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The efficacy of green finance for environmental sustainability: Does control of corruption makes a difference?

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ABSTRACT

Green finance (GF) plays a crucial role in reducing greenhouse gas (GHG) emissions and promoting environmental sustainability (ES). However, the efficacy of GF may vary, depending on several factors, particularly the extent of control of corruption. This study investigates the effect of control of corruption on the efficacy of GF using data on 37 Asian countries for the period 2000–2020. The results demonstrate that the efficacy of GF in reducing the GHG emissions and improving ES in a country depends on the level of corruption there. Specifically, GF has a significant GHG reduction effect in the presence of strong corruption control or low corruption levels. These findings remain robust to several robustness checks, including alternative measurements of ES and corruption control and different estimators. This highlights the significance of enhancing control of corruption at the national level to optimize efficient utilization of GF resources and advancing ES. The study also presents policy implications based on these findings.

1. Introduction

Harmonizing the goal of economic growth with environmental sustainability (ES) has become a central focus of the global economic discourse. The 2021 report by the United Nations Intergovernmental Panel on Climate Change stressed that a drastic reduction in greenhouse gas (GHG) emissions is imperative for human survival. In this context, green finance (GF) stands out as an important catalyst for both environmental protection and sustainable development (Chin, Ong, Ooi, & Puah, 2022). GF incorporates the twin goals of ES and economic progress into investment and financial decisions. It influences the flow of funds to support for projects and initiatives that cater to these goals (Chin et al., 2022).

GF has been shown to mitigate GHG emissions and is instrumental for ES in four major economies—China, the US, India, and Brazil (Muhammad Asif Khan, Ahmed, & Hull, 2023). M. C. Udeagha and N. Ngepah (2023) also demonstrate that GF, fintech (financial technology), and energy innovation contribute to ES in the BRICS countries. Mehboob, Ma, Mehboob, and Zhang (2024) examine the influence of GF, environmental innovation, environmental taxation, and geopolitical risk on mitigating environmental degradation in China. Their findings indicate that GF, environmental innovation, and environmental taxation contribute to the reduction of GHG emissions from both consumption and production activities. However, geopolitical risk creates obstacles to ES.

Likewise, Khan, Riaz, Ahmed, and Saeed (2022) investigate the influence of GF on the ecological footprint, and their results reveal that GF effectively diminishes ecological footprints, indicating its potential for enhancing ES. Furthermore, Chi-Chuan Lee and Lee (2022) examine the influence of GF on reducing emissions of carbon dioxide (CO_2) and fostering green growth. They reveal that GF significantly contributes to reduction in CO_2 emissions, especially in small island developing states and economically robust countries. These insights are important for policy makers, providing guidance on how to facilitate a shift toward achieving net-zero emissions and improving ES.

Likewise, Saeed Meo and Karim (2022) show that GF reduces CO_2 emissions and assert that GF is the best financial strategy for reducing CO_2 emissions and protecting ES. However, they find that the effect of GF on CO_2 varies across various quantiles of the variables and argue that this variation might be due to the country-specific characteristics. Gong, Gong, and Rasool (2024) and C. Li, M. Z. Faridi, and R. Nazar (2023) report similar findings.

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The impact of GF on GHG emissions is widely explored in the literature, which consistently highlights its role in reducing GHG emissions and protecting ES and demonstrates variability in the effectiveness of GF interventions in different countries. However, the studies often overlook the underlying mechanisms that drive these variations and the strategies for raising the efficacy of GF.

This study fills a crucial gap by investigating the role of controlling corruption as a contextual factor that influences the effectiveness of GF initiatives in reducing CO_2 emissions. By focusing on corruption control, this study introduces a novel dimension to the discussion, shedding light on how governance factors impact climate change mitigation efforts. Understanding this is vital for policy makers and stakeholders, because it offers insights into the impact of governance on the success of GF interventions in combating CO_2 emissions and protecting ES. Based on the effectiveness of GF, green investment and financing are continually rising, though there is still a long way to go in achieving the goal of carbon neutrality. The UN estimates that "the transition to low-carbon and climate-resilient economies requires additional investment at an order of magnitude of at least USD 60 trillion, from now until 2050."[1]

Obtaining GF on such a massive scale presents a significant challenge, particularly for developing countries. Hence, it is imperative to design the most effective strategies for increasing the quantity of GF, while maximizing efficiency in the limited pool of available GF resources. One way in which countries can do so is by strengthening the institutional framework, such as through controlling corruption (CC), a fundamental element in that framework. This is pertinent as robust CC may influence the amount and efficient use of GF funds available for addressing ES issues (Devine, McCollum, & Orlova, 2022). The existing literature shows that corruption negatively influences green growth (Tawiah, Zakari, & Alvarado, 2023), green innovation (Zakari, Tawiah, Oyewo, & Alvarado, 2023), and other factors that are crucial for improving the ES. The degree of corruption may significantly condition the effect of GF on ES. Corruption may negatively influence ES through increasing resource misallocation (World Bank, 2019). This could weaken the intended positive effect of GF on ES and undermine the efficacy of GF. In contrast, in an institutional environment with less corruption, GF can drive ES more effectively by ensuring transparent and accountable use of GF funds for sustainable initiatives.

Moreover, corruption can undermine the effectiveness of environmental policies supported by GF. Regulations and incentives may not be enforced rigorously, allowing polluting practices to persist, despite financial allocation for sustainability. Moreover, corruption can erode investor confidence in the GF mechanisms, reducing the inflow of funds (Vagliasindi, 2012). The absence of a transparent environment can deter environmentally conscious investors, limiting the potential for emissions reduction and ES.

In view of this discussion, our study explores how corruption—a pervasive challenge—conditions the outcomes of GF, providing a crucial perspective on the interplay between GF, CC, and ES. Consistent with the global push for sustainable development, our emphasis on the moderating influence of corruption levels on the GF-ES relationship significantly contributes to the existing literature. Our findings yield valuable policy implications for stakeholders engaged in sustainable development initiatives, particularly in developing countries that are contending with escalating GF challenges. Strengthening institutional frameworks, particularly by controlling corruption, is a key strategy for optimizing the efficiency of limited GF resources. By elucidating how corruption can undermine environmental policies supported by GF, we contribute to the broader discourse on the implications of corruption for sustainability. In conclusion, our study offers actionable insights for sustainable development. By revealing the moderating effect of corruption on the GF-ES relationship, we provide a roadmap for policy makers in navigating the challenges associated with GF effectively.

[1] https://www.unepfi.org/climate-change/climate-change/.

The paper is structured as follows: Section 2 reviews the relevant literature and outlines the hypotheses to be tested. Section 3 discusses the data and methods employed in the analysis. Section 4 presents and discusses the empirical results. Finally, Section 5 offers our conclusions drawn from the findings and discusses their policy implications.

2. Literature review and hypothesis

2.1. Green finance and environmental sustainability

Climate change is a critical global challenge. The United Nations' sustainable development goals specifically address the escalating issues related to environmental pollution and depletion of natural resources, advocating for the implementation of contemporary principles such as sustainable development. Historically, the financial sector has displayed little concern about the environment. However, a paradigm shift has occurred, and the sector now actively incorporates environmental considerations. It has introduced myriad financial products with a primary objective of environmental protection. Numerous research studies have explored the connection between GF and its impact on promoting ES (Li, Jia, & Change, 2017; Meo & Abd Karim, 2022; Sadiq et al., 2023; M. C. Udeagha & N. J. W. D. S. Ngepah, 2023; Y. Wang & Zhi, 2016). GF contributes to enhanced environmental sustainability and resource utilization. Unlike traditional finance, GF places a strong emphasis on environmental protection, sustainable development, and the promotion of green industries. Li and Jia (2017) similarly advocate using effective environmental finance and sustainable finance as a key strategy for reducing environmental degradation.

Jones (2015) asserts that GF plays a pivotal role in stimulating investment in emerging technologies, innovation, and, in particular, renewable energy sources. Green bonds, which are considered representative of GF, are long-term financial instruments whose proceeds are allocated exclusively to environmentally friendly projects aimed at reducing pollution. (Meo & Abd Karim, 2022), which covers the period November 2008 to June 2019, measures market capitalization of green bonds per capita against per capita CO_2 emissions, finding a significant correlation between GF and carbon emissions. Sadiq et al. (2023) explore the interplay among green finance, eco-innovation, renewable energy output (REO), renewable energy consumption (REC), and carbon taxes on CO_2 emissions. Their empirical findings from a cross-sectional autoregressive distributed lag (CS ARDL) analysis confirm the efficacy of green finance, eco-innovation, REO, REC, and carbon taxes in mitigating CO_2 emissions and the effects of industrialization. In particular, the results indicate a negative relationship among these factors in the economies of BRICS countries.

