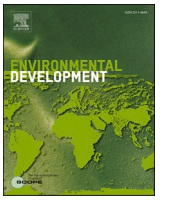
Environmental Development 52 (2024) 101059

Contents lists available at ScienceDirect

Environmental Development

journal homepage: www.elsevier.com/locate/envdev



The impact of corruption on climate risk – An international evidence

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ARTICLE INFO

Keywords:
Climate risk
Corruption
Climatic disaster
Developing countries
Developed countries
Disasters

ABSTRACT

Prior studies suggest that climate disasters increase corruption due to the windfall of donations. However, is it possible that corruption increases the probability of occurrence and consequences of climatic disasters? This paper investigates the intricate relationship between corruption and climate risk using a comprehensive panel dataset spanning 171 countries from 2006 to 2019. Employing robust econometric methodologies, including fixed effects and a two-step generalised method of moments, we explore whether corruption exacerbates the probability and severity of climate-related disasters. Our findings reveal a significant positive association between corruption levels and climate risk, indicating that corruption amplifies both the frequency and consequences of climate disasters. Importantly, this relationship holds across diverse geographical locations and development statuses, with a particularly pronounced impact observed in developing countries where corruption compounds existing infrastructural vulnerabilities. These findings highlight the imperative for policymakers to address corruption alongside environmental and geographical factors in crafting effective strategies to mitigate climate-related disasters and enhance global resilience.

1. Introduction

The escalating frequency and severity of climate-related disasters underscore the pressing global concern posed by climate risk While the impacts of these disasters vary widely across nations, influenced by factors such as governance quality, socioeconomic conditions, and geographical characteristics (Cevik and Jalles, 2023), the intricate interplay between corruption and these contextual factors remains inadequately understood. Despite extensive research on the determinants of climate risk (Adger et al., 2005; Escaleras et al., 2007; IPCC, 2014), the role of corruption in shaping its outcomes remains a critical gap in current knowledge.

Existing research has predominantly examined the aftermath of disasters on corruption levels (Khurana et al., 2022; Leeson and Sobel, 2008; Nguyen, 2017; Nikolova & Marinov, 2017; Yamamura, 2014; Zafar et al., 2023).For instance, Zafar et al. (2023) highlight that disasters often lead to increased corruption, attributed to the influx of aid and donations. However, these studies typically treat disasters as natural occurrences with corruption being a subsequent consequence, rather than considering corruption as a potential contributing factor to the occurrence and magnitude of climatic disaster. This notable gap in the literature prompts further exploration,

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https://doi.org/10.1016/j.envdev.2024.101059
Received 26 September 2023; Received in revised form 25 July 2024; Accepted 31 August 2024
Available online 6 September 2024
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as highlighted by Escaleras et al. (2007), Sanderson et al. (2022) and Ambraseys and Bilham (2011), who specifically focused on earthquakes and corruption within the construction industry. Moreover, a recent literature review by Sanderson et al. (2022) underscores the need for comprehensive research on how corruption exacerbates disasters. This paper aims to address this gap by empirically investigating corruption as a potential driver of climate risk.

Our motivation is prompted by the observed disparities in the probability and consequences of climate disasters across countries, which remain inadequately explained, especially beyond geographical factors (Sanderson et al., 2022). For instance, why do disasters of comparable magnitude, such as floods, hurricanes, storms, and wildfires, result in significantly varied damages, including death tolls or income loss, in different countries? We seek to address this question by investigating the influence of crucial institutional structures, such as corruption, on climate risk. Specifically, we aim to determine the extent to which corruption affects climate risk and whether it can elucidate why low-polluting countries are susceptible to high climate risk. Climate risk captures both the probability of occurrence and consequences of climate disasters (Eckstein et al., 2021).

Corruption, defined as the abuse of power for private gain (Shleifer and Vishny, 1993), can significantly impact climate risk through various mechanisms. Firstly, corruption undermines climate mitigation efforts by hindering the enactment and enforcement of stringent environmental regulations, emission reduction strategies, and clean energy initiatives (Ganda, 2020; Tawiah et al., 2023a,b). Weak environmental regulations resulting from corruption contribute to environmental degradation, including unsustainable exploitation of natural resources, deforestation, illegal logging, and pollution. These activities exacerbate climate change, rendering regions more susceptible to climate-related disasters such as landslides, droughts, and wildfires. Consequently, the lack of progress in addressing the root causes of climate change amplifies the frequency and severity of climate-related disasters.

Moreover, corruption weakens a country's resilience capacity against climate disasters. It compromises communities' ability to build resilience by impeding transparency and accountability in governance, which are essential for effective disaster preparedness and adaptation strategies (Cevik and Jalles, 2023). The absence of transparent and accountable governance hampers the development and implementation of long-term strategies aimed at mitigating the impacts of climate disasters. As a result, corrupt practices hinder efforts to enhance resilience, leaving communities more vulnerable to the adverse effects of climate change-induced disasters. From the ex-ante perspective, corruption increases the climate risk through its impact on scale and probability of occurrence.

After the occurrence of disaster, corruption increases the climate risk through its impact on the consequence. Corruption can cause the abuse of funds, erosion of trust in government institutions, undue delay and uneven distribution of resources to affect victims inequality (Apergis et al., 2010; Escaleras et al., 2007; Gyimah-Brempong and de Gyimah-Brempong, 2006; Yamamura, 2014).

To this the end, we use large sample of panel data to examine the impact of corruption on climate risk. We employ robust econometric modelling on sample of 171 countries between 2006 and 2019. In line with prior studies, (Ding et al., 2021; Huang et al., 2018), we use the climate risk index by Germanwatch. We also use two widely used corruption indices namely: Control of corruption and Bayesian corruption index. Consistent with our expectation, we find a significant and positive relationship between corruption and climate risk. The results suggest that corruption increases the probability and consequences of climate risk. Given the potential reverse causality between climate disaster and corruption and possible effect of prior year climate risk, we perform different economic identification strategies to check the robustness of the results to potential endogeneity. The results of the two-steps System Generalised Method of Moments show that our results are not sensitivity to potential endogeneity problem.

Considering the geographical distribution of climate disasters, we conducted a continental analysis to ensure the robustness of our findings across different regions. Our analysis revealed consistent results across all continents, affirming the significant impact of corruption on increasing climate risk globally. However, we observed that the effect was particularly pronounced in low economic and financial developing countries, where corruption exacerbates existing challenges in infrastructure planning and development.

This disparity underscores the disproportionate burden borne by developing nations in the face of climate-related challenges, as corruption further hampers their ability to prepare for and respond to disasters effectively. By exacerbating weaknesses in infrastructural planning and development, corruption amplifies the vulnerability of these countries to the adverse impacts of climate change. Therefore, addressing corruption becomes even more imperative in such contexts to enhance resilience and mitigate the consequences of climate-related disasters.

