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Research article

Fintech and environmental efficiency: The dual role of foreign direct investment in G20 nations

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ABSTRACT

This study investigates the relationship between financial technology (fintech) and environmental efficiency across G20 countries, emphasizing the moderating effect of foreign direct investment (FDI) from 2010 to 2022. Employing Data Envelopment Analysis (DEA) through both Slack-Based Measure (SBM) and Epsilon-Based Measure (EBM), alongside Tobit regression and the Generalized Method of Moments (GMM) for analytical rigor, the research reveals that fintech exerts a positive influence on environmental efficiency within these countries. Furthermore, it demonstrates that FDI contributes to enhancing environmental efficiency. However, when FDI is combined with fintech investments, it yields a negative impact. This detrimental effect stems from FDI's emphasis on short-term gains, rapid expansion, and a globally oriented supply chain that favors cost efficiency at the expense of sustainability. The study highlights the necessity for investments in fintech that comply with environmental standards and offers policy recommendations to improve environmental efficiency. It urges policymakers to promote environmentally sustainable investment practices within the fintech sector to aid in achieving sustainable development goals.

1. Introduction

The global ecological crisis highlights the vulnerability of all regions and economic sectors to the far-reaching effects of climate change (Ahmed et al., 2022). In response, the financial sector has undergone significant transformations, propelled by advancements in technology. The advent of financial technology (Fintech) represents a major shift in financial market dynamics, introducing innovative business models and processes that align economic growth with environmental sustainability (Tao et al., 2022). As part of the fourth industrial revolution and Industry 4.0, Fintech plays a crucial role in advancing circular economy practices, thus contributing to both economic prosperity and environmental protection (Pizzi et al., 2021; Beier et al., 2020). Fintech's impact extends beyond reducing standardized financial costs and addressing information asymmetry; it also enhances resource efficiency and promotes sustainable financing solutions, underscoring its importance in achieving sustainable development goals (Nenavath, 2022). With soaring revenues and an influx of entrepreneurs, Fintech's influence spans mobile devices, artificial intelligence, and blockchain, supporting a broad spectrum of financial activities (Howarth, 2023; Croutzet and Dabbous, 2021). This technological diversity not only improves financial intermediation but also strengthens regulatory frameworks and fosters environmental sustainability by promoting clean energy solutions (Udeagha and Muchapondwa, 2023; Li et al., 2023).

Global financial inclusion trends show significant progress, with the World Bank's Global Findex Survey revealing substantial increases in account ownership, especially in developing countries and G20 nations, indicating a shift towards digital financial services (Demirgüç-Kunt et al., 2022; ADB, 2022). Concurrently, the global economy's gradual shift towards liberalization and financial globalization, including foreign direct investment (FDI), presents a complex picture of economic growth juxtaposed with environmental concerns. While FDI is lauded for its economic contributions, its environmental impact remains a contentious issue, with studies suggesting both positive and negative effects on environmental quality (Ahmad et al., 2021; Murshed et al., 2021; Solarin et al., 2017; Khan and Ozturk, 2020). Recent changes in

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the global financial landscape have highlighted the increasing convergence of technology and financial services, which has dramatically changed the way capital flows across borders (Anifa et al., 2022; Lee and Shin, 2018; Zhou et al., 2022). The surge in fintech innovation has not only increased access to financial services, but also provided new avenues for FDI (Manzoor, 2023). For example, fintech companies are increasingly attracting cross-border investment as they offer new solutions for sustainability and environmental efficiency. This trend is particularly important as the global economy seeks a sustainable post-pandemic recovery path with a focus on green investments (Xames et al., 2023). On the regulatory front, there have been significant developments that highlight the importance of our research (Manzoor, 2023). For example, the European Union's Action Plan on Financing Sustainable Growth has introduced measures that promote sustainable finance, including directives that encourage FDI in technologies enhancing environmental efficiency (Khudyakova, 2019). Similarly, several countries in Asia have implemented policies that promote investments in green technologies that directly impact the fintech industry by promoting innovation that supports environmental sustainability (Tolliver et al., 2021).

Furthermore, recent studies on the relationship between Fintech and environmental efficiency demonstrate mixed outcomes. For instance, Qin et al. (2024), Liu et al. (2024a,b,c,d), Fan et al. (2024), Sadiq et al. (2024), and Chang and Wu (2024) report positive impacts of Fintech on environmental quality, green productivity, and climate sustainability in regions such as China and the G5 countries. Conversely, research by Xia and Liu (2024), Zhang et al. (2024a,b), Pu et al. (2024), Ahmad et al. (2024), and Tu (2024) across the G7, BRICS, and European Union finds that Fintech may worsen ecological footprints and decrease environmental quality. Similarly, the effects of FDI on environmental efficiency vary. Positive influences are observed by Liu et al. (2024a,b,c,d), Gonzalo Hernández Soto (2024), and in studies by Viglioni et al. (2024) and Zhang et al. (2024a,b), which show improved eco-efficiency and reduced ecological footprints in China, Latin America, and G20 countries. However, studies like Boateng et al. (2024), Y. He et al. (2024), and Yuan et al. (2024) identify either negative or insignificant impacts of FDI on CO2 emissions and overall environmental pollution.