In their investigation in China from 2001 to 2017, T. Zhang and Zhao (2024) explore the dynamic connections among green finance, environmental pollution, and economic development. Their empirical findings raise several key insights: an inverted U-shaped environmental Kuznets curve between economic development and pollutant emissions; a significant positive correlation between green finance and economic development, in which increases in economic development attract more investment in green finance; and the surge in environmental pollutant emissions necessitates greater investment in green finance, which, in turn, has a substantial controlling influence on pollutant emissions. Similarly, (Hu, Chen, Dinis, & Xiang, 2023) examine panel data on 30 provinces in China from 2007 to 2020 to assess the impact of green finance on CO_2 emissions. Their results indicate that a direct reduction in CO_2 emissions is attributable to green finance. Moreover, as implementation of green fiscal policies intensifies, the indirect effect of green finance increases proportionately. Notably, in regions characterized by high environmental quality, green finance has a greater capacity to facilitate technological innovation, consequently restraining CO_2 emissions.

The efficacy of green credit as a well-established tool for green finance has garnered extensive attention, particularly its capacity to

mitigate carbon emissions in agriculture. Nenavath and Mishra (2023) emphasize the substantial impact of green credit policies on reduction in agricultural carbon emissions, employing resource allocation utility, technology innovation utility, and signaling utility pathways. Yue, Zhou, and Liu (2024) explore the influence of GF on industrial green total factor productivity (IGTFP) in China from 2011 to 2019. Their study shows a significant improvement in IGTFP associated with the development of green finance; a trend confirmed through robustness tests. Furthermore, their research notes that the effect of GF on IGTFP varies across cities, which has a positive correlation with increases in their size. The study also shows a positive effect of green technological innovation on GF's influence on IGTFP. Notably, the discussion highlights the supportive role of digital financial inclusion in the development of green finance.

C. Li, M. Z. Faridi, and R. J. B. I. R. Nazar (2023) explore the relationship between GF and GHG across a panel of 10 countries from 2008 to 2019. Employing the quantile-on-quantile technique to assess time-series dependence independently in each country, the findings suggest that GF contributes to greater environmental quality by limiting GHG emissions in a majority of the economies studied, particularly at specific quantiles of the data. The research indicates varying levels of asymmetry among the variables across different countries, emphasizing the need for policy makers to carefully implement GF and ES policies. (L. Wang, Yang, & Cai, 2024) study the impact of GF on reductions in regional emissions, using provincial panel data from 2008 to 2019 and a fixed effects model, and obtain significant findings. Their empirical results show a negative influence of GF on the intensity of sulfur dioxide, showing a substantial reduction in the emissions of regional pollutants associated with the development of GF. Green credit and green investment, among other instruments of GF, demonstrate more pronounced effects in reducing emissions than green securities and green insurance. The primary mechanisms that facilitate reduction in regional emissions are due to the advanced industrial structure and innovations in green technology. Additionally, the study illustrates geographic variation in the development of GF.

Chi-Chuan Lee et al. (2022) explore the impact of climate finance flows from 2000 to 2018 on CO_2 emissions in recipient countries. Their findings indicate a significant decrease in CO_2 emissions because of climate finance, and this reduction is particularly notable in small island developing states and countries with more robust economic development.

GF is also important for improvement in various dimensions of the ES. Recently, Chi-Chuan Lee, Song, and An (2024) examine the impact of GF on China's energy transition, considering the role of climate risk in 2011–2020. The findings indicate that GF significantly promotes energy transition, particularly in regions with more advanced socioeconomic conditions. Additionally, they identify a threshold effect of climate risk, moderating the GF–energy transition nexus beyond a certain point. This shows the need for nuanced policy responses to foster sustainable energy transition in China. Similar, Huynh and Hoang (2024) report a positive effect of GF on increases in renewable energy transition. Furthermore, their results reveal that higher energy efficiency, quality of governance, and environmental regulations significantly and positively moderate the effect of GF on the transition to clean energy.

In addition to examining energy transition dynamics, the literature also examines energy inequality, particularly in relation to GF. GF is also found to have a significant effect on green productivity growth. Analyzing panel data on 30 Chinese provinces, Chi-Chuan Lee and Lee (2022) reveal that GF development drives expansion in green productivity. This positive impact is more pronounced in provinces with greater economic and social development, lower public involvement in environmental protection, and higher pollution.

Chi-Chuan Lee, Song, and Lee (2023) observe a significant U-shaped correlation between GF and the urban-rural energy gap in China. They propose that a moderate increase in GF could effectively mitigate energy inequality. Moreover, this association is particularly dominant in China's western regions and is further accentuated in provinces with activity that requires higher levels of energy and development of digital finance, but lower levels of economic and social activity.

Furthermore, they identify three mechanisms through which GF might impact ES: capital support, resource allocation, and technological innovation. The capital support effect of GF involves supporting the establishment of energy infrastructure and accelerating progress in renewable energy projects and thereby increase access to modern energy sources for rural communities (Bilal & Shaheen, 2024; Chien-Chiang Lee & Zhao, 2023). The resource allocation effect of GF involves the strategic distribution of capital resources to promote fair and balanced transitions to sustainable energy and to enhance the quality of energy infrastructure. This entails a careful and deliberate allocation of financial resources to ensure effective support for such initiatives, as shown by Lee and Lee (2022) and Yang et al. (2021). In the technological innovation effect, GF drives innovation in energy technology, which changes the pattern of energy consumption in both rural and urban areas. The production of high-quality modern household devices with higher energy efficiency can lower energy consumption and GHG emissions (Ahmed, Hua, & Bhutta, 2024; Zhao, Zeng, Zhao, Zeng, & Jiang, 2024). Based on the literature, we propose the following hypothesis:

Hypothesis 1. The GF has positive effect on ES.

2.2. Green finance and ES: Moderating role of control of corruption

The literature mostly shows the instrumental role of GF in addressing ES and its potential to mitigate GHG emissions. Nevertheless, the effectiveness of GF may be contingent on various contextual factors, one of which could be the level of corruption in a country. The literature shows that corruption negatively influences green growth (Tawiah et al., 2023), green innovation (Zakari et al., 2023), and other factors, which are crucial for improving ES. The degree of corruption may significantly condition the effect of GF on ES.

The literature indicates that corruption can hinder the effectiveness of GF in achieving ES goals by distorting resource allocation, impeding regulatory enforcement, fostering rent-seeking behavior, and undermining GF initiatives. Corruption leads to misallocation of resources, in which funds intended for environmental projects may be diverted for personal gain or used inefficiently. This can hinder the effectiveness of GF initiatives in directing capital to sustainable projects (Svensson, 2005; S. Wang, Zhao, & Chen, 2020). The World Bank (2019) also contends that corruption may negatively influence ES by increasing resource misallocation. This could weaken the intended positive effect of GF on ES and undermine the efficacy of GF. In contrast, in an institutional environment with less corruption, GF can more effectively drive ES by ensuring transparent and accountable use of GF funds for sustainable initiatives.

Moreover, corruption undermines the enforcement of environmental regulations by allowing polluting industries to evade compliance through bribery or other illicit means (Z. Wang, Danish, Zhang, & Wang, 2018; Y.-J. Zhang, Jin, Chevallier, & Shen, 2016). This weakens the regulatory framework designed to promote ES, thus limiting the impact of GF efforts.

Similarly, corruption creates opportunities for rent-seeking, in which individuals or firms seek to gain economic benefits through manipulation of government policies or regulations (Kar, Mandal, Marjit, & Mukherjee, 2020; Robinson, 1998). In the context of GF, rent-seeking behavior may divert funds from genuinely sustainable projects and toward those that offer greater opportunity for personal gain, thereby undermining environmental goals.

Moreover, this corruption can erode investor confidence in GF mechanisms, reducing the inflow of funds (Vagliasindi, 2012). The absence of a transparent environment can deter environmental-conscious investors, limiting the potential for ES and reduction in GHG emissions.