This study contributes to the existing literature in several significant ways. Our research provides timely insights into the growing concern of climate disasters, which are increasingly threatening communities worldwide. While previous studies, such as (Ambraseys and Bilham, 2011; Escaleras et al., 2007; Sanderson et al., 2022), have touched on the relationship between corruption and disasters, our paper offers new perspectives on how corruption influences both the occurrence and magnitude of climate-related events. Unlike prior research limited to specific disasters like earthquakes, our analysis offers a comprehensive examination of various factors through which corruption impacts climate risk.

Moreover, our study goes beyond merely assessing the magnitude of disasters by also considering their occurrence and extent. By incorporating data on the probability and consequences of climate-related events, we capture both the anticipatory and reactive aspects of the relationship between corruption and disasters. Specifically, our analysis delves into the influence of corruption on both the likelihood and severity of climate disasters, providing a more holistic understanding of this complex phenomenon.

Furthermore, our research contributes to the limited literature on the non-environmental and geographical drivers of climate disasters. We highlight the significant role of social and behavioural factors, such as corruption, in exacerbating the occurrence and consequences of climate-related events. By shedding light on these non-environmental determinants, we underscore the importance of addressing corruption to mitigate the impacts of climate change effectively.

Finally, our findings emphasize the profound and far-reaching effects of corruption on a community's ability to prepare for and respond to disasters. Corruption undermines the allocation of resources and weakens governance structures, impeding effective disaster response efforts. Addressing corruption is therefore essential to ensure that communities are equipped with the necessary

resources and infrastructure to withstand the adverse effects of disasters. By combating corruption, governments and organizations can enhance the efficiency and efficacy of disaster response measures, ultimately minimizing the impact of climate-related events on society.

The remainder of the paper is as follows. The next section presents the literature and arguments supporting the relationship between corruption and climate risk. In Section 3, we outline the research methodology and econometric identification strategies. The results and discussions are presented in Section 4 and the paper concludes in Section 5 with policy implications and suggestions for future research.

2. Literature review

Climate risk refers to the potential adverse impacts of climate variability and change on human and natural systems (IPCC, 2014). Climate risk represents the likelihood of experiencing negative consequences, such as economic losses, social disruptions, environmental degradation, and human suffering, as a result of climate-related events and trends (Adger et al., 2007; IPCC, 2014) These risks can manifest in various forms, including damage to infrastructure, disruption of food and water supplies, displacement of populations, loss of biodiversity, and increased frequency or intensity of climate related disasters. Empirically our measure of climate risk is captures both the probability of occurrence and consequences of climate disasters (Eckstein et al., 2021)

A scan through the literature indicate that numerous factors contribute to climate risk, ranging from geographical (Loarie et al., 2009) to socio-economic activities. However, in recent years, the more convincing factors are the human induced factors including carbon emissions. Human activities, such as burning fossil fuels, deforestation, and industrial processes, release greenhouse gases (GHGs) into the atmosphere (IPCC, 2014). These gases trap heat, leading to global warming and changes in climate patterns, which can increase climate risks such as extreme weather events, sea-level rise, and ecosystem disruptions (Chaudhry et al., 2020).

Rosenzweig et al. (2011) also suggest that rapid urbanization and the expansion of infrastructure in vulnerable areas can increase climate risks, such as heatwaves, urban flooding, and infrastructure damage. Poorly planned urban development can exacerbate the urban heat island effect and impede natural drainage systems, leading to increased vulnerability to climate extremes. Furthermore, socioeconomic factors, including poverty, financial development, inequality, population growth, and access to resources, influence vulnerability to climate risks. Marginalized communities often lack resources and infrastructure to cope with climate extremes, increasing their susceptibility to climate-related disasters and disruptions (Adger et al., 2007). Related to socio-economic factors is corruption, which has not be explored in the literature.

Corruption is the abuse of power for private gain, which can take various forms including bribery, embezzlement, nepotism, patronage, and fraud (Kaufmann and Kraay, 2018; Shleifer and Vishny, 1993; Transparency International, 2021). It involves unethical or illegal actions by individuals or institutions in positions of authority or influence, often for personal or organizational benefit at the expense of the public interest or common good. Corruption as a social cancer (Shleifer and Vishny, 1993) is found to affect different areas of human life.

However, when it comes to climate disasters, prior studies only explain how these disasters increase or decrease corruption (Leeson and Sobel, 2008; Nikolova & Marinov, 2017; Yamamura, 2014). These studies argue that disasters bring windfall monies into the country, through foreign aids and donations. For instance, Yamamura (2014) reports that disasters increase public sector corruption in both developing and developed countries due to the flow of emergency relief funds and donations. Although, these studies provide evidence into the relationship between corruption and climate disaster, it is not always the case that climate disasters cause corruption. It is probable that corruption increases the chances of climate disaster happening and the extent of its effect on humanity. We argue that corruption affects climate risk from both the ex-ante and ex-post perspectives.

Corruption exerts a significant ex-ante effect on various aspects of environmental governance and urban planning, ultimately exacerbating the risks associated with climate disasters. As highlighted by Ambraseys and Bilham (2011), corrupt practices often lead to inadequate town and country planning, resulting in improper construction in vulnerable areas such as waterways. Zoning regulations and building permits, which are susceptible to corruption and extortion, contribute to the proliferation of low-quality building stock and substandard urban development.

The consequences of such corrupt practices become starkly evident during climate disasters, where poorly planned and constructed infrastructure proves especially vulnerable. For instance, in the aftermath of events like hurricanes, floods, or wildfires, inadequately constructed buildings and critical infrastructure are more prone to failure, amplifying the magnitude of damage and loss of life. This was tragically exemplified in Haiti, where high casualty rates were attributed to corruption-induced poor planning and zoning practices (Cevik and Jalles, 2023).

Moreover, corruption undermines the integrity of environmental impact assessments for new projects and construction ventures, as noted by Neu et al. (2015) and Williams and Dupuy (2017). Bribery, collusion, and conflicts of interest are common corrupt practices that compromise the accuracy and objectivity of environmental impact assessments, leading to environmentally harmful developments. Private entities often engage in bribery to circumvent regulations and exploit disaster-prone areas for development, such as water catchment zones or sewage ways, as highlighted by Paliwal (2006).

Furthermore, corruption can also contribute to environmental degradation and neglect of infrastructure, which can make communities more vulnerable to disasters in the first place. For example, a lack of proper waste management and environmental regulations due to corruption can result in the build-up of hazardous materials that can exacerbate the effects of disasters (United Nations, 2013). Corruption also increases the magnitude and scale of climate related disaster. For example, the scale and magnitude of flooding on a deforested area will be bigger than a forest area (Sommer, 2022).