This study is pivotal as it explores the relationship between Fintech and environmental efficiency across G20 nations from 2010 to 2022, specifically examining the moderating effect of FDI. This investigation addresses critical gaps in the existing literature, which shows varied outcomes. By determining how FDI influences the impact of Fintech on environmental sustainability, the study aims to provide empirical insights for policymakers on utilizing Fintech alongside FDI to enhance environmental outcomes. This research is crucial for crafting tailored regulatory frameworks and guiding global sustainability efforts, given the significant economic and environmental influence of G20 countries. The findings of this study equip policymakers with the necessary evidence to devise and implement policies that exploit the potential of Fintech to promote environmental efficiency across the G20 nations. Amid the rapid industrial growth witnessed in these countries, the research identifies and emphasizes the vital intersection between economic advancement and environmental stewardship. It advocates for the identification and harnessing of mechanisms capable of fostering environmental efficiency, especially within the ambit of the G20 economies.

Moreover, the study emphasizes FDI as a critical factor, proposing its role as an essential catalyst in securing significant financial resources from international investors. This is aimed at bridging financing gaps and supporting projects, including those in the Fintech sector. Fig. 1 shows fluctuations in Fintech and FDI that have been observed within this region. FDI is also depicted as a complementary force to domestic investments, enabling the mobilization of capital for the expansive development of energy infrastructure. The influx of foreign investment introduces advanced technology, expertise, and knowledge across various sectors such as energy production, resource extraction, mining, and the transmission of energy. Such technology transfer is pivotal in modernizing and enhancing the sectors related to energy and resources, thereby tackling the environmental challenges prevalent in the G20 countries. Consequently, this study thoroughly explores the impact of FDI on the nexus between Fintech and environmental efficiency within the context of the G20 nations.

The rest of the article is structured follows. In Section 2, we provide a comprehensive review of pertinent literature, offering a foundation for understanding the context. Section 3 portrays the data and methodology, and in Section 4, we present the findings derived from the research. In Section 5, summarizes a conclusion of key insights and offers practical policy implications based on the study's outcomes.

2. Literature review

Environmental degradation poses a critical global challenge, highlighting the urgent environmental issues facing humanity. The intensifying effects of climate change have significantly compromised the

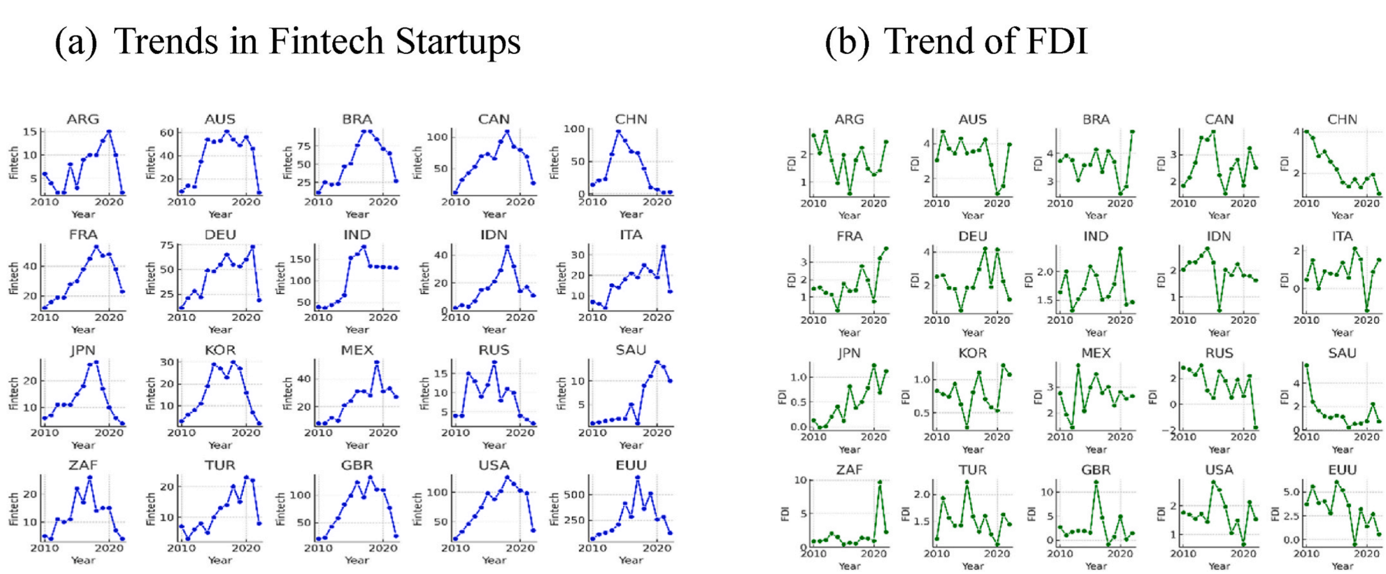

Fig. 1. Trend in Fintech Startups (a) and Inwards FDI (b). Note: Panel (a) illustrates the number of Fintech startups in G20 countries, including the European Union. Whereas Panel (b) shows foreign direct investments received by the G20 countries.