Z. Wang, Zhang, and Wang (2018) look at the moderating effect of corruption on the association between economic growth and CO_2 emissions with a panel of BRICS countries. Their empirical results highlight the pivotal moderating role of corruption in shaping the connection between economic growth and CO_2 emissions, indicating a decrease in CO_2 emissions with increases in control of corruption. Further analysis reveals the moderating influence of corruption on the correlation between urbanization and CO_2 emissions, exposing subpar environmental performance in countries marked by corruption. Moreover, Fu and Jian (2021) examine the causal effect of laws stringency on corporate innovation and the moderating role of bribery expenditures, which, they conclude, facilitates this effect.

Green innovation plays a vital role in achieving a balance between growth and mitigating climate change. A corroborating study by Wen et al. (2023) confirms that corruption has a markedly negative impact on green innovation. Hao, Xu, Guo, and Wu (2022) conduct a study along the same lines, using panel data on China's 30 provinces from 2005 to 2016. Applying a panel threshold model, their research shows the interplay between environmental crises, environmental decentralization, and regional corruption. Their results reveal that, as the degree of corruption in a region increases, the impact of environmental decentralization on environmental crises diminishes.

Furthermore, Quan, Zhang, Zhong, and Zhu (2023) explore the influence of corruption on firms' green innovation activities at Chinese listed firms over the period 2007 to 2017. Their findings suggest that firms operating in corrupt provinces have fewer green patents and patent citations. This shows that local corruption hampers corporate green innovation by raising opportunity costs for green investment and reducing demand for corporate green innovation. Similarly, Rui, Sun, and Xu (2024) find a negative effect of corruption in bank lending on firms' green innovation performance aimed at reduction in CO_2 emissions. The literature highlights the importance of corruption control in promoting the efficacy of GF in promoting ES. Therefore, we propose the following hypothesis:

Hypothesis 2. The level of corruption significantly conditions the efficacy of GF for ES.

3. Data and methodology

3.1. Data description

This study uses data from 37 Asian countries from 2000 to 2020 (for the list of countries, see Appendix A, Table A1). Asia is the most populous region in the world and the largest contributor to environmental degradation (World Bank, 2019). Moreover, many Asian countries are highly vulnerable to climate change and its negative impacts on the economy and human well-being. According to the Institute for Economics and Peace (2019), nearly one million people worldwide have suffered from the impacts of climate change, and a significant share of them live in Asia, which is home to 60 percent of the global population. In 2019, Asia faced a barrage of climate-related crises, leading some to call it the most disaster-prone region. Record-breaking heatwaves exceeding 50 °C have claimed numerous lives in Pakistan and India, and intense rainfall has triggered severe flooding in Bangladesh, India, Pakistan, and Nepal. In addition, Indonesia, Thailand, Vietnam, and Malaysia as well as other countries across Asia have been experienced numerous storms due to climate change, inflicting long-term harm to their populations (Huynh & Hoang, 2024).

Despite these challenges, Asia has a significant gap in GF for addressing environmental issues and building climate-resilient infrastructure projects (ADB, 2020). As the most populous and most rapidly growing region, Asian countries face the challenge of sustaining economic growth while also tackling environmental degradation (Tolliver, Fujii, Keeley, & Managi, 2021). This requires urgent steps to foster a favorable environment for rising GF and ensuring ES, particularly in Asia.

One way to do this is by strengthening the institutional framework. Within this framework, this study focuses on controlling corruption (CC), a fundamental element in the institutional framework. This is pertinent, as robust CC may influence the amount and efficient use of GF funds available to address ES issues (Devine et al., 2022). Corruption poses a significant challenge in numerous Asian countries, as indicated by the (Transparency International, 2022). This issue stems not only from government dependence on inefficient anti-corruption agencies but also from a lack of political commitment to allocating funds and enforcing anti-corruption measures (Quah, 2018).

This discussion emphasizes the proper selection of Asian countries as the sample for investigating our research questions. Our dependent variable is ES, which is proxied by GHG emissions, which is measured in kilotons (kt) of CO_2 equivalents. We also use CO_2 emissions as an alternative proxy for ES in robustness testing. The independent variable is GF, which is total investment in renewable energy in US $billions, reported by the International Renewable Energy Agency (IRENA). The moderating variable is control of corruption (CC), which is measured by the control of corruption estimates (CC_estimates) and rank (CC_rank) in the World Bank World Governance Indicators (Kaufmann, Kraay, & Mastruzzi, 2009). The CC_estimates are from −2.5 to +2.5, and higher values indicate less corruption or greater control of corruption, and lower values indicate the opposite. The CC_rank shows a country's rank relative to all countries covered by the indicator and ranges from 0 to 100, where 0 is the lowest rank and 100 is the highest rank. In this study, CC_estimates are used as the main proxy, and CC_rank as an alternative proxy for a robustness check.

The selection of these proxies for dependent, independent, and moderating variables is consistent with the relevant literature (See for example, Devine et al., 2022; Muhammad Asif Khan et al., 2023; Tawiah et al., 2023). Several control variables are also considered in the model, following the literature, such as gross domestic product (GDP) per capita, financial development, trade, foreign direct investment, education, energy use, urban population, and gross fixed capital formation. The definitions and data sources of the variables are given in Table 1.

Table 2 lists the descriptive statistics for the main variables, offering valuable insights into their distribution and characteristics.

3.2. Econometric model and methods

We test our hypothesis using the following empirical model:

$$ES_{it} = \alpha_0 + \beta_1 GF_{it} + \beta_2\ Corruption_{it} + \beta_3\ GF_{it} \times Corruption_{it} + \beta_3\ X_{it} + \mu_i + \phi_t + \varepsilon_{it} \quad (1)$$

where i and t denote the country and the time, respectively. α_0 is the intercept, and ES is environmental sustainability, which is the dependent variable, proxied by GHG emissions. The explanatory variable is GF. Corruption is the level of corruption in a country, which is the moderating variable; $GF_{it} \times Corruption_{it}$ is the interaction term between GF and corruption. X_{it} is vector of control variables, including GDP per capita, financial development, trade, foreign direct investment, education, energy use, urban population, and gross fixed capital formation. $\beta_1 - \beta_4$ are coefficients of GF, corruption and an interaction term, and control variables respectively. μ_i and ϕ_t are country and year fixed effects, respectively and ε_{it} is an error term. The coefficients of interest are β_1 and β_3, which are expected to be negative and statistically significant if they support our hypothesis.

In the initial analysis, we employ a fixed effect regression, incorporating country and year fixed effects along with robust standard error estimation. This methodology controls unobserved heterogeneity across different countries and years. The fixed effect regression model enables us to estimate the average impact of the independent variable on the dependent variable in each country and year, and the country and year

Table 1
Variables operationalization and Data Sources.

Variable	Definition	Source
Green Finance (GF)	It refers to the total investment in renewable energy measured in billions of US dollars.	International Renewable Energy Agency (IRENA)
Greenhouse gas (GHG)	It signifies the total emissions of greenhouse gases measured in kilotons of CO2 equivalent.	World Bank World Development Indicators (WDI)
Carbon dioxide (CO2)	Carbon dioxide emissions in kt.	WDI
Control of Corruption estimates (CC_estimates)	The CC_esitmates ranges from −2.5 to +2.5, where higher values indicate lower corruption or higher control of corruption, and lower values indicate the opposite.	World Governance Indicators (WGI)
Control of Corruption Rank (CC_rank)	The Control of Corruption Rank (CC_rank) reflects a country's rank in comparison to all countries included in the indicator, ranging from 0 to 100. A rank of 0 represents the lowest rank, while 100 corresponds to the highest rank.	WGI
GDP per capita (GDP_Pca)	GDP per capita (constant 2015 US$).	WDI
Foreign direct investment (FDI)	Foreign direct investment (FDI) denotes the net inflows of foreign direct investment as a percentage of GDP, according to World Development Indicators (WDI).	WDI
Trade	Total Trade measured as a percentage of GDP	WDI
Financial Development (Finan. Dev.)	It corresponds to domestic credit provided to the private sector as a percentage of GDP.	WDI
Education	School enrollment, primary (% gross)	WDI
Energy_use	Energy_use represents the amount of energy used per capita, measured in kilograms of oil equivalent.	WDI
Urban Population (Urban_Pop)	Urban population growth (annual %)	WDI
Gross fixed capital formation (GFCF)	Gross fixed capital formation (GFCF) denotes the percentage of GDP attributed to gross fixed capital formation.	WDI

fixed effects account for any unobserved heterogeneity across these dimensions. The use of robust standard errors addresses potential issues related to heteroskedasticity and autocorrelation in the error term.