Corruption also manifests as an ex-post effect, impacting the management of disaster responses and the allocation of relief funds in

the aftermath of climate events. When disasters strike, the efficiency and effectiveness of government agencies' responses are often compromised by corrupt practices, delaying critical interventions and exacerbating the impact on affected communities. Cevik and Jalles (2023) highlight how relief funds intended for disaster management can become avenues for personal enrichment for corrupt officials, leading to delays and inefficiencies in the distribution of aid.

Embezzlement, bribery, and other corrupt activities divert crucial funds away from disaster preparedness, response, and recovery efforts (Yamamura, 2014), resulting in inadequate infrastructure, insufficient early warning systems, and poorly equipped emergency services. As a consequence, communities are left more vulnerable to the impacts of climate disasters, with heightened risks of casualties and property damage (Escaleras et al., 2007).

Moreover, corruption exacerbates income inequality (Apergis et al., 2010; Gyimah-Brempong and de Gyimah-Brempong, 2006), further compounding the inequitable distribution of relief and recovery resources. Relief efforts may disproportionately benefit influential or wealthy individuals and groups, leaving marginalized communities without adequate support. This exacerbates social disparities and increases the vulnerability of already disadvantaged populations to the adverse effects of climate disasters.

Bureaucratic corruption significantly impacts decision-making processes and the timely release of funds essential for immediate disaster response efforts. Delays resulting from corruption can exacerbate the severity of disasters, as prompt interventions are crucial in mitigating casualties and minimizing damages (Alexander, 2017). The diversion of public funds through corrupt practices undermines the ability of countries and communities to adequately prepare for and respond to disasters. When resources intended for disaster preparedness and response are misappropriated, affected communities are left vulnerable due to a lack of necessary infrastructure and support systems (Alexander, 2017).

Furthermore, corruption erodes accountability in disaster response initiatives. Historical evidence, as noted by Uberti (2022), suggests that corrupt practices diminish public trust in government and relief organizations, impeding their ability to mount effective disaster response efforts. Transparency International's annual survey corroborates this assertion, highlighting the detrimental impact of corruption on public trust (Transparency International, 2021). The erosion of trust undermines cooperation with evacuation orders and adherence to safety guidelines during disasters, as individuals are less likely to comply with directives from authorities they perceive as corrupt (Cevik and Jalles, 2023).

The relationship between corruption and disasters is entangled. However, the above discussion indicates that corruption is more likely to increase the likelihood of climate disasters and amplifies its consequences. Therefore, we specify our hypothesis as follows.

H1. *Corruption is positively and significantly associated with increase in climate risk.*

3. Research method

3.1. Sample data and selection

We begin our sample selection from all 209 countries and jurisdictions listed in the World Development Indicators database. We drop 26 countries that are not covered by the Germanwatch climate risk report, the source of climate risk data (Example, North Korea, Liechtenstein, Marshall Islands, Palau, Syria, San Marino Timor Island, etc). Next, we drop 12 countries with more than 3 years missing data on any variable (Example, Chinese Tapei, Cuba, Djibouti, Kosovo Nauru, North Macedonia, South Sudan). Our final sample selection yields 171 countries between 2006 and 2019. The sample period is limited due to the data availability on climate risk. Despite the limitations of the data, our sample includes both developing and developed countries and satisfactory representation from different continents. The large size of the data does not only increase the reliability of the findings but also allow for cross-sectional analysis.

3.2. Definition and measurement of variables

Climate risk is defined as the extent to which countries have suffered direct loss associated with extreme weather-related events such as storms, floods, and heat waves and probability of climate related disaster occurring (Eckstein et al., 2021). Consistent with prior studies (Ding et al., 2021; Huang et al., 2018), we use the climate risk index by Germanwatch. The data is reported in two-year lag, implying that an index of 2021 is based on actual events of 2019. Climate risk captures short and long periods enough to estimate the long-term economic consequences. We also use the climate risk data because it ensure accuracy and reliability in the measurement (Ding et al., 2021; Huang et al., 2018). Climate risk data from Germanwatch is widely used in the literature such as (Burnell, 2012; Ding et al., 2021; Garschagen and Romero-Lankao, 2015; Huang et al., 2018; Liu et al., 2023; Rivera and Wamsler, 2014)

Corruption: Consistent with existing corruption literature (Barbopoulos et al., 2014; Habib and Zurawicki, 2002; Tawiah et al., 2022; Tawiah et al., 2023a,b), we use perception-based corruption indicators to measure the level of corruption in each country. There are different sources of corruption indicators, and each has some unique features and methodological approach. Therefore, to ensure the robustness of our results we use two main source of corruption measurement. Tawiah et al. (2022) suggests that these measures capture slightly different levels of corruption in a country; hence, they help in overcoming the limitation of our results being bias due to the measurement of the corruption.

The first measure of corruption is Control of Corruption (CCPT) of World Governance Indicators by Kaufmann and Kraay (2018). The control of corruption index is part of the six governance indicators based on 30 different sources and ranges from −2.5 to 2.5 with higher values indicating less corruption. However, we use the reciprocal format which rescales the index to range between 0 and 5 with 0 being the lowest level of corruption and 5 being the highest. The third measure of corruption is the Bayesian Corruption Index (BCI) from the Quality of Government Institute. The BCI ranges from 0 to 100 but with higher values indicating higher corruption. BCI is

based on the opinions of companies, non-governmental organizations, and officials on the level of corruption in a country.

Control variables: Consistent with prior studies (Anbarci et al., 2005, 2006; Escaleras et al., 2007), we include battery of variables to control for other factors that may influence climate risk. Arguably, disaster is significantly influenced by geographical factors such as *Topography* and *Sea level* (Loarie et al., 2009). For example, small island developing states are expose to high climate risk (Pelling and Uitto, 2001; Sjöstedt and Povitkina, 2017). We also control for demographic features including *Population* and *Population density* (Karácsonyi et al., 2021). Economic factors can also drive disaster. Countries with high income (*Economic development*) are like to be more resilience to disasters. Similarly, prior studies show that *Financial developmen*t is positively associated with disasters (Zhang and Managi, 2020). Industrialisation mix can also influence disasters. We include *Agriculture and Manufacturing industry* as control variables. We also control for the *Regulatory quality* and *Carbon emissions*. The description and sources of variable are presented in Table 1

3.3. Model specification

Ordinary least square is the common estimator in prior studies (Escaleras et al., 2007; Liu et al., 2023). Consequently, we perform the Hausman's test to choose between the random and fixed effect. The results indicate that the fixed effect is more appropriate. In addition to this empirical evidence on fixed effect, we also use it because the fixed effect panel econometric modelling mitigates the effect of omitted variables. Moreover, the fixed effect estimation approach address the potential endogeneity arising from the correlation between the time-invariant country fixed effect with the time-varying explanatory variables (Hausman, 1989).

$$\begin{aligned} Climate\ risk_{\ it} = {} & a + \beta_1(Corruption)_{it} + \beta_2(Economic\ development)_{it} + \beta_3(Population)_{it} + \beta_4(Population\ density)_i \\ & + \beta_5(Agricultural\ industry)_{it} + \beta_6(Manufacturing\ industry)_{it} + \beta_7(Financial\ development)_{it} + \beta_8(Topography)_{it} + \beta_9(Sea\ level)_{it} \\ & + \beta_{10}(carbon\ emission)_{it} + \beta_{11}(Regulatory\ quality)_{it} + + \varepsilon_{it} \end{aligned}$$

3.4. Other econometric identification strategies

While existing corruption can exacerbate the consequences of climate, the influx of relief funds can also create new opportunities for governmental corruption (Leeson and Sobel, 2008; Nikolova & Marinov, 2017; Yamamura, 2014). Hence there is potential reverse causality between corruption and climate risk. Indeed, most studies on corruption and disasters focused on this direction. Therefore, we employ robust identification strategy to address this concern.

