1293-1301.

Gorus, M. S., &Aslan, M. (2019). Impacts of economic indicators on environmental degradation: evidence from MENA countries. Renewable and Sustainable Energy Reviews, 103, 259-268.

Gupta, A. K., Babu, N. R., Lux, F. B., & Bansal, S. (2024). Climate Change Adaptation in Industrial Areas for Disaster Resilience. In *Disaster Risk and Management Under Climate Change* (pp. 231-261). Singapore: Springer Nature Singapore.

Jawaid, S. T., & Saleem, S. M. (2017). Foreign capital inflows and economic growth of Pakistan. *Journal of Transnational Management*, *22*(2), 121-149.

Kling, G., Volz, U., Murinde, V. &Ayas, (2021). The impact of climate vulnerability on firms' cost of capital and access to finance.World Development, 137, 105131.

Kling, G., Volz, U., Murinde, V., & Ayas, S. (2021). The impact of climate vulnerability on firms' cost of capital and access to finance. World Development, 137, 105131.

Kuznets, S. (1955). Economic growth and income inequality.The American Economic Review, 45(1), 1–28. American Economic Association.

Lundgren, K., Kuklane, K., Gao, C., &Holmer, I. (2013). Effects of heat stress on working populations when facing climate change. Industrial health, 51(1), 3-15.

Mendelsohn, R. (2007). Measuring climate impacts with cross-sectional analysis. Climatic Change, 81(1), 1.

Menk, L., Terzi, S., Zebisch, M., Rome, E., Lückerath, D., Milde, K., &Kienberger, S. (2022). Climate change impact chains: a review of applications, challenges, and opportunities for climate risk and vulnerability assessments. Weather, Climate, and Society, 14(2), 619-636.

Murray, V., &Ebi, K. L. (2012).IPCC special report on managing the risks of extreme events and disasters to advance climate change adaptation (SREX). J Epidemiol Community Health, 66(9), 759-760.

Nasir, J., Nasir, B., & Ashfaq, M. (2022). Integrated impact assessment of climate change vulnerability and adaptations for agricultural production system of Punjab, Pakistan. *Pakistan Journal of Agricultural Sciences*, *59*(5).

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. Journal of the Royal Statistical Society Series B: Statistical Methodology, 31(2), 350-371.

Sinnarong, N., Panyadee, C., &Aiikulolac, O. I. (2019).The Impact of Climate Change on Agriculture and Suitable Agro-Adaptation in Phufa Sub-District, Nan Province, Thailand. Journal of Community Development Research (Humanities and Social Sciences), 12(3), 47-60.

Tonmoy, F. N., ElZein, A., &Hinkel, J. (2014). Assessment of vulnerability to climate change using indicators: a meta-analysis of the literature. Wiley Interdisciplinary Reviews: Climate Change, 5(6), 775-792.

Ullah, A., Khan, M. U., Ali, S., & Hussain, S. W. (2012). Foreign direct investment and sectoral growth of Pakistan economy: Evidence from agricultural and industrial sector (1979 to 2009). *African Journal of Business Management*, *6*(26), 7816.

Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. Journal of Environmental Economics and Management, 88, 1-17.