integrity of natural ecosystems, leading to a noticeable decline in their quality. Historical analysis reveals that although climatic variations are part of the Earth's natural dynamics, the rate of change has accelerated markedly in the last century, coinciding with the rise of industrialization and modernization (Tri and Hoang, 2022). At the core of financial technology (Fintech) is the innovative integration of financial services with advanced technology. Fintech has become a key facilitator of green growth, offering a viable means to enhance environmental efficiency on a national scale. The technological advancements that underpin Fintech play a crucial role in boosting the operational efficiency of firms in the financial sector by providing rapid access to essential market data (Dynan et al., 2006).

The evolution of global financial markets is largely driven by the introduction of groundbreaking financial technologies that have radically altered the landscape of the financial sector. This transformative dynamic has had profound and enduring effects on the global economic structure, with significant environmental implications. Fintech is instrumental in refining financial processes, lifestyles, and operational frameworks for businesses, individuals, and entrepreneurs. By employing technologies such as machine learning, artificial intelligence, mobile platforms, and digital assistants, Fintech is essential for enhancing financial management across various sectors (). By 2030, the emergence of environmentally sustainable growth paradigms is projected to generate an annual economic output of approximately \$12 trillion. Fintech is strategically positioned to assist businesses in conducting comprehensive analyses and reducing waste production. Moreover, it enables investors to direct their funds towards environmentally friendly projects, utilizing sophisticated technological tools like advanced big data analytics, cryptocurrencies, and other cutting-edge platforms (Lisha et al., 2023).

Furthermore, the impact of FDI on environmental efficiency exhibits considerable variability across different geographic and economic contexts, as illustrated by recent studies. In China, He et al. (2024) found FDI's effect on CO2 emissions to be insignificant, whereas Liu et al. (2024a,b,c,d) observed a positive impact on eco-efficiency, suggesting FDI may facilitate the adoption of greener technologies (B. He et al., 2024; Liu et al., 2024a,b,c,d). Contrastingly, in the Belt and Road Initiative nations, the influence of Chinese OFDI on CO2 emissions showed mixed results, indicating variability based on country-specific factors (Liu et al., 2024a,b,c,d). Latin America experienced a negative impact, with FDI worsening ecological footprints, highlighting potential environmental degradation (Gonzalo Hernández Soto, 2024). Similarly, a global study across 182 countries by Boateng et al. (2024) linked FDI with increased CO2 emissions, suggesting investments might often support environmentally detrimental practices. However, in top remittance-receiving countries, FDI was associated with improvements in CO2 emissions, possibly due to investments in cleaner technology (Dilanchiev et al., 2024). These findings underscore the complex, context-dependent nature of FDI's environmental impact, emphasizing the need for nuanced environmental policies to steer FDI towards sustainable outcomes. Thus, this study is pivotal as it explores the relationship between Fintech and environmental efficiency across G20 countries, particularly focusing on the moderating role of FDI from 2010 to 2022. It aims to explain how FDI influences the environmental outcomes of Fintech interventions, addressing a notable gap in existing literature that presents mixed findings. For instance, while some studies illustrate a positive correlation between fintech and environmental efficiency, others point to negative impacts. Likewise, the impact of FDI on environmental outcomes also varies, with some research highlighting beneficial effects, whereas others indicate negative or negligible impacts.

Understanding these dynamics is critical for multiple reasons. First, it provides empirical evidence to policymakers about how Fintech, in conjunction with FDI, can foster improved environmental outcomes. Second, it explains the conditions under which Fintech and FDI either support or undermine environmental sustainability, thereby aiding in the formulation of more precise and effective regulatory frameworks. Third, given that G20 nations are key players in the global economy and significantly influence the world's environmental and economic landscape, insights from this study could significantly impact global sustainability efforts. These findings have the potential to inform both national and international policies, integrating technological advancements in finance with environmental objectives, thereby shaping broader strategies for sustainable development.

2.1. Fintech and environmental efficiency

Recent research highlights the multifaceted relationship between Fintech and environmental efficiency, revealing how Fintech can significantly influence environmental sustainability across different global regions. Positive impacts are noted in several studies; for instance, Qin et al. (2024) report a beneficial effect of Fintech on environmental quality in China, suggesting that Fintech facilitates improvements in environmental metrics. Similarly, Liu et al. (2024a,b,c,d) and Fan et al. (2024) find that Fintech contributes positively to environmental sustainability and green productivity in China, highlighting its potential to support sustainable business practices. These positive relationships suggest that Fintech's innovative applications can enhance resource efficiency and support sustainable financial solutions, such as green credit and investment, which play pivotal roles in fostering green growth (Sadiq et al., 2024; Chang and Wu, 2024).