Although the fixed effect estimation address some potential endogeneity issues, it is limited in mitigating the endogeneity of the lagged effect of the dependent variable. (Arellano and Bond, 1991) suggest Generalised Method of Moment (GMM) to address these problems. However, the GMM drops valuable information leading to measurement error bias. Further, Blundell and Bond (1998) argue that GMM estimation suffers from the possibility of weak instruments.

To overcome these challenges, we use the System GMM. According to Blundell and Bond (1998) the System GMM uses additional

Table 1
Variable description and measurement.

Variable name	Definition	Source
Climate risk	The extent to which countries have suffered direct loss associated with extreme weather-related events such as storms, floods, and heat waves	Germanwatch climate risk index
Control of corruption	Corruption measurement as part of governance indicators ranging from +2.5 to −2.5, transformed to 0 to 5 for this study	Worldwide Governance Indicators
Bayesian corruption	Bayesian corruption index also ranges between 0 and 100	Quality of Government database
Economic development	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars.	World Development Indicators
Population	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates. (We use the log form)	World Development Indicators
Population density	Population density is midyear population divided by land area in square kilometres.	World Development Indicators
Agricultural industry	Agriculture industry contribution to GDP. Agriculture, forestry, and fishing corresponds to ISIC divisions 1–3 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production.	World Development Indicator
Manufacturing industry		
Financial development	It is measured by the financial development index which summarizes how developed financial institutions and financial markets are in terms of their depth, access, and efficiency	Financial Development Index database by IMF
Topography	The measures whether a country is land locked or Island. It is measured in ordinary scale ranging from 0 – landlocked; 1-Island; 2 – small Island developing countries.	World Population Review
Sea level	Measure the average elevation above the see level (in meters)	World Population Review
Carbon emissions	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	World Development Indicators
Regulatory quality	This measures the quality of regulations in the country as part of the World Governance Indicators. It ranges from +2.5 to −2.5.	World Governance Indicators

moment conditions and tackles the problem of weak instruments suffered by GMM. Consistent with prior studies (Arellano and Bond, 1991; Tawiah et al., 2022), we use the lag structures of the explanatory to as instrument for the endogenous variable. For robustness check, we use one-year, two-years and three-years lags in different estimations. We rewrite our empirical model, equation (1), to estimate using System GMM as follows:

$$\text{Climate risk}_{it} = \beta_j \text{corruption}_{ijt} + X'_{it}\text{Controls} + \Delta\varepsilon_{ijt} \quad (3)$$

For the consistency of System GMM estimation, we use the two-step model. For the validity of the instrument, we employ the over-identification test developed by Hansen (1982). To check whether the assumption of no second-order serial correlation is satisfied, we employ Arellano and Bond (1991). Although S-GMM help overcome to some potential endogeneity issues, it is limited in yielding robust results with long panel data. Therefore, to overcome this challenge, we use 3 – year averages to create short panel and a wide cross-section.

3.5. Limitations of the methodology

As with any corruption literature, our measure of corruption is based on perception, not actual corruption (Treisman, 2007, 2014). These perception-based indicators might not accurately capture the actual corruption in the country. Nonetheless, prior studies have established that these perception-based indicators are closely related to the actual corruption in most cases (Treisman, 2007). We drop some countries due to missing data. Furthermore, our control variables might not capture all factors that could influence climate risk.

4. Results and discussion

4.1. Descriptive statistics

The descriptive statistics of the variables are presented in Table 2. The statistics include the mean, standard deviation, median, 25th and 75th percentile. The mean of the two alternative measurements of corruption differ, indicating that each source captures the different level of perceived corruption. Notwithstanding these differences, the mean of the corruption indices shows that most of the sample countries have some level of corruption in the country. But there is high variation, as evidenced in the large standard deviation. Regarding climate risk, the mean of 87.79 show high risk among the countries over the sample period. The 75th percentile (117.3) and standard deviation (40.07) are high indicating large variations across the sample. The descriptive statistics of most control variables are consistent with standard assumption and prior studies (Liu et al., 2023).

4.2. Correlation matrix

As part of pre-regression check, we perform pairwise correlation matrix among the independent variables. The results of the Pearson pairwise correlation matrix is presented in Table 3. The high correlation coefficient between two corruption measurements confirms the appropriateness of using those as alternative to each other. Except for the correlation among the corruption, none of the coefficients is above the standard threshold of 0.8 to posses multi-collinearity threat (Field, 2000; Tabachnick and Fidell, 2013).

4.3. Main results

The results of the baseline estimations are presented in Table 4. The table contains two sets of estimations corresponding to the two measurement of corruption namely; control of corruption and the Bayesian corruption index. In addition to using three different measurements of the independent variable to ensure robustness, we also include the year and country effect. Arguably, both corruption

Table 2
Summary statistics.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Mean	SD	25th	Median	75th
Climate risk	87.79	40.07	56	84.50	117.3
Bayesian corruption	47.35	16.17	37.17	51.31	59.38
Control of corruption	2.541	0.992	1.922	2.796	3.262
Carbon emission	40.69	502.9	0.657	2.693	6.483
Financial development	0.271	0.812	0.103	0.294	0.845
Population density	329.6	1581	32.42	80.28	186.6
Agricultural industry	26.26	13.06	17.92	24.37	31.40
Manufacturing industry	15.664	37.75	0.415	12.181	36.998
Regulatory quality	−0.008	0.965	−0.704	−0.164	0.649
Population	15.49	2.416	14.26	15.78	17.09
Economic development	8.585	1.566	7.408	8.631	9.735
Topography	0.969	0.587	1	1	1
Sea level	650.3	614.7	250	455.5	909

Table 3
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11
Control Cpt	1										
Bayesian cpt	0.92	1									
Econ. Devep	−0.61	−0.65	1								
Population	0.2	0.2	0	1							
Pop.density	−0.15	−0.2	0.2	−0.09	1						
Agriculture industry	0.11	0.08	−0.2	−0.01	−0.03	1					
Manufacturing industry	0.19	0.08	0.16	0.3	−0.16	0	1				
Financial development	−0.12	−0.11	0.09	−0.14	0.08	0.02	−0.12	1			
Topography	−0.1	−0.09	0.07	−0.37	0.03	−0.02	−0.21	0.03	1		
Sea level	0.15	0.12	−0.27	0.04	−0.09	0.07	−0.03	−0.07	−0.2	1	
Carbon emission	−0.03	−0.04	−0.34	−0.49	0.1	0.13	−0.14	0.03	0.12	−0.07	1
Regulatory quality	−0.56	−0.64	0.62	−0.02	0.22	−0.14	−0.12	0.14	0.01	−0.2	−0.1

Table 4
Baseline results.