To address potential endogeneity concerns in our analysis, we employ a two-step dynamic system generalized method of moments (GMM) estimator (Arellano & Bond, 1991; Blundell & Bond, 1998). This approach is particularly useful when dealing with endogenous regressors, helping to mitigate bias inherent in fixed effect regression models. The two-step dynamic system-GMM estimator uses lagged dependent variables as instruments to address endogeneity concerns, assuming that the past values of these variables are exogenous and uncorrelated with the error term. This method eliminates potential bias arising from feedback effects between dependent and independent variables. Widely recognized in the relevant literature, this estimator has been successfully applied in similar studies (see for example, Khan, Gu, Khan, & Oláh, 2020; Rashid Khan et al., 2019).

Furthermore, it demonstrates proficiency in handling endogenous covariates, ensuring the generation of unbiased estimates (Bond, Hoeffler, & Temple, 2001). To confirm the reliability of the system-GMM estimates, we perform the Hansen J-test of overidentifying restrictions and Arellano-Bond's AR(1) and AR(2) autocorrelation tests (Roodman, 2006).

Equation (1) is revised as follows for dynamic estimation using two-step system-GMM:

$$ES_{it} = \alpha_0 + \beta_1 GF_{it-1} + \beta_2 GF_{it} + \beta_3\ Corruption_{it} + \beta_4\ GF_{it} \times Corruption_{it} + \beta_5\ X_{it} + \varepsilon_{it} \quad (2)$$

In Equation (2), only $\beta_1 GF_{it-1}$ is introduced, signifying the inclusion of the lagged dependent variable for dynamic estimation. All the other components of the equation are unchanged from Equation (1).

4. Results and discussion

4.1. Baseline results

We estimate Equation (1) using a fixed effects regression with country-clustered robust standard errors for baseline estimation, and the results are reported in Table 3. We first examine the individual effects of GF and CC on ES measured by GHG emissions, without the interaction term. Column (1) shows that both GF and CC have negatively significant effects on GHG emissions, consistent with previous studies (e.g., Devine et al., 2022; Khan et al., 2023). Then, we include the interaction term between GF and CC to investigate how CC moderates the effect of GF on ES. Column (2) shows a negatively significant coefficient of the interaction term, indicating that higher CC or having less corruption enhances the efficacy of GF and supports our hypothesis.

To further test our hypothesis, we divide the sample into four groups based on the CC_estimates score, which measures the level of control of corruption (CC) in each country and estimates the effect of GF on GHG in each group. The results in Columns (3)–(5) indicate that GF has a significant and negative effect on GHG emissions only in the countries with higher CC (third and fourth quartiles), whereas it has no significant effect in the countries with low CC (first and second quartiles). These findings further support our hypothesis and suggest that GF has the desired ES benefits only in a transparent and corruption-free environment. We interpret these findings as evidence that CC influences the amount and efficient use of GF funds available to address ES issues, as argued by Devine et al. (2022). Moreover, corruption may undermine the benefits of GF by affecting the implementation of environmental policies supported by GF.

4.2. System-GMM estimation

In line with the baseline analysis, we extend our investigation using a system-GMM estimator to estimate Equation (1), employing the same methodology as before. This approach enables us to account for potential endogeneity issues and obtain unbiased estimates, which address concerns related to the fixed effects model. The results in Column 1 of

Table 2
Summary statistics.

Variable	Mean	SD	Min	Median	Max
GF (BillionS)	122.48	298.013	0.0000294	11.17361	3386.854
GHG (Tones)	439,030.60	1,630,000	553.2003	47636.41	12,900,000
CO2 (Tones)	322,078.62	1,350,000	00.0000	25260.7	10,900,000
CC_estimates	−0.63	0.681	−1.718197	−0.7422129	1.66271
CC_rank	30.97	23.227	00.0000	26.31579	93.75

Table 3
The Effect of GF on ES: Conditioning effect of Corruption.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Full sample	Q1 = very high Corruption	Q2 = high Corruption	Q3 = low corruption	Q4 = very low corruption
Variables	GHG	GHG	GHG	GHG	GHG	GHG
GF	−0.0054**	−0.0118***	0.0021	0.0046	−0.0067*	−0.0542***
	(0.0025)	(0.0043)	(0.0045)	(0.0031)	(0.0036)	(0.009)
CC_estimates	−0.0257**	−0.0103*				
	(0.0127)	(0.0062)				
GF × CC_estimates		−0.0127***				
		(0.0038)				
GDP_percapita	0.4333***	0.4351***	0.2554***	0.4985***	0.6077***	0.4419***
	(0.0244)	(0.0244)	(0.0415)	(0.055)	(0.062)	(0.0727)
Finan.Dev.	0.0677***	0.0677***	0.0368	−0.0716***	0.0154	0.0832***
	(0.009)	(0.009)	(0.0234)	(0.0168)	(0.0301)	(0.0138)
Trade	0.0137	0.0132	0.0241	0.0415	0.0222	−0.0079
	(0.0184)	(0.0184)	(0.0499)	(0.0313)	(0.0483)	(0.0192)
FDI	−0.178***	−0.1784***	−0.1704***	0.0538	0.1308***	−0.3161***
	(0.028)	(0.0279)	(0.0543)	(0.0487)	(0.0479)	(0.0574)
Education	0.1925***	0.1938***	0.1789***	0.5698***	−0.1975	−0.9928***
	(0.0369)	(0.0368)	(0.055)	(0.1557)	(0.1396)	(0.1735)
Energy_use	0.1847***	0.1831***	0.5209***	0.1445***	0.2357**	0.2178***
	(0.0238)	(0.0237)	(0.0665)	(0.0218)	(0.1068)	(0.069)
Urban_Pop	0.0178***	0.0177***	0.0232***	0.0116	−0.0027	−0.0005
	(0.005)	(0.005)	(0.0073)	(0.0122)	(0.0153)	(0.0072)
GFCF	0.0045***	0.0045***	0.0055***	0.0104***	0.0076***	−0.0008
	(0.0008)	(0.0008)	(0.0015)	(0.0012)	(0.0011)	(0.0013)
_cons	5.9882***	5.9972***	5.4183***	3.7162***	5.4234***	10.9925***
	(0.2396)	(0.2391)	(0.5916)	(0.6189)	(0.7885)	(0.8886)
Country fe	Yes	Yes	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes	Yes	Yes
	(0.2396)	(0.2391)	(0.5916)	(0.6189)	(0.7885)	(0.8886)
R-square	0.7153	0.7169	0.8208	0.8022	0.8592	0.7969
F-stat	145.1926	132.8307	44.8006	53.6215	98.3452	71.9169
Adj R^2	0.696	0.6973	0.7781	0.7573	0.834	0.7661

Note: Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4
The Effect of GF on ES: Conditioning effect of Corruption.

		(2)	(3)	(4)	(5)	(6)
	Full sample	Full sample	Q1 = very high Corruption	Q2 = high Corruption	Q3 = low corruption	Q4 = very low corruption
Variables	GHG	GHG	GHG	GHG	GHG	GHG
L.GHG	0.9763***	0.969***	1.0404***	0.9943***	0.9989***	0.9942***
	(0.0192)	(0.0228)	(0.0783)	(0.017)	(0.021)	(0.0515)
GF	−0.0063***	−0.0036***	−0.0058	0.0013	−0.0573**	−0.0358**
	(0.0012)	(0.0013)	(0.0038)	(0.0014)	(0.0231)	(0.0156)
CC_estimates	−0.0345**	0.0006***				
	(0.0155)	(0.0002)				
GF × CC_estimates		−0.0002***				
		(0.0001)				
GDP_percapita	0.0097	0.0119	−0.0592	0.0012	−0.1172*	−0.0549
	(0.0224)	(0.0267)	(0.1282)	(0.0409)	(0.0587)	(0.0576)
Finan.Dev.	0.0016**	−0.026	−0.0233	−0.0093	0.0563	−0.0788
	(0.0006)	(0.0168)	(0.0309)	(0.0212)	(0.0402)	(0.0587)
Trade	0.1302**	0.1296**	0.0722	0.005	0.0455	0.1094
	(0.0585)	(0.0625)	(0.1495)	(0.0601)	(0.0764)	(0.1601)
FDI	0.0242	0.0245	−0.0281	0.0332*	0.037	0.0109
	(0.0234)	(0.028)	(0.0471)	(0.0184)	(0.0403)	(0.0563)
Education	−0.2648	−0.2658	0.1014	0.0661	0.2547**	−0.5099
	(0.1227)	(0.157)	(0.1543)	(0.0812)	(0.0953)	(0.7277)
Energy_use	−0.0437	−0.0529	−0.037	0.008	0.0429	0.1656
	(0.0319)	(0.0364)	(0.0981)	(0.0371)	(0.0492)	(0.2055)
Urban_Pop	0.0104	0.0049	0.0086	0.0236	−0.04	0.0154
	(0.0179)	(0.0154)	(0.0123)	(0.0164)	(0.0294)	(0.0255)
GFCF	0.0081***	0.0083***	0.0045	0.0002	−0.0031	0.009
	(0.0012)	(0.0015)	(0.0074)	(0.0019)	(0.0038)	(0.0055)
_cons	1.018	1.1131	−0.5038	−0.373	−0.7893	1.3041
	(0.8601)	(1.053)	(1.0149)	(0.9028)	(0.5415)	(3.7672)
Observations	58	589	105	140	166	178
AR-I [p-value]	0.001	0.010	0.006	0.000	0.000	0.000
AR-II [p-value]	0.173	0.371	0.263	0.492	0.553	0.316
Hansen [p-value]	0.458	0.412	0.471	0.238	0.304	0.389