Conversely, several studies indicate that the impact of Fintech on environmental outcomes can vary, with negative implications also observed in certain contexts. For example, Xia and Liu (2024) and Zhang et al. (2024a,b) report negative associations between Fintech and ecological footprints in the G7 and BRICS economies, respectively. These findings suggest that while Fintech can drive financial sector efficiency, it may also lead to increased resource consumption and ecological strain under certain conditions. This duality underscores the complexity of Fintech's role in environmental sustainability, necessitating nuanced policy interventions to harness its benefits while mitigating adverse impacts. The mixed findings across different studies highlight the importance of context-specific strategies that align Fintech developments with sustainable environmental practices, ensuring that technological advances in the financial sector contribute positively to global sustainability goals (Ahmad et al., 2024; Tu, 2024).

2.2. FDI and environmental efficiency

The relationship between FDI and environmental efficiency presents a complex and varied landscape across different regions and studies. The empirical evidence suggests that the impact of FDI on environmental outcomes such as CO2 emissions and ecological footprints is not uniform, reflecting the nuanced interactions between economic activities and environmental policies. For instance, He et al. (2024) found an insignificant relationship between FDI and CO2 emissions in China using a spatial difference-in-differences model, suggesting that FDI, in this case, did not significantly alter the emission levels. Similarly, Yuan et al. (2024) reported an insignificant impact of FDI on environmental pollution in China, indicating a neutral effect. However, other studies report more varied impacts; for example, Liu et al. (2024a,b,c,d) observed mixed effects of Chinese OFDI on CO2 emissions across 46 Belt and Road Initiative (BRI) nations, and Guo and Yin (2024) noted mixed outcomes in China, affected by economic shocks, illustrating the conditional nature of FDI's environmental impacts.

On the other hand, several studies have identified positive and negative effects of FDI on environmental metrics. Liu et al. (2024a,b,c,d) found a positive relationship between FDI and eco-efficiency in China, suggesting that FDI can contribute to better environmental management practices. This positive trend was also supported by findings from Dilanchiev et al. (2024) in top remittance-receiving countries, Viglioni et al. (2024) in G20 countries, and Zhang et al. (2024a,b) in East Asian economies, all noting that FDI was associated with reductions in CO2 emissions. Conversely, studies like those by Gonzalo Hernández Soto (2024) in Latin America and Boateng et al. (2024) across 182 countries have documented negative impacts, where FDI exacerbated ecological footprints and increased CO2 emissions, highlighting the potential environmental costs associated with foreign investments in regions with less stringent environmental regulations. These findings illustrate the dual potential of FDI to either support or undermine environmental sustainability, contingent upon regional economic conditions, the nature of the FDI, and the prevailing environmental policies and practices. For more details, Table 1 provides an extensive summary of recent research findings related to Fintech, FDI, and Environmental Efficiency.

3. Data and methodology

3.1. Data resources and variables

This study examines the environmental efficiency of G20 nations from 2010 to 2022, a period selected based on the availability of pertinent data. The research encompasses a broad set of 20 countries, including Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Korea Republic, Mexico, Russian Federation, Saudi Arabia, South Africa, Türkiye, the United Kingdom, the United States, and the European Union. The specific focus on these years addresses the challenge of limited data, particularly in the fintech sector, which has only recently emerged as a significant area of study.

To assess environmental efficiency, the study utilizes two methodologies: Data Envelopment Analysis with Slack-Based Measure (DEA-SBM) and Data Envelopment Analysis with Epsilon-Based Measure (DEA-EBM). These methods incorporate three inputs—energy consumption, capital stock, and labor—and two outputs: gross domestic product (as the desired output) and CO2 emissions (as the undesired output). Each country is considered a Decision-Making Unit (DMU) in this analysis. The primary data source for this research is the World Development Indicators (WDIs) from the World Bank database, which provides extensive descriptive statistics for the input and output variables, detailed in Table 2. Additionally, data specific to the fintech sector were sourced from the CrunchBase database, detailing the annual presence of fintech companies in each country. Table 3 elaborates on the variables used in the econometric analysis, including definitions,

Table 1
Summary of recent studies related to fintech, FDI, and environmental efficiency.