VARIABLES	(1)	(2)
	Climate risk	Climate risk
Control of corruption	1.170***	
	(2.631)	
Bayesian corruption		0.592***
		(4.235)
Economic development	-4.202***	-3.865**
	(-2.750)	(-2.402)
Population	-8.012*	-11.489**
	(-1.698)	(-2.195)
Population density	0.020***	0.019***
	(3.023)	(2.667)
Agricultural industry	0.044**	0.038**
	(2.486)	(2.288)
Manufacturing industry	0.529***	0.588***
	(6.364)	(6.795)
Financial development	-0.028**	-0.007**
	(-2.931)	(-2.225)
Topography	23.251***	22.609***
	(8.445)	(7.699)
Sea level	0.223***	0.211***
	(6.698)	(6.138)
Carbon emission	-0.588	-0.720*
	(-1.512)	(-1.793)
Regulatory quality	-2.570**	-0.649**
	(-2.206)	(-2.306)
Constant	-25.028***	-13.442
	(-2.668)	(-1.279)
Country effect	Yes	Yes
Year effect	Yes	Yes
R-Squared	0.039	0.048
Observations	2,116	1,942
Number of countries	171	171
Wooldridge test	0.12	0.11

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

and climate risk are country and time sensitive (Liu et al., 2023). For easy interpretation the corruption measure as continuous variable with high value indicating high corruption.

The coefficient of corruption exhibits a positive and statistically significant association with climate risk at the 1% significance level across both columns, indicating a robust link between corruption and climate risk. These findings align with expectations and lend support to the hypothesis that corruption exacerbates climate risk. Corruption elevates the likelihood of climate disasters by weakening regulatory frameworks and fostering inadequate urban planning practices, such as construction in flood-prone areas. Moreover, corrupt practices result in the use of substandard materials and a lack of maintenance in infrastructure projects (Sanderson et al., 2022).

Furthermore, corruption intensifies the consequences of climate disasters by facilitating the misuse of donations and the uneven

distribution of resources among affected regions. Additionally, corruption engenders delays in decision-making processes and the allocation of funds crucial for immediate disaster response efforts. The erosion of trust and accountability within a country due to corrupt practices exacerbates the mismanagement of funds, further amplifying the impact of climate disasters (Anbarci et al., 2005; Escaleras et al., 2007).

The results of most control variables are consistent with standard assumption and prior studies. For example, population density is positive and significantly associated with climate risk. This is consistent with Escaleras et al. (2007) who reports positive relationship between population and climate disaster. Arguably highly populated countries are more likely to suffer mor causalities than less populated countries. On the contrary, we find negative relationship between economic growth and climate risk, suggesting that growing countries have less tendencies to experience climate related disasters.

4.4. Endogeneity test

Having established the impact of corruption on climate risk, we now examine the robustness of our results against potential endogeneity issues, specifically focusing on omitted variable bias. Consistent with prior studies (Amin and Islam, 2023), we employ the Oster (2019) test. This test operates on the premise that, under specific assumptions, the selection of observables can be used to identify the likely bias from the selection of omitted variables.

The Oster test serves two primary functions. Firstly, it infers the degree of unobserved selection necessary to reduce the impact of the variable of interest (corruption) on the dependent variable (climate risk). This is represented by the δ value. A higher δ value indicates a lower likelihood that the result is driven by omitted variable bias. According to Oster (2019), a maximum R^2 value that is 1.3 times the R^2 from the underlying regression is sufficient, whereas a value that is 2 times higher is a more rigorous standard. Secondly, the Oster test bounds the estimates based on the assumption that the selection of unobservable is, at worst, equal to the selection of observables ($\delta = 1$).

The results of these tests are presented in Table 5A. Column 1 contains the results for the control of corruption, while Column 2 provides results on Bayesian corruption. The δ and β values are presented in Panel I and Panel II, respectively. For an Rmax of 1.3, the δ values are 4.78 and 5.68, suggesting that the selection of unobserved variables would need to be over 4.5 times that of the observables to explain the relationship between corruption and climate risk. Even with the more rigorous standard of Rmax = 2, the δ value remains higher than 1, which is sufficient to rule out significant omitted variable bias (Amin and Islam, 2023). Panel II presents the β values, showing the lower bound on the positive and statistically significant relationship between corruption and climate risk. The coefficients are qualitatively similar to the baseline estimations, confirming that our results are not driven by omitted variable bias.

From our preceding analysis, we have established that omitted variable bias is less likely to be a concern, ruling out endogeneity issues due to unobserved variables. However, endogeneity may arise from reserve causality. For instance, greater climate risk leads to more foreign aid and this causes more corruption (Becerra et al., 2015). Prior studies suggest that climate-related disasters increase corruption due to the windfall of foreign aid and donations (Khurana et al., 2022; Leeson and Sobel, 2008; Nguyen, 2017; Nikolova & Marinov, 2017; Yamamura, 2014; Zafar et al., 2023). So, controlling for foreign aid will eliminate this source of reverse causality. Therefore, in this section, we run our baseline equation with the inclusion of foreign aid as an extra control variable. The results are presented in Table 5B. The coefficient of the two measures of corruption is positive and highly significant at 1%, confirming our findings that corruption is associated with high climate risk and elevating the concern of endogeneity rising from reverse causality.

As stated earlier in the methodology, we employ the two-step, system-generalised method of moments to address any further potential problems. We perform several pre and post-imper estimations tests to ensure the appropriateness of the estimations. For

Table 5A
Oster test for omitted variable bias.

	Control of corruption	Bayesian corruption
Panel A: Oster test for δ		
$R_{max} = 1.3^* R^2$	4.78	5.68
$R_{max} = 2^* R^2$	1.56	1.82
Observations	2,116	1,942
Panel: Oster test for β (with δ=1)		
Baseline estimates (from Table 4)	1.170***	0.592***
	(2.631)	(4.235)
$R_{max} = 1.3^* R^2$	1.089***	0.510**
	(3.002)	(3.561)
$R_{max} = 2^* R^2$	0.987***	0.473
	(2.567)	(3.212)
Observations	2,116	1,942

Notes: Column 1 provides results with control of corruption as independent variable and column 2 contains results with Bayesian corruption as independent variable. R2 values used are as obtained from the OLS regressions and shown in Table 4. They are equal to 0.039 for the results in column 1 and 0.048 for the results in column 2. Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 5B
Endogeneity check –additional control.