Note: This table reports the results of two steps dynamic system GMM estimator. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 5
Heterogeneity analysis: Development level.

	(1)	(2)	(3)	(4)
	HIC	UMIC	LMIC	LIC
	GHG	GHG	GHG	GHG
GF	−0.0148*	−0.0077**	−0.0007	−0.0006
	(0.0083)	(0.0036)	(0.0027)	(0.0022)
CC_estimates	0.0047	0.0081	−0.0026	0.0053
	(0.0138)	(0.0148)	(0.0102)	(0.0077)
GDP_percapita	0.5753**	0.4159***	0.2763***	0.9092***
	(0.2332)	(0.0435)	(0.0332)	(0.0924)
Finan.Dev.	−0.1606*	0.1908***	0.0062	0.1665***
	(0.0803)	(0.0193)	(0.007)	(0.0432)
Trade	−0.1852*	−0.191***	−0.1634***	0.1187**
	(0.0933)	(0.0385)	(0.0435)	(0.0495)
FDI	0.0116	−0.056**	−0.0727***	−0.0228**
	(0.1122)	(0.0231)	(0.0141)	(0.0089)
Education	0.0986**	0.2795**	−0.0608	0.3467
	(0.0423)	(0.1357)	(0.1306)	(0.3491)
Energy_use	0.6787**	0.1479***	0.4227***	0.486***
	(0.2323)	(0.0282)	(0.0458)	(0.0788)
Urban_Pop	0.0053	0.0364***	−0.0027	−0.0165
	(0.005)	(0.0093)	(0.0051)	(0.0243)
GFCF	−0.0055	0.0011	0.0084***	−0.0093***
	(0.0047)	(0.0014)	(0.0009)	(0.0032)
_cons	3.5535***	5.7453***	7.1859***	−5.4991**
	(1.1)	(0.6271)	(0.7631)	(2.3346)
Observations	21	332	225	40
R-squared	0.2971	0.7153	0.8683	0.9133
F-stat	349.1732	76.8875	134.4447	29.4829
Adj R^2	0.2943	0.6921	0.8553	0.8792

*Note: The table presents the outcomes of heterogeneity analysis categorized by development levels. HIE denotes high-income countries, LIE signifies low-income countries, LMIE represents low-middle-income countries, and UMIE denotes upper-middle-income countries. Robust standard errors are in parentheses. ***p<.01, **p<.05, *p<.1.*

Table 6
Heterogeneity analysis: Financial development.

	(1)	(2)	(3)	(4)
	VL_FD	L_FD	H_FD	H_FD
	GHG	GHG	GHG	GHG
GF	−0.0066**	−0.0168*	0.0009	0.0024
	(0.0032)	(0.0091)	(0.0028)	(0.0027)
CC_estimates	0.0188	0.0037	−0.024*	0.0082
	(0.0291)	(0.0091)	(0.0132)	(0.0131)
GDP_percapita	−0.0909	0.5715***	0.4174***	0.7285***
	(0.1465)	(0.0515)	(0.0837)	(0.0555)
Finan.Dev.	0.1761***	−0.0307	−0.0352	0.0107
	(0.0244)	(0.0327)	(0.0596)	(0.0342)
Trade	−0.2732**	0.0016	−0.0225	−0.0393
	(0.1112)	(0.0378)	(0.0586)	(0.0557)
FDI	0.0119	−0.0227*	−0.0402*	−0.0195
	(0.0578)	(0.0126)	(0.0239)	(0.016)
Education	0.7041	0.1974***	−0.1736	−0.358**
	(0.471)	(0.0311)	(0.1439)	(0.1596)
Energy_use	0.3552**	0.1142**	0.4252***	0.046
	(0.1669)	(0.0504)	(0.1055)	(0.071)
Urban_Pop	0.0178	0.0145***	−0.0578**	0.0095
	(0.0282)	(0.0045)	(0.0224)	(0.0066)
GFCF	0.0033	0.0042***	0.0064***	−0.0066**
	(0.0038)	(0.001)	(0.0015)	(0.003)
_cons	6.2962**	4.9819***	6.0141***	7.0564***
	(2.79)	(0.3545)	(0.8379)	(0.8961)
Observations	107	176	142	193
R-squared	0.5164	0.7979	0.8203	0.7636
F-stat	8.9703	56.852	52.0296	53.9366
Adj R^2	0.3898	0.7544	0.7777	0.7282

Note: This table displays the results of heterogeneity analysis classified by levels of financial development. VL_FD represents very low financial development, L_FD denotes low financial development, H_FD signifies high financial development, and VH_FD indicates very high financial development. Robust standard errors are presented in parentheses. Robust standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4, which examine the individual effects of GF and CC on ES measured by GHG emissions without the interaction term, confirm the negative and significant impacts of both GF and CC on GHG emissions. This is consistent with the findings in prior studies (e.g., Devine et al., 2022; Khan et al., 2023) and demonstrates the robustness of our baseline results. In Column (2), we introduce the interaction term between GF and CC, and the results are consistently negative and significant. They corroborate our initial hypothesis, which emphasizes that having greater CC enhances the effectiveness of GF in promoting ES.

To deepen our investigation, we divide the sample into four groups based on the CC_estimates score and estimate the effect of GF on GHG emissions in each group in Columns (3)–(5). The results demonstrate that GF has a significant and negative effect on GHG emissions only in countries with higher CC (third and fourth quartiles), but no significant effect is observed in countries with lower CC (first and second quartiles). These findings further substantiate our hypothesis, indicating that the positive impacts of GF on ES manifest predominantly in transparent and corruption-free environments. These findings further confirm our hypothesis and are consistent with the arguments presented by Devine et al. (2022).

4.3. Heterogeneity analysis: The role of economic development and financial development

In this section, we further explore the role of economic development and financial development in determining the effect of GF on GHG emissions. To assess the influence of economic development, we divide our sample into four groups based on the World Bank's income development classifications: high-income countries, low-income countries, lower-middle-income countries, and upper-middle-income countries.

Then, we examine the effect of GF on GHG emissions in each group. The findings in Table 5 illustrate that countries with higher economic development (higher-income and upper-middle-income countries) made more effective use of GF for mitigating GHG emissions and fostering ES. These outcomes are consistent with those in prior research—such as Chi-Chuan Lee et al. (2022), which has similar results and argues that more developed countries make better use of GF because of the superior use of technology in high-income or more developed countries and greater ability to explore alternative energy sources.

Additionally, we examine the impact of financial development (Finan.Dev.), as measured by the ratio of domestic credit to the private sector as a percentage of GDP. To do so, we divide our sample into four quartiles based on different levels of financial development: very high, high, low, and very low financial development.

The findings in Table 6 reveal that GF plays a significant role in reducing GHG emissions primarily in countries with less financial development. These results are consistent with those in prior papers, for example, Chi-Chuan Lee et al. (2022). Moreover, they show that GF is increasingly important, in tandem with conventional finance methods, in supporting ES. Unlike traditional finance, which tends to focus on maximizing profits (Tao et al., 2022), GF effectively channels funds to low-carbon and climate-resilient projects. Hence, there is a strong argument for directing funding to countries with fewer financial resources in order to address global environmental issues efficiently.