Relationship between Fintech and Environmental Efficiency					
References	Sample	Time range	Research method	Directions	Findings
Qin et al. (2024)	China	2012 to 2019	STIRPAT, GMM and 2SLS	Fintech to environmental quality	Positive
Xia and Liu (2024)	G7 countries	2000 to 2020	MMQR and CCEMG	Fintech to ecological footprint	Negative
Zhang et al. (2024a,b)	BRICS economies	2016 to 2023	CS-ARDL and NARDL	Fintech to environmental quality	Negative
K. Liu et al. (2024b)	China	2000 to 2020	QARDL	Fintech to environment sustainability	Positive
Pu et al. (2024)	BRICS countries	1995 to 2022	MMQR	Fintech to environment sustainability	Negative
Fan et al. (2024)	China	2011 to 2020	Two-way fixed regression model	Fintech to green productivity	Positive
Ahmad et al. (2024)	European Union	1990 to 2020	CuP-FM, CuP-BC and FMOLS	Fintech to ecological footprint	Negative
Tu (2024)	Asian economies	2018 to 2021	MMQR, DOLS, FMOLS and FEOLS	Fintech to environmental quality	Negative
Sadiq et al. (2024)	China	2013 to 2022	OLS, GMM, 2SLS and QR	Fintech to sustainable climate change	Positive
Chang and Wu (2024)	G5 countries	1990 to 2021	CS-ARDL, AMG and CCEMG	Fintech to green productivity	Positive
Relationship between FDI and Environmental Efficiency					
He et al. (2024)	China	2004 to 2015	Spatial difference-in-differences (DID) model	FDI to CO2 emission	Insignificant
Liu et al. (2024a,b,c,d)	46-BRI nations	2005 to 2018	Driscoll– Kraay methods	Chinese OFDI to CO2 emission	Mixed
Liu et al. (2024a,b,c,d)	China	2006 to 2020	Theil Index and Geodetector	FDI to eco-efficiency	Positive
Gonzalo Hernández Soto (2024)	Latin America	1990 to 2022	STIRPAT mode	FDI to Ecological Footprints	Negative
Boateng et al. (2024)	182 countries	2000 to 2018	IVGMM	FDI to CO2 emissions	Negative
Dilanchiev et al. (2024)	Top remittance-receiving countries	2000 to 2021	PMG-ARDL and CS-ARDL	FDI to CO2 emissions	Positive
Viglioni et al. (2024)	G20 countries	2001 to 2017	FMOLS and DOLS	FDI to CO2 emissions	Positive
Zhang et al. (2024a,b)	East Asian economies	2000 to 2022	CUP-FM and DOLS	FDI to CO2 emissions	Positive
Yuan et al. (2024)	China	2012 to 2021	Spatial econometric model	FDI to environmental pollution	Insignificant
Guo and Yin (2024)	China	1990 to 2022	NARDL	FDI to CO2 emissions	Mixed in shocks

Notes: STIRPAT, Stochastic Impacts by Regression Population, Affluence and Technology; GMM, Generalized Method of Moments; 2SLS, Two-Stage Least Squares; MMQR, Method of Moments Quantile Regression; CCEMG, Common Correlated Effects Mean Groups; CS-ARDL, Cross-sectionally Augmented Autoregressive Distributed Lag; NARDL, Nonlinear Autoregressive Distributed Lag; QARDL, Quantile Autoregressive Distributed Lag; CuP-FM, Continuously Updated Full modified; CuP-BC, Continuously Updated and Bias Corrected; FMOLS, Fully Modified Least Squares; DOLS, Dynamic Ordinary Least Square; FEOLS, Fixed-effects Ordinary Least Square; OLS, Ordinary Least Squares; QR, Quantile regression; AMG, Augmented Mean Group; DID, Difference in Differences; IVGMM, Instrumental Variable - Generalized Method of Moments; PMG-ARDL, Pooled Mean Group-Autoregressive Distributed Lag.

Table 2
Descriptive statistics of input and output variables.

I/O	Variables	Unit	Mean	Maximum	Minimum	Std. Dev.
Input	Labor	Labor force	1.17E+08	7.82E+08	11,040,155	1.85E+08
	Capital stock	USD	9.67E+12	5.44E+13	5.61E+11	1.27E+13
	Energy consumption	Kg of oil equivalent	3593.841	10,978.59	558.7866	2104.393
Output	GDP	USD	3.69E+12	2.09E+13	3.12E+11	4.94E+12
	CO2 emission	Kiloton	7.778481	17.97375	1.223211	4.701447

Note: I/O, input output; GDP, gross domestic product; USD, United States dollar.

Table 3
Descriptive statistics of the variables.

Variables	Unit	Mean	Median	Maximum	Minimum	Std.Dev.	J-B	Prob.	Obs.
SBM-based environmental efficiency (ES)	DEA-Score	0.616	0.476	2.088	0.268	0.393	250.420	0.000	260
EBM-based environmental efficiency (EE)	DEA-Score	0.536	0.473	1.050	0.268	0.211	47.210	0.000	260
Fintech companies (FnTs)	No. of the active Fintech companies	46.756	22.000	668.000	1.000	73.399	9603.661	0.000	260
Foreign Direct Investment (FDIg)	% of GDP	2.005	1.782	12.079	−1.787	1.458	1380.099	0.000	260
Research and development (RD)	% of GDP	1.685	1.503	5.065	−0.076	1.089	18.835	0.000	260
Industrialization (INDS)	% of GDP	27.844	26.456	63.240	16.396	8.731	147.508	0.000	260
Natural resource management (TNR)	% of GDP	4.298	1.436	50.204	−0.014	7.956	2506.572	0.000	260
Urbanization (UB)	% of population	75.214	79.761	92.347	30.930	13.787	152.054	0.000	260
Economic development (ED)	USD	25,006.150	23,297.130	62,789.130	1238.015	17,624.390	19.542	0.000	260
Trade (TD)	% of GDP	55.226	54.752	105.945	22.486	19.632	10.415	0.005	260

Note: ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency.

measurement units, and descriptive statistics. The data compilation from the World Bank, updated as of 2023, ensures that the study is grounded in the most current information available, supporting the empirical integrity and methodological rigor of the research.