VARIABLES	(1)	(2)
	Climate risk	Climate risk
Control of corruption	1.071***	
	(2.692)	
Bayesian corruption		0.772***
		(4.048)
Foreign aid	-0.003	-0.002
	(-1.063)	(-0.752)
Economic development	-1.603*	-1.015**
	(-1.890)	(-2.532)
Population	-4.537	-9.014
	(-0.736)	(-1.294)
Population density	0.051**	0.066**
	(2.253)	(2.540)
Agricultural industry	0.040**	0.037**
	(2.137)	(2.040)
Manufacturing industry	0.501***	0.524***
	(4.963)	(4.962)
Financial development	0.082	0.093
	(1.116)	(1.248)
Topography	25.831***	25.000***
	(8.369)	(7.921)
Sea level	-0.246***	-0.246***
	(-6.700)	(-6.420)
Carbon emission	0.126	0.101
	(0.185)	(0.147)
Regulatory quality	-1.317**	-3.206**
	(-2.484)	(-2.203)
Constant	-341.367***	-219.357*
	(-2.921)	(-1.696)
Country effect	Yes	Yes
Year effect	Yes	Yes
R-Squared	0.021	0.040
Observations	1,507	1,386
Number of countries	127	127

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

robust results, we use 3 – a 3-year average to reduce the panel and increase the cross-sectional of the data. S-GMM can be sensitive to the lag structures. Therefore, we run three S-GMM using different lag structures; (1, 2, 3) lags of the explanatory variables as instruments. The results of the S-GMM are presented in Table 5A. Like the main results present results using two alternative measurements of corruption.

The coefficient of corruption in all columns of Table 5A is positive and enters into significance at 1% or better. The results confirm the main findings that corruption increases climate risk. Consistent with prior studies (Tawiah et al., 2022), we performed several post-estimation tests including the autoregressive AR (1) and AR (2) and Hansen test. For instance, in column 1, the Arellano-Bond test for AR(1) in first differences is 0.000. The p-value of the Arellano-Bond test for AR(2) in first differences is 0.291, confirming the robustness of the results. Regarding the test of over-identification restrictions, the p-value of the Hansen test is 0.346, indicating that the estimation is not over-identified.

Consistent with Buccirossi et al. (2013), we address potential endogeneity issues by using the lag of the explanatory variables instead of their current year values. We transformed corruption and all the explanatory variables, except for sea level and topography (because they don't change over time), into a year lag. The results are presented in Table 5C. The results are qualitatively similar to the baseline estimations confirming that corruption is positively and significantly associated with high climate risk.Table 5D

4.5. Channel analysis

Among the various factors linking corruption to climate risk, the weakening of regulations is a crucial mechanism. Corruption impairs the enactment and enforcement of high-quality regulations aimed at preventing climate-related disasters (Ganda, 2020; Tawiah et al., 2023a,b). In this section, we empirically test whether corruption indeed undermines regulatory quality. To do so, we employ fixed-effects ordinary least squares regression models on corruption and regulatory quality, controlling for relevant variables.

First, following Tawiah (2022), we utilize data on environmental stringency from the OECD to measure the quality of environmental regulations. Although this index offers detailed information on environmental regulation at the country level, it is limited to

Table 5C
Endogeneity check – SGMM.

VARIABLES	1-Year lag		2-Years lags		3-Years lags	
	(1)	(2)	(3)	(4)	(5)	(6)
	Climate risk	Climate risk	Climate risk	Climate risk	Climate risk	Climate risk
Control of corruption	0.710***		0.451***		0.461***	
	(2.601)		(2.555)		(2.887)	
Bayesian corruption		0.396***		0.065**		0.037**
		(3.000)		(2.504)		(2.107)
Lag Climate risk	0.364***	0.341***	0.862***	0.857***	0.955***	0.953***
	(17.816)	(16.664)	(61.644)	(58.054)	(93.010)	(92.310)
Economic development	-2.441*	-2.375*	-0.182**	-0.220**	-1.298***	-1.227***
	(-1.834)	(-1.747)	(-2.349)	(2.407)	(-3.937)	(-3.319)
Population	-3.720***	-3.541***	-0.824***	-0.753***	-0.137***	-0.033**
	(-5.234)	(-4.819)	(-3.672)	(-3.115)	(-2.945)	(-2.217)
Population density	0.006***	0.005***	0.001***	0.001***	0.001***	0.001***
	(4.875)	(3.755)	(4.899)	(3.651)	(3.793)	(3.798)
Agricultural industry	0.032**	0.031**	0.007**	0.008***	0.014**	0.015**
	(2.504)	(2.363)	(2.485)	(2.645)	(1.971)	(2.052)
Manufacturing industry	0.370***	0.369***	0.100***	0.104***	0.030	0.043
	(3.811)	(3.831)	(2.728)	(2.765)	(1.193)	(1.604)
Financial development	-0.037	-0.030	-0.002	-0.003	-0.000	-0.002
	(-1.409)	(-1.077)	(-0.240)	(-0.262)	(-0.020)	(-0.234)
Topography	8.353***	8.883***	2.656***	2.956***	1.722***	1.773***
	(3.266)	(3.359)	(3.451)	(3.662)	(3.887)	(3.848)
Sea level	-0.008***	-0.009***	-0.002**	-0.002***	-0.001*	-0.001*
	(-3.315)	(-3.604)	(-2.503)	(-2.771)	(-1.894)	(-1.864)
Carbon emission	0.995***	0.816***	0.116	0.065	0.125*	0.136**
	(3.685)	(2.799)	(1.198)	(0.625)	(1.839)	(1.967)
Regulatory quality	-7.136**	-5.330**	-0.816*	-1.060**	-0.576*	-0.780**
	(-2.446)	(-2.180)	(-1.876)	(-2.249)	(-1.872)	(-2.322)
Constant	-14.639***	-14.356***	-34.367***	-21.357*	-4.831	-4.577
	(-8.813)	(-8.624)	(-2.921)	(-1.696)	(-1.134)	(-1.050)
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.291	0.265	0.239	0.238	0.240	0.239
Hansen test	0.346	0.327	0.389	0.376	0.426	0.431
Observations	833	805	833	805	833	805
Number of countries	170	170	170	170	170	170

z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

OECD and a few BRIC countries. The results, presented in column 1 of Table 6, reveal a negative and significant coefficient of corruption, indicating that corruption weakens environmental regulations.