4.4. Robustness testing

To confirm the robustness of our findings, we employ several tests, whose results are discussed in this section. First, we use an alternative measure of ES, namely CO_2 emissions to confirm the consistency of our results, with the same steps as in the baseline analysis. The results in Table 7 confirm the robustness of our initial findings obtained with the GMM estimation. This robustness check essentially offers confidence

Table 7
Robustness with alternative Measure of ES.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Full sample	Q1 = very high Corruption	Q2 = high Corruption	Q3 = low corruption	Q4 = very low corruption
	CO2	CO2	CO2	CO2	CO2	CO2
GF	−0.0067*	−0.0103*	−0.001	−0.0023	0.002	−0.0127***
	(0.0036)	(0.0062)	(0.009)	(0.0062)	(0.0058)	(0.0038)
CC_estimates	−0.0002***	−0.0005				
	(0.0001)	(0.0005)				
GF × CC_estimates		−0.0003**				
		(0.0001)				
GDP_percapita	0.6709***	0.672***	0.2664***	0.7741***	1.0254***	0.4279***
	(0.0352)	(0.0352)	(0.0827)	(0.1081)	(0.1197)	(0.0798)
Finan.Dev.	0.0744***	0.0744***	0.1576***	−0.0305	−0.0328	0.0681***
	(0.013)	(0.013)	(0.0466)	(0.0329)	(0.0583)	(0.0151)
Trade	−0.0783*	−0.0786*	−0.3721***	0.115	−0.0422	−0.3142***
	(0.0404)	(0.0404)	(0.1082)	(0.0957)	(0.0926)	(0.063)
FDI	0.0137	0.0132	0.0241	0.0415	0.0222	−0.0079
	(0.0184)	(0.0184)	(0.0499)	(0.0313)	(0.0483)	(0.0192)
Education	0.0496	0.0503	0.0033	0.8655***	0.7394***	−0.7876***
	(0.0532)	(0.0532)	(0.1095)	(0.3061)	(0.2697)	(0.1906)
Energy_use	0.4064***	0.4055***	1.3076***	0.3134***	0.309	0.5799***
	(0.0343)	(0.0343)	(0.1324)	(0.0428)	(0.2065)	(0.0758)
Urban_Pop	0.0071	0.0071	0.0046	0.0171	0.0132	−0.0022
	(0.0072)	(0.0072)	(0.0145)	(0.024)	(0.0295)	(0.0079)
GFCF	0.0068***	0.0068***	0.0017	0.012***	0.008***	0.0041***
	(0.0011)	(0.0011)	(0.003)	(0.0023)	(0.0021)	(0.0015)
_cons	2.0158***	2.0209***	0.632	−2.2004*	−2.7125*	7.132***
	(0.3456)	(0.3459)	(1.1785)	(1.2164)	(1.5238)	(0.9758)
Observations	618	618	110	147	172	191
r2_w	0.7322	0.7324	0.7604	0.7139	0.7974	0.8614
F-stat	157.999	143.5601	31.0237	32.9896	63.4037	113.9303
Adj R2	0.7141	0.7138	0.7032	0.649	0.7611	0.8404

Note: This table reports the results of robustness check performed using alternative measure of ES. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 8
Robustness With Alternative measure of Corruption Control.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Full sample	Q1 = very high Corruption	Q2 = high Corruption	Q3 = low corruption	Q4 = very low corruption
	GHG	GHG	GHG	GHG	GHG	GHG
GF	−0.0256**	−0.0031	0.0021	0.0046	−0.0051	−0.0053**
	(0.0127)	(0.0029)	(0.0045)	(0.0031)	(0.0034)	(0.0025)
CC_estimates	−0.0267**	−0.0104				
	(0.0127)	(0.0124)				
GF × CC_estimates		−0.0649**				
		(0.0251)				
GDP_percapita	0.4333***	0.4345***	0.2554***	0.4985***	0.6077***	0.4419***
	(0.0245)	(0.0244)	(0.0415)	(0.055)	(0.062)	(0.0727)
Finan.Dev.	0.0678***	0.0676***	0.0368	−0.0716***	0.0154	0.0832***
	(0.009)	(0.009)	(0.0234)	(0.0168)	(0.0301)	(0.0138)
Trade	−0.1777***	−0.1782***	−0.1704***	0.0538	0.1308***	−0.3161***
	(0.028)	(0.028)	(0.0543)	(0.0487)	(0.0479)	(0.0574)
FDI	0.0056	−0.0214	−0.007	−0.0063	−0.021	0.0015
	(0.0036)	(0.0434)	(0.0177)	(0.0159)	(0.025)	(0.0175)
Education	0.1924***	0.1935***		0.5698***	−0.1975	−0.9928***
	(0.0369)	(0.0368)	(0.055)	(0.1557)	(0.1396)	(0.1735)
Energy_use	0.1848***	0.1839***	0.5209***	0.1445***	0.2357**	0.2178***
	(0.0238)	(0.0237)	(0.0665)	(0.0218)	(0.1068)	(0.069)
Urban_Pop	0.0178***	0.0176***	0.0232***	0.0116	−0.0027	−0.0005
	(0.005)	(0.005)	(0.0073)	(0.0122)	(0.0153)	(0.0072)
GFCF	0.0044***	0.0045***	0.0055***	0.0104***	0.0076***	−0.0008
	(0.0008)	(0.0008)	(0.0015)	(0.0012)	(0.0011)	(0.0013)
_cons	5.9936***	5.9798***	5.4183***	3.7162***	5.4234***	10.9925***
	(0.2397)	(0.2396)	(0.5916)	(0.6189)	(0.7885)	(0.8886)
Observations	618	618	110	147	172	191
r2_w	0.7152	0.7164	0.8208	0.8022	0.8592	0.7969
F-stat	145.1303	132.4957	44.8006	53.6215	98.3452	71.9169
Adj R2	0.696	0.6967	0.7781	0.7573	0.834	0.7661

Note: This table reports the results of robustness check performed using alternative measure of Control of Corruption. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 9
Robustness With alternative estimator-PCSE.

	(1)	(2)	(3)	(4)	(5)	(6)
	GHG	GHG	GHG	GHG	GHG	GHG
GF	−0.0307**	−0.003*	−0.0012	−0.002	0.0088*	−0.0051**
	(0.0148)	(0.0015)	(0.0087)	(0.013)	(0.0047)	(0.0025)
CC_estimates	−0.0345**	−0.026				
	(0.0155)	(0.0168)				
GF × CC_estimates		−0.0987**				
		(0.0376)				
GDP_percapita	0.0363	0.0031	0.5734***	0.1828	−0.3938	−1.2526***
	(0.0936)	(0.0945)	(0.1432)	(0.2569)	(0.2599)	(0.2142)
Finan.Dev.	0.1261***	0.1402***	−0.0938	0.3051**	0.6797***	0.1422**
	(0.0445)	(0.0461)	(0.0893)	(0.1339)	(0.1905)	(0.0699)
Trade	−0.736***	−0.8262***	−0.79***	−1.5135***	−1.2748***	−2.1811***
	(0.097)	(0.1009)	(0.1735)	(0.2249)	(0.2296)	(0.2431)
FDI	−0.0385	−0.0455	−0.0728	−0.2056**	−0.1391	0.048
	(0.0276)	(0.0297)	(0.0695)	(0.0946)	(0.1018)	(0.0789)
Education	−0.1059	−0.1214	−0.1775	−3.1943***	−2.6272**	1.1032
	(0.124)	(0.132)	(0.1612)	(0.7551)	(1.1282)	(1.2332)
Energy_use	0.8978***	0.9584***	0.966***	0.8572***	1.6406***	2.5506***
	(0.1116)	(0.1137)	(0.1415)	(0.1823)	(0.2028)	(0.2642)
Urban_Pop	0.0236**	0.0261**	0.0449*	0.0529	0.158	0.0425*
	(0.0102)	(0.0111)	(0.0262)	(0.0661)	(0.1058)	(0.0231)
GFCF	0.0087**	0.0094**	−0.0017	0.0105	0.0273***	0.009
	(0.0035)	(0.0037)	(0.0049)	(0.0124)	(0.0096)	(0.0092)
_cons	7.1247***	7.3876***	4.1622***	23.3495***	17.0444***	7.2311
	(0.8599)	(0.8802)	(1.3723)	(3.5419)	(5.8581)	(5.8972)
Observations	618	618	110	147	172	191
R-squared	0.8883	0.8823	0.9719	0.9273	0.9299	0.9419

Note: This table reports the results of robustness check performed using alternative estimator i.e., PCSE. Standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

that the relationship between GF, CC, and ES remains consistent even when we use an alternative measurement.