3.2. Environmental efficiency

This study utilized DEA as a methodological approach to assess environmental efficiency employing two distinct techniques: the SBM (ES) and the EBM (EE). The study employed modified undesirable models of SBM and EBM within an input-output DEA analysis framework to quantify environmental efficiency.

3.2.1. SBM analysis

The SBM approach, introduced by Tone in (2001), utilizes slack variables for the assessment of efficiency and is acknowledged for its superior accuracy over traditional models like BCC and CCR. This method is particularly valued for its precise efficiency measurement without discrepancies, a feature that has been underscored in research by Luo et al. (2021). Initially, the SBM model did not differentiate between expected and unexpected outputs, a gap that was later filled by Tone, 2003 through the development of an enhanced SBM model. This revised version effectively incorporates the evaluation of unexpected outputs. In our research, we employed this advanced SBM model designed to account for unexpected outputs to determine the environmental efficiency across the G20 nations.

Equation (1) delineates the SBM model incorporating unexpected outputs. Here, X denotes inputs, and y^D and y^{UD} signify expected and unexpected outputs, respectively. The parameters ω_i, α_j and β_k represent the intensity of the respective variables in the model.

$$\theta_0^* = \min \frac{1 - \frac{1}{i}\sum_{i=1}^{i} \frac{s_i^x}{x_{i0}}}{1 + \frac{1}{j+k}\left(\sum_{j=1}^{j} \frac{s_j^D}{y_{j0}^D} + \sum_{k=1}^{k} \frac{s_k^{UD}}{y_{k0}^{UD}}\right)} \tag{1}$$

s.t. $x_{i0} = \omega_{i0} X + s_i^x$

$$y_{j0}^U = \alpha_{j0} Y + s_j^D$$

$$y_{k0}^{UD} = \beta_{k0} Y + s_k^{UD}$$

$$s_i^x \geq 0, s_j^D \geq 0, s_k^{UD} \geq 0, \omega_i \geq 0, \alpha_j \geq 0, \beta_k \geq 0$$

In the given context, s_i^x denotes input surplus, s_j^D indicates the deficiency in expected output, and s_k^{UD} stands for the excess in unexpected output. The variable θ corresponds to efficiency, taking values within the range of 0–1.

3.2.2. EBM analysis

In our research, the EBM-DEA methodology was applied to evaluate environmental efficiency while overcoming some of the SBM model's constraints. The non-radial approach of SBM models, which focuses on efficiencies derived from slack variables without assuming proportionality, seeks to optimize inefficiencies in both inputs and outputs by locating points at the maximum distance from the efficiency frontier. Nonetheless, such a method might compromise the integrity of original ratio data for projecting efficiency front values, occasionally leading to inconsistent findings. To address these concerns, we adopted an enhanced variant of the EBM model that accounts for unexpected outputs, a refinement introduced by Tone and Tsutsui in (2010). This adapted EBM framework is specifically designed for the precise evaluation of environmental efficiency. The EBM model for evaluating environmental efficiency is expressed as follows:

$$\delta^* = min \frac{\gamma - \varepsilon x \sum_{i=1}^{m} \frac{\omega_i^- s_i^-}{x_{ik}}}{\psi + \varepsilon y \sum_{r=1}^{s} \frac{\omega_r^{+g} s_r^{+b}}{y_{rk}} + \varepsilon y \sum_{p=1}^{q} \frac{\omega_p^{-b} s_p^{-b}}{b_{pk}}} \tag{2}$$

s.t.

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \gamma x_{ik} \quad i = 1, 2, \ldots, m$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^{+g} = \psi y_{rk} \quad r = 1,2,\ldots,s$$

$$\sum_{j=1}^{q} b_{pj}\lambda_j + s_p^{-b} = \psi b_{pk} \quad p\ldots,q$$

$$\lambda_j \geq 0,\ s_i^- \geq 0,\ s_r^{+g} \geq 0, s_p^{-b} \geq 0$$

Within the equations, aggregate number of inputs indicated by m, whereas s and q denote the aggregate amount of expected and unexpected outputs. The terms s_i^-, s_r^{+g} and s_p^{-b} represent the slack associated with inputs i, expected outputs r, and unexpected outputs p, accordingly. Additionally, ω_r^{+g} and ω_p^{-b} convey the weights allocated to expected and unexpected outputs. The parameter δ indicates the efficiency, with values spanning from 0 to 1.

The study selects the subsequent input variables, expected output, and unexpected output variables.