To address the challenge of limited sample size, we adopt a more generic measure of regulatory quality from the World Governance Indicators. This index reflects the quality of various regulations in a country, including environmental rules, and is available for our entire sample. The results, presented in column 2 of Table 6, are consistent with those of column 1. After establishing a relationship between corruption and regulatory quality, we test the relationship between regulation and climate risk. The results, which are presented in columns 5 and 6, show that good regulation reduces climate risk. Therefore, as corruption reduces regulatory quality, then is to claim that the findings in Table 6 provide empirical evidence supporting the association between corruption and increased climate risk through the weakening of regulations.

4.6. Developed and developing countries

The development status of a country is significant drive on different outcomes including climate disaster and risk. For instance, Liu et al. (2023) shows that the impact of climate disaster on international trade differ significantly between developed and developing countries. Prior studies show that the impact of corruption on environmental issues such as green growth differ between developed and developing countries (Hellman and Schankerman, 2000; OECD, 2020; Tawiah et al., 2023a,b). Furthermore, our sample is dominated by developing countries. Therefore, our result might be biased due to the uniqueness of the different development of the sample countries. To overcome this challenge and allay the concern of biased results, we perform additional analysis using sub-sample of developed and developing countries. Following prior studies (Liu et al., 2023; Tawiah et al., 2023a,b) we classify countries into developing and developed according to the United Nations. The results are presented in Table 7. Columns 1 and 2 contains the results of developed countries whiles the results of developing countries are presented in columns 3 and 4. Similar to the main results, the coefficient of corruption is positive and significant in all the four columns of Table 7, indicating that corruption increases climate risk

Table 5D
– Lag of explanatory variables.

VARIABLES	(1)	(2)
	CCI	BCI
Lag Control of corruption	1.182***	
	(3.012)	
Lag Bayesian corruption		0.662**
		(3.553)
Lag Economic development	7.501***	7.137***
	(2.707)	(2.591)
Lag Population	-8.178	-5.251
	(-0.945)	(-0.618)
Lag Population density	0.019	0.018*
	(1.618)	(1.826)
Lag Agricultural industry	-0.029	-0.035
	(-1.008)	(-1.243)
Lag Manufacturing industry	-0.463***	-0.470***
	(-3.432)	(-3.559)
Lag Financial development	-0.056**	-0.047*
	(-2.261)	(-1.745)
Topography	252.436***	236.655***
	(11.213)	(10.282)
Sea level	0.247***	0.225***
	(9.271)	(7.876)
Lag Carbon emission	-0.507	-0.651
	(-0.964)	(-1.312)
Lag Regulatory quality	0.221	-0.457
	(0.051)	(-0.120)
Constant	-322.194**	-307.064**
	(-2.224)	(-2.239)
Country effect	Yes	Yes
Year effect	Yes	Yes
R-Squared	0.040	0.049
Observations	2,129	1,955
Number of countries	171	171

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 6
– Channel analysis.

VARIABLES	ESR		Regulatory quality		Climate risk	
	(1)	(2)	(3)	(4)	(5)	(6)
	CCI	BCI	CCI	BCI	ESR	Regulatory quality
Control of corruption	-0.018***		-0.454***			
	(-7.110)		(-10.087)			
Bayesian corruption		-0.015***		-0.403***		
		(-9.613)		(-19.496)		
ESR					-3.895***	
					(-3.967)	
Regulatory quality						-4.191**
						(-2.079)
Constant	-0.622*	-1.210***	-0.578**	-1.277***	-233.498	473.028**
	(-1.887)	(-2.711)	(-2.014)	(-3.379)	(-1.573)	(2.562)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Country effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395	395	2,294	2,101	395	2,323
R-squared	0.224	0.126	0.254	0.276	0.063	0.050
Number of countries	33	33	178	177	33	174

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 7
Developed and developing countries.

VARIABLES	Developed countries		Developing countries	
	(1)	(2)	(3)	(4)
	CCI	BCI	CCI	BCI
Control of corruption	0.703**		1.323**	
	(2.342)		(2.071)	
Bayesian corruption		0.021**		0.379**
		(2.044)		(2.136)
Economic development	-16.910***	-15.646***	-13.830***	-14.404***
	(-5.348)	(-4.760)	(-4.342)	(-4.167)
Population	5.241	-7.277	-6.948	-9.882
	(0.481)	(-0.631)	(-0.719)	(-0.873)
Population density	0.007**	0.008**	0.067**	0.067**
	(2.188)	(2.204)	(2.373)	(2.179)
Agricultural industry	0.047	0.061	0.023**	0.015**
	(0.797)	(1.023)	(2.269)	(2.167)
Manufacturing industry	0.362*	0.439**	0.896***	0.881***
	(1.946)	(2.303)	(4.887)	(4.471)
Financial development	-0.065	-0.117*	0.329**	0.312*
	(-1.088)	(-1.691)	(2.116)	(1.861)
Topography	23.164***	21.819***	21.332***	19.812***
	(3.577)	(3.295)	(-3.192)	(-2.666)
Sea level	-0.199**	-0.132**	-0.182***	-0.177***
	(-2.355)	(2.518)	(-4.877)	(-4.202)
Carbon emission	-0.652	-1.295**	-0.535	-0.427
	(-1.291)	(-2.539)	(-0.793)	(-0.611)
Regulatory quality	-9.212**	-9.860***	-14.559***	-15.846***
	(-2.533)	(-2.684)	(-3.100)	(-3.075)
Constant	-50.150*	-18.574***	-45.435**	-47.069*
	(-1.792)	(-2.629)	(-2.012)	(-1.822)
Country effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
R-Squared	0.122	0.126	0.136	0.136
Observations	583	537	1533	1510
Number of countries	46	46	125	125

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

regardless of the development status of the country and main results are not driven by the certain class of countries. However, we observed that the coefficient is larger in developing countries than developed countries. Also, the significant level is higher in developing countries, suggesting that our findings of corruption increase climate risk is more pronounced in the developing countries than developed countries. This is not unsurprising because corruption is found to be have more impact in developing countries (Tawiah et al., 2023a,b).

4.7. Continental analysis (Africa, America, Asia Europe and pacifics

Geographical location remains a crucial factor of for the frequency and occurrence of climate disasters. Furthermore, priors studies and commentary suggest that some continents are more prone to climate disasters than others (Escaleras et al., 2007; Liu et al., 2023). For instance, Africa is known to be a hub of climate disasters (UN Climate Change, 2020). Hence our results of corruption amplifying climate risk is likely to be influenced by geographical location of the country. Therefore, in this section we additional analysis based on the geographical location of the country. We group countries into five continents namely: Africa, Asia, Europe, North America, South America and the Pacific. The results are presented in Table 8. The coefficient of corruption remains positive and significant in all the columns, suggesting that corruption increases climate risk regardless of the geographical location of the country. However, the relationship is stronger in Africa, followed by South America and the Pacific.