Next, we employ an alternative measure of CC, specifically CC_rank, and the results are in Table 8. The findings from this test, which uses the same steps as in our baseline estimation, are consistent with our initial results, hence confirming the relationships observed earlier. The consistency in the estimated coefficients and their significance levels confirms the reliability of our model across different proxies for corruption control. This robustness check adds an extra layer of confidence in the robustness and generalizability of our study, confirming the resilience of the patterns identified in the impact of GF and CC on environmental outcomes.

In our final robustness check, we employ an alternative estimator, namely panel-corrected standard errors (PCSE). The results in Table 9 are consistent with our baseline estimates, which confirm the stability and reliability of our model. The use of PCSE as an alternative estimator shows the robustness of the relationships observed and suggests that the patterns identified in the influence of GF and CC on ES persist across different econometric techniques. This additional robustness test, as well as the earlier tests, bolsters the credibility of our study, emphasizing the resilience and generalizability of the connections established in different analytical frameworks.

5. Conclusion and policy implications

Climate change poses severe challenges for the world, particularly for Asia, and requires urgent action to reduce GHG emissions and protect ES. GF could be a promising instrument for achieving this goal, but the amount needed is too large to be practical. Therefore, strategies to attract more GF and enhance the efficacy of existing GF are needed. The efficacy of GF may be contingent on several factors, particularly the extent of corruption control. This study investigates the effect of CC on the efficacy of GF using data on 37 Asian countries over the period 2000–2020. To perform empirical analysis, we use panel fixed effect regression with robust standard errors and two-step system-GMM estimation.

The results demonstrate that the efficacy of GF in reducing GHG emissions and improving ES depends on the level of corruption in the country. In particular, GF has a pronounced GHG reduction effect in the presence of robust corruption control or minimal corruption. This finding highlights the significance of enhancing CC at the national level to optimize the efficient use of GF resources and of advancing ES. In a nutshell, this study shows that CC may be one such strategy, as it increases the efficiency of GF and its positive impacts on ES. A corruption-free institutional environment enables GF to deliver the intended benefits and may attract more climate-conscious investment. Thus CC can be an effective strategy for achieving carbon neutrality goals by leveraging GF for ES.

These findings are robust to several robustness tests and have some implications for stakeholders, as follows.

Our study highlights the critical need to strengthen national-level control of corruption. Beyond being an ethical imperative, strengthening anticorruption measures is a strategic way to optimize the efficient use of GF resources. Moreover, policy makers should adopt a targeted approach in allocating GF resources, prioritizing countries with robust corruption control mechanisms. This strategic allocation can significantly enhance the positive impact of GF on reducing GHG emissions and of international collaboration in combating corruption. Collaborative efforts can foster a global environment that is conducive to the effective use of GF for sustainable development. In essence, our study not only sheds light on the nuanced interplay between corruption, GF, and environmental outcomes but also provides actionable insights for policy makers, fostering a pathway toward more sustainable and resilient futures for Asian countries and, by extension, the global community.

5.1. Limitations and directions for future research

The study is confined to Asian countries; hence, caution is needed in generalizing its findings to other regions. Future research could broaden the scope to include diverse geographic contexts, providing more comprehensive understanding. Furthermore, future research could explore the other governance mechanisms that enhance or hinder GF

effectiveness, which can further refine environmental policy recommendations.

Moreover, consideration of external factors, such as global economic conditions or geopolitical influences, could enrich the analysis by accounting for broader contextual elements that affect the relationship under scrutiny. Incorporating these considerations into future research can contribute to a more nuanced understanding of the complex interplay between corruption control, GF efficacy, and environmental outcomes, thereby guiding more effective strategies for taking action to address climate change.

CRediT authorship contribution statement

Yacong Shi: Introduction, Research design, Revise methods and conclusions, Writing – review & editing. **Qiju Zhu:** Performed statistical analysis in incorporating the revisions, Contributed review of literature to hypothesis development, Writing – review & editing. **Muhammad Atif Khan:** Conceived the idea, research design and data analysis Collected the Data Wrote the Paper.

Appendix A

Table A1
List of Countries in Sample

Serial No.	Country	Serial No.	Country	Serial No.	Country
1	Afghanistan	14	Jordan	27	Philippines
	Armenia	15	Kazakhstan	28	Sri Lanka
3	Azerbaijan	16	Korea, Dem. People's Rep.	29	Syrian Arab Republic
4	Bangladesh	17	Kyrgyz Republic	30	Tajikistan
5	Bhutan	18	Lao PDR	31	Thailand
6	Cambodia	19	Lebanon	32	Timor-Leste
	China	20	Malawi	33	Turkiye
8	Cyprus	21	Malaysia	34	Turkmenistan
9	Georgia	22	Maldives	35	Uzbekistan
10	India	23	Mongolia	36	Vietnam
11	Indonesia	24	Myanmar	37	Yemen, Rep.
12	Iraq	25	Nepal		
13	Israel	26	Pakistan		

References

ADB. (2020). *Green climate fund*. Asian Development Bank. Retrieved from https://www.greenclimate.fund/ae/adbonMarch2024.

Ahmed, D., Hua, H. X., & Bhutta, U. S. (2024). Innovation through green finance: A thematic review. *Current Opinion in Environmental Sustainability, 66*, Article 101402. https://doi.org/10.1016/j.cosust.2023.101402

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297. https://doi.org/10.2307/2297968

Bilal, M. J., & Shaheen, W. A. (2024). Towards sustainable development: Investigating the effect of green financial indicators on renewable energy via the mediating variable. *Renewable Energy, 221*, Article 119819. https://doi.org/10.1016/j.renene.2023.119819

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bond, S. R., Hoeffler, A., & Temple, J. (2001). GMM estimation of empirical growth models. Retrieved from https://EconPapers.repec.org/RePEc:cpr:ceprdp:3048.

Chin, M.-Y., Ong, S.-L., Ooi, D. B.-Y., & Puah, C.-H. (2022). The impact of green finance on environmental degradation in BRI region. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-022-02709-5

Devine, A., McCollum, M., & Orlova, S. (2022). Cleaning up corruption and the climate: The role of green building certifications. *Finance Research Letters, 47*, Article 102929. https://doi.org/10.1016/j.frl.2022.102929

Fu, T., & Jian, Z. J. E. E. (2021). *Corruption pays off: How environmental regulations promote corporate innovation in a developing country, 183*, Article 106969.

Gong, Z., Gong, L., & Rasool, Z. (2024). From Brown to green: Exploring asymmetric nexus between green finance and carbon footprint in BRICS+6 alliance. *Borsa Istanbul Review*. https://doi.org/10.1016/j.bir.2024.01.010

Hao, Y., Xu, L., Guo, Y., & Wu, H. (2022). The inducing factors of environmental emergencies: Do environmental decentralization and regional corruption matter? *Journal of Environmental Management, 302*, Article 114098.

Hu, J., Chen, H., Dinis, F., & Xiang, G. J. E. I. (2023). *Nexus among green finance, technological innovation, green fiscal policy and CO2 emissions: A conditional process analysis, 154*, Article 110706.

Huynh, C. M., & Hoang, H. H. (2024). Climate change and income inequality in Asia: How does institutional quality matter? *Journal of the Asia Pacific Economy*, 1–25. https://doi.org/10.1080/13547860.2024.2315700

Jones, A. W. (2015). Perceived barriers and policy solutions in clean energy infrastructure investment. *Journal of Cleaner Production, 104*, 297–304.

Kar, S., Mandal, B., Marjit, S., & Mukherjee, V. (2020). Seeking rent in the informal sector. *Annals of Public and Cooperative Economics, 91*(1), 151–164. https://doi.org/10.1111/apce.12253

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2009). Governance matters VIII: Aggregate and individual governance indicators, 1996-2008. In *World bank policy research working paper(4978)*.