(1) Input variables: capital stock, labor, and energy consumption. The study the perpetual inventory method for the computation of capital stock, as expressed by the formula:

$$K_{i,t} = (1 - \delta_{i,t})K_{i,t-1} + I_{i,t}$$

Here, $K_{i,t-1}$ denotes the capital stock of country i in year t, $I_{i,t}$ signifies the current gross fixed capital formation in million US dollars, and $\delta_{i,t}$ represents the capital depreciation rate set at 6%. In the inaugural year, the capital stock in 2010 equated to the fixed capital formation for that year, divided by 10%.

(2) Expected output variables: GDP (current USD).
(3) Unexpected output variables: CO2 (Kiloton).

3.3. Model

To explore the complex relationship between Fintech and environmental efficiency with moderating effect of FDI, this study incorporates a comprehensive set of explanatory variables. These variables, including research and development (RD) and industrialization (INNDS) to recognize the association. Equation (3) articulates the econometric model underpinning this investigation:

$$EE = f(\mathrm{lFNTs}, \mathrm{lFDIg}, \mathrm{lRD}, \mathrm{lINDS}, \mathrm{lTNR}, \mathrm{lUB}, \mathrm{lED}, \mathrm{lTD}) \tag{3}$$

Here EE symbolizes the environmental efficiency, lFNTs and lFDIg designate number of Fintech companies and foreign direct investment, respectively. lRD and lINDS denoted research and development and industrialization. While lTNR, lUB, lED, and lTD signifies natural resource rent, urbanization, economic development, and trade respectively.

3.4. Estimations Procedure

3.4.1. Cross sectional dependence test (CSD)

Addressing CSD in panel data is crucial for preventing inaccuracies and biases in econometric analyses, as highlighted by Bilgili and Ulucak (2018) and Grossman and Krueger (1995). In our study, we utilize the parametric testing framework developed by Pesaran (2004) to investigate the extent of cross-sectional dependence present in our panel data models. The formulation of the cross-section dependence test statistic (CD) is articulated as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}\right) \tag{4}$$

Here, the time interval is denoted by T, the cross-section units by N, and $\widehat{\rho}_{ij}$ signifies the pairwise correlation coefficients among residuals obtained from separate Ordinary Least Squares estimations. The null-hypothesis posits the absence of cross-section dependence, while the CD statistic is expected to follow a standard normal distribution asymptotically, indicating its robustness even in cases of small panel datasets (Pesaran, 2004).

To enhance the robustness of our investigation into cross-section dependence, we incorporate two more supplementary tests. Firstly, we employ Friedman's test, utilizing the chi-square distributed statistic proposed by (Friedman, 1937). Secondly, we utilize Frees' test, which makes use of the Q distribution introduced by (Frees, 1995, 2004). Friedman (1937) introduced a nonparametric test grounded in the Spearman's rank correlation coefficient. The statistic proposed by Friedman relies on Spearman's correlation and is expressed as:

$$R_a = \frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} r_{ij}\right) \tag{5}$$

Here, r_{ij} represents the estimated sample value of the rank correlation coefficient for the residuals. Elevated values of R_a indicate the presence of non-negligible cross-sectional correlations.

The statistical measure introduced by Frees (1995) and further expounded upon in Frees (2004) is derived from the summation of squared rank correlation coefficients and is formulated as:

$$R_a^2 = \frac{2}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} r_{ij}^2\right) \tag{6}$$

3.4.2. Slope homogeneity test

To identify slope homogeneity, the study incorporates the slope homogeneity test methodology outlined by Pesaran and Yamagata (2008), which is a standardized approach derived from Swamy's assessment (Swamy, 1970). The statistical formulation for Swamy's test is as follows:

$$\widetilde{S} = \sum_{i=1}^{N}(\widehat{\beta}_i - \widehat{\beta}_{WFE})\frac{x_i' M_\tau x_i}{\widehat{\sigma}_i^2}(\widehat{\beta}_i - \widehat{\beta}_{WFE}) \tag{7}$$

Here, β_i represents the pooled estimator derived through Ordinary Least Squares (OLS), while β_{WFE}, represents the weighted fixed effect pooled estimator, $M_t = I_T - Z_i(Z_i'Z_i)^{-1}Z_i'$ and $Z_i = (\tau_T, x_i)$, where τ_T is a $T \times 1$ vector of ones, and explanatory variables are denoted by x_i, the error variance estimator is signified by $\widehat{\sigma}_i^2$. when N is fixed and $T \to \infty$, the $\widetilde{S}$ test exhibits an asymptotic Chi-squared distribution. The statistic proposed by Pesaran and Yamagata (2008), is formulated as follows:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S} - k}{\sqrt{2k}}\right)$$

When considering the null hypothesis suggesting homogeneity in slope across countries, $\widetilde{\Delta}$ follows as a standard normal distribution, given the condition of $(N,T) \to \infty$, as long as $\sqrt{N}/T \to \infty$, and assuming normally distributed error terms. The utilization of the bias-adjusted version enhances the small sample properties of $\widetilde{\Delta}$:

$$\widetilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S} - k}{\sqrt{\frac{2k(T-k-1)}{T} + 1}}\right)$$