5. Conclusion and policy implications

It is well-established that the consequences of our actions on the climate are not proportionate to the level of pollution we generate. Climate disasters can strike unpredictably, making it imperative to understand how non-environmental factors influence the severity of these disasters. In this paper, we have focused on the impact of a critical social issue, corruption, on climate risk. We argue that corruption has both ex-ante and ex-post effects on climate disasters. Ex-ante, corruption weakens environmental regulations and contributes to environmental degradation, as well as poor infrastructural development. These factors increase the likelihood of climate

Table 8
Continental analysis.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Africa	Asia	Europe	North America	South America	Pacific
Control of corruption	1.434***	0.057**	0.073**	0.085**	0.673**	0.415**
	(2.835)	(2.182)	(1.982)	(2.055)	(2.530)	(2.529)
Economic development	3.669	-9.009**	12.951***	9.098	-7.196	11.534***
	(1.222)	(-2.458)	(3.831)	(1.282)	(-0.726)	(2.965)
Population	-3.280***	9.718	10.965	-20.438	-59.083	2.237
	(-2.733)	(0.668)	(1.168)	(-0.940)	(-1.450)	(0.188)
Population density	0.041*	0.304**	0.014**	0.100**	0.183**	0.202*
	(1.800)	(2.517)	(2.054)	(2.085)	(2.496)	(1.697)
Agricultural industry	-0.008	0.172**	-0.052	0.136*	-0.132	0.007
	(-0.185)	(2.063)	(-0.825)	(1.651)	(-0.411)	(0.066)
Manufacturing industry	0.041	-0.638***	-0.707***	-1.170**	1.491***	-0.488*
	(0.286)	(-3.205)	(-3.866)	(-2.535)	(2.691)	(-1.733)
Financial development	0.101	-0.115	0.033	-0.004	0.406	-0.088
	(1.246)	(-1.456)	(0.243)	(-0.094)	(1.515)	(-0.266)
Topography	8.512***	4.615**	3.415**	26.772	29.207**	29.840**
	(3.216)	(2.381)	(2.087)	(0.879)	(2.050)	(2.433)
Sea level	0.192**	2.590	0.019	0.206***	-0.043	0.087***
	(2.262)	(1.372)	(0.379)	(3.615)	(-0.219)	(2.705)
Carbon emission	-1.017	-0.874	-0.562	0.032	-3.870	-6.714***
	(-0.952)	(-1.198)	(-0.755)	(0.033)	(-1.293)	(-4.358)
Regulatory quality	-8.721**	-13.402**	4.616	5.393	-28.740**	6.410
	(-2.128)	(-2.451)	(1.020)	(0.900)	(-2.008)	(1.162)
Constant	54.844***	-49.497	-17.119	26.855	10.478***	-15.176**
	(3.431)	(-1.301)	(-0.850)	(0.836)	(3.149)	(-2.136)
Country effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.039	0.110	0.090	0.087	0.301	0.276
Observations	580	404	518	200	126	170
Number of countries	48	33	43	16	10	14

Robust z-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

disasters occurring. On the ex-post side, corruption leads to delays in the delivery of relief items, mismanagement and diversion of donations, and uneven distribution of relief resources. These actions exacerbate the consequences of climate disasters.

We conducted robust econometric modelling using data from 171 countries spanning the period 2006 to 2019. Our analysis utilized two different sources of corruption indicators and climate risk data from Germanwatch. As anticipated, our findings revealed a significant and positive relationship between corruption and climate risk. Specifically, corruption was found to increase both the likelihood and severity of climate disasters. Further analyses indicate that this relationship held true across countries with varying levels of economic and financial development, as well as different continental locations. These results suggest that nations with higher levels of corruption are more prone to experiencing heightened climate disasters and their associated impacts compared to those with lower corruption levels. Notably, our study also revealed that the impact of corruption on climate risk is more pronounced in developing countries, where corruption exacerbates existing challenges in infrastructural planning and development. Importantly, our results remained robust to alternative measurements and econometric identification strategies, including the two-step system generalised method of moments. This underscores the reliability and validity of our findings.

Corruption can significantly impede communities' ability to recover from disasters and hinder their return to normalcy. Therefore, it is imperative for authorities to implement measures aimed at preventing and addressing corruption in disaster response efforts. By doing so, resources can be effectively allocated, and affected populations can receive the necessary support to facilitate their recovery process.

Corruption can severely hinder the ability of communities to recover from disasters and make it more difficult for them to return to a state of normalcy. It is important for authorities to take measures to prevent and address corruption in the context of disaster response to ensure that resources are used effectively and that affected populations receive the support they need. Given our findings of negative impact of corruption on climate risk, we suggest future research to extend this stream of literature on how social factors drive climate risk and climate disasters. Some of these social factors include democracy and political instability.

While our empirical evidence strongly suggests that corruption tends to increase climate risk, it is important to acknowledge that corruption may also have the potential to reduce climate risk in certain contexts. This perspective aligns with the "greasing the wheel" hypothesis, which posits that corruption can sometimes be beneficial rather than solely detrimental ((Egger and Winner, 2005; Kebede et al., 2023; Tawiah et al., 2023a,b). For instance, research by Kebede et al. (2023) illustrates that certain forms of corruption are necessary to facilitate the provision of loans in microfinance, suggesting that corruption can sometimes grease the wheels of economic activity.

In the realm of climate risk, corruption might expedite decision-making processes, enabling swift actions to address immediate environmental concerns or respond to climate-related emergencies. By bypassing bureaucratic red tape, corruption may allow for more agile responses to pressing environmental challenges. Moreover, corruption may play a role in facilitating the implementation of informal adaptation measures at the local level. In communities where formal mechanisms are inadequate or inaccessible, informal networks and practices enabled by corruption may serve as crucial coping mechanisms in the face of climate-related adversities. Additionally, corruption might empower political leaders to take bold and politically expedient actions to tackle climate-related issues. This could involve the implementation of stringent environmental regulations or the initiation of large-scale mitigation initiatives that may not have been feasible under strict bureaucratic procedures.

Overall, while corruption is often associated with negative outcomes, it is essential to recognize its potential complexities and nuances, particularly in the context of addressing climate risk. Further research is warranted to better understand the varied impacts of corruption on climate risk mitigation and adaptation efforts.

Funding information

The project was supported by.

Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R391), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Major project of philiosophy and social science research in Jiangsu universities “Research on the Rule of Law in Regional Social Governance” (2023SJZD005)

CRediT authorship contribution statement

Dejun Zhou: Supervision, Project administration, Funding acquisition. **Vincent Konadu Tawiah:** Writing – original draft, Methodology, Data curation, Conceptualization. **Noha Alessa:** Writing – review & editing, Project administration, Funding acquisition, Formal analysis.

Declaration of competing interest

There is no conflict of interest on this paper.

Data availability

Data will be made available on request.

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