Khan, M. A., Ahmed, M., & Hull, R. (2023). The impact of climate mitigation finance on greenhouse gas. *Journal of Environmental Planning and Management*, 1–19. https://doi.org/10.1080/09640568.2023.2227759

Khan, M. A., Gu, L., Khan, M. A., & Oláh, J. (2020). Natural resources and financial development: The role of institutional quality. *Journal of Multinational Financial Management, 56*, Article 100641. https://doi.org/10.1016/j.mulfin.2020.100641

Khan, M. A., Riaz, H., Ahmed, M., & Saeed, A. (2022). Does green finance really deliver what is expected? An empirical perspective. *Borsa Istanbul Review, 22*(3), 586–593. https://doi.org/10.1016/j.bir.2021.07.006

Lee, C.-C., & Lee, C.-C. (2022). How does green finance affect green total factor productivity? Evidence from China. *Energy Economics, 107*, Article 105863. https://doi.org/10.1016/j.eneco.2022.105863

Lee, C.-C., Li, X., Yu, C.-H., & Zhao, J. (2022). The contribution of climate finance toward environmental sustainability: New global evidence. *Energy Economics, 111*, Article 106072. https://doi.org/10.1016/j.eneco.2022.106072

Lee, C.-C., Song, H., & An, J. (2024). The impact of green finance on energy transition: Does climate risk matter? *Energy Economics, 129*, Article 107258. https://doi.org/10.1016/j.eneco.2023.107258

Lee, C.-C., Song, H., & Lee, C.-C. (2023). Assessing the effect of green finance on energy inequality in China via household-level analysis. *Energy Economics, 128*, Article 107179. https://doi.org/10.1016/j.eneco.2023.107179

Li, C., Faridi, M. Z., & Nazar, R. (2023). How does green finance asymmetrically affect greenhouse gas emissions? Evidence from the top-ten green bond issuer countries. *Borsa Istanbul Review, 23*(4), 887–894. https://doi.org/10.1016/j.bir.2023.03.002

Li, C., Faridi, M. Z., & Nazar, R. J. B. I. R. (2023). *How does green finance asymmetrically affect greenhouse gas emissions? Evidence from the top-ten green bond issuer countries*.

Li, W., Jia, Z. J. M., & Change, A. S.f. G. (2017). *Carbon tax, emission trading, or the mixed policy: Which is the most effective strategy for climate change mitigation in China?, 22* pp. 973–992).

Mehboob, M. Y., Ma, B., Mehboob, M. B., & Zhang, Y. (2024). Does green finance reduce environmental degradation? The role of green innovation, environmental tax, and

geopolitical risk in China. *Journal of Cleaner Production, 435*, Article 140353. https://doi.org/10.1016/j.jclepro.2023.140353
Meo, M. S., & Abd Karim, M. Z. (2022). The role of green finance in reducing CO2 emissions: An empirical analysis. *Borsa Istanbul Review, 22*(1), 169–178.
Nenavath, S., & Mishra, S. J. H. (2023). Impact of green finance and fintech on sustainable economic growth: Empirical evidence from India. *9*(5).
Peace, I. f. E.. (2019). Global Peace index 2019: Measuring Peace in a complex world. *Sydney*. Retrieved from http://visionofhumanity.org/reports. (Accessed 19 April 2020).
Quah, J. S. T. (2018). Combating corruption in Asian countries: Learning from success & failure. *Dædalus, 147*(3), 202–215. https://doi.org/10.1162/daed_a_00511
Quan, X., Zhang, K., Zhong, R., & Zhu, Y. (2023). Political corruption and green innovation. *Pacific-Basin Finance Journal, 82*, Article 102169.
Rashid Khan, H. U., Islam, T., Yousaf, S. U., Zaman, K., Shoukry, A. M., Sharkawy, M. A., … Hishan, S. S. (2019). The impact of financial development indicators on natural resource markets: Evidence from two-step GMM estimator. *Resources Policy, 62*, 240–255. https://doi.org/10.1016/j.resourpol.2019.04.002
Robinson, M. (1998). Corruption and development: An introduction. *European Journal of Development Research, 10*(1), 1–14. https://doi.org/10.1080/09578819808426699
Roodman, D. (2006). *How to do xtabond2: An introduction to "Difference" and "System" GMM in stata*. Center for Global Development. WP no 103.
Rui, L., Sun, W., & Xu, F. J. F. R. L. (2024). *The impact of bank credit corruption on firms' carbon emission reduction innovations: Empirical evidence from China, 60*, Article 104884.
Sadiq, M., Chau, K. Y., Ha, N. T. T., Phan, T. T. H., Ngo, T. Q., & Huy, P. Q. J. G. F. (2023). *The Impact of green finance, eco-innovation, renewable energy and carbon taxes on CO2 emissions in BRICS countries: Evidence from CS ARDL estimation*, Article 101689.
Saeed Meo, M., & Karim, M. Z. A. (2022). The role of green finance in reducing CO2 emissions: An empirical analysis. *Borsa Istanbul Review, 22*(1), 169–178. https://doi.org/10.1016/j.bir.2021.03.002
Svensson, J. (2005). Eight questions about corruption. *The Journal of Economic Perspectives, 19*(3), 19–42. https://doi.org/10.1257/089533005774357860
Tao, H., Zhuang, S., Xue, R., Cao, W., Tian, J., & Shan, Y. (2022). Environmental finance: An interdisciplinary review. *Technological Forecasting and Social Change, 179*, Article 121639. https://doi.org/10.1016/j.techfore.2022.121639
Tawiah, V., Zakari, A., & Alvarado, R. (2023). Effect of corruption on green growth. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03152-w
Tolliver, C., Fujii, H., Keeley, A. R., & Managi, S. (2021). Green innovation and finance in Asia. *Asian Economic Policy Review, 16*(1), 67–87. https://doi.org/10.1111/aepr.12320
Transparency International. (2022). *Corruption perceptions index. URL:*.
Udeagha, M. C., & Ngepah, N. (2023). The drivers of environmental sustainability in BRICS economies: Do green finance and fintech matter? *World Development Sustainability, 3*, Article 100096. https://doi.org/10.1016/j.wds.2023.100096
Udeagha, M. C., & Ngepah, N. J. W. D. S. (2023). *The drivers of environmental sustainability in BRICS economies: Do green finance and fintech matter?, 3*, Article 100096.
Vagliasindi, M. (2012). The role of policy driven incentives to attract ppps in renewable-based energy in developing countries: A cross-country analysis. In *World bank policy research working paper, 6120*.
Wang, Z., Danish, Zhang, B., & Wang, B. (2018). The moderating role of corruption between economic growth and CO2 emissions: Evidence from BRICS economies. *Energy, 148*, 506–513. https://doi.org/10.1016/j.energy.2018.01.167
Wang, L., Yang, X., & Cai, Q. J. H. (2024). Influence mechanism of green finance on regional emission reduction. *10*(1).
Wang, Z., Zhang, B., & Wang, B. J. E. (2018). *The moderating role of corruption between economic growth and CO2 emissions: Evidence from BRICS economies, 148* pp. 506–513).
Wang, S., Zhao, D., & Chen, H. (2020). Government corruption, resource misallocation, and ecological efficiency. *Energy Economics, 85*, Article 104573. https://doi.org/10.1016/j.eneco.2019.104573
Wang, Y., & Zhi, Q. J. E. P. (2016). *The role of green finance in environmental protection: Two aspects of market mechanism and policies, 104* pp. 311–316).
Yue, H., Zhou, Z., & Liu, H. J. E. R. (2024). *How does green finance influence industrial green total factor productivity? Empirical research from China, 11* pp. 914–924).
Zakari, A., Tawiah, V., Oyewo, B., & Alvarado, R. (2023). The impact of corruption on green innovation: The case of OECD and non-OECD countries. *Journal of Environmental Planning and Management, 66*(6), 1336–1368. https://doi.org/10.1080/09640568.2022.2027234
Zhang, Y.-J., Jin, Y.-L., Chevallier, J., & Shen, B. (2016). The effect of corruption on carbon dioxide emissions in APEC countries: A panel quantile regression analysis. *Technological Forecasting and Social Change, 112*, 220–227. https://doi.org/10.1016/j.techfore.2016.05.027
Zhang, T., & Zhao, F. J. E. S. R. (2024). A study on the relationships among green finance. *Environmental Pollution and Economic Development, 51*, Article 101290.
Zhao, X., Zeng, B., Zhao, X., Zeng, S., & Jiang, S. (2024). Impact of green finance on green energy efficiency: A pathway to sustainable development in China. *Journal of Cleaner Production, 450*, Article 141943. https://doi.org/10.1016/j.jclepro.2024.141943