3.4.3. Panel unit root tests

The study conducted multiple panel unit root tests to ascertain the stationarity of the variables. Initially, the Levin, Lin, and Chu (LLC) test proposed by Levin et al. (2002) introduces a fundamental augmented Dickey–Fuller (ADF) considering the following:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + \hat{X'}_{it} + \epsilon_{it} \tag{8}$$

The approach outlined by Levin et al. (2002) involves estimating α from standardized proxies of Δy_{it} and y_{it}, which are devoid of autocorrelations and deterministic components. The test indicates that, given the null hypothesis, the resultant estimate of $\widehat{\alpha}$ follows an asymptotically normal distribution, evaluated using a modified t-statistic.

$$t^*_\alpha = \frac{t_\alpha - (N\widetilde{T})S_N \widehat{\alpha}^{-2} se(\widehat{\alpha})\mu_{mT^*}}{\sigma_{mT^*}} \longrightarrow N(0,1)$$

Here, t_α represents the standard t-statistic for the null hypothesis $\widehat{\alpha} = 0$, $\widehat{\alpha}^2$ denotes the estimated variance of the error term η, and $se(\widehat{\alpha})$ signifies the standard error of $\widehat{\alpha}$ and

$$\widetilde{T} = T - \left(\sum_i \frac{p_i}{N}\right) - 1$$

Im et al. (2003) commence their analysis by formulating specific ADF regressions for every cross-section:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + \hat{X'}_{it}\delta + \epsilon_{it} \tag{9}$$

Following the estimation of specific ADF regressions, the computation of the average t statistics for α_i from these regressions is represented as $t_{iT_i}(p_i)$:

$$\overline{t_{NT}} = \left(\sum_{i=1}^{N} t_{iT_i}(p_i)\right) \Big/ N$$

The Im et al. (2003) test statistic necessitates determining the quantity of lags and specifying the deterministic element for every cross-sectional ADF equations. The test allows for the inclusion of distinct constants or both specific constants and trend terms.

$$W_{\overline{t_{NT}}} = \frac{\sqrt{N}\left[\overline{t_{NT}} - N^{-1}\sum_{i=1}^{N} E(\overline{t_{iT}}(p_i))\right]}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(\overline{t_{iT}}(p_i))}} \longrightarrow N(0,1)$$

The Fisher-type test, encompassing both the Fisher-ADF and Fisher-PP variants, introduced by Maddala and Wu (1999) and Choi (2001), entails aggregating the p-values derived from the test statistic assessing the presence of a unit root across each cross-sectional unit. The formulation of the Maddala and Wu statistic is presented as follows:

$$P_{MW} = \lambda = -2\sum_{i=1}^{N} \ln \pi_i,$$

The P_{MW} test conforms to a chi-square distribution with 2N degrees of freedom, assuming cross-sectional independence. Here, π_i signifies the p-value derived from the unit root test. Choi (2001) proposes the subsequent standardized statistic:

$$Z_{MW} = \frac{\sqrt{N}\{N^{-1}\lambda - E[-2\ln(\pi_i)]\}}{\sqrt{Var[-2\ln(\pi_i)]}}$$

3.4.4. Panel cointegration test

The research integrates two panel cointegration tests as a means to detect the presence of cointegration among variables and formulate a model as follows:

$$x_{it} = \beta_i + \rho_{it} + \beta_{1i} y_{1,it} + \beta_{2i} y_{2,it} + \beta_{3i} y_{3,it} + \varepsilon_{it} \tag{10}$$

Where i represents the number of countries, t denotes the time span covered in the study, and β_i and ρ_i stand for the constant and trend specific to each cross-section, respectively. Pedroni (2004) unveiled a suite of seven test statistics, categorized into two primary types: panel cointegration tests and group mean panel cointegration tests. The within-dimension assessments encompass four specific statistics: the Panel PP-Statistic, Panel v-Statistic, Panel rho-Statistic, and Panel ADF-Statistic. On the other hand, the group mean panel cointegration tests include the ADF-Statistic, Rho-Statistic, and PP-Statistic. These tests by Pedroni are designed to account for heterogeneity within the examined samples. Cointegration analysis under this framework is conducted by examining residuals, as detailed below: $\varepsilon_{it} = \eta_1 \varepsilon_{it-1} + \mu_{it}$.

Apart from the seven tests proposed by Pedroni, the Kao (1999) test, assuming homogeneity across the selected sample, will also be employed to ensure robustness. The Kao (1999) cointegration is expressed as:

$$x_{it} = y_{it}\beta + Z'_{it}\delta + \varepsilon_{it}$$

In this context, where x_{it} and y_{it} represent integration of order one processes, ε_{it} is the white noise error term, and the variable Z'_{it} is exogenous to any fixed effect. The null hypothesis proposed by Kao and Pedroni suggests the absence of cointegration, while the alternative hypothesis proposes cointegration.

3.4.5. Tobit regression model

Introduced by the Nobel Laureate Tobin (1958), the Tobit regression model is designed for scenarios where the dependent variable is non-negative (latent variable) and is influenced by independent variables, particularly in cases of censored or truncated data (Sağlam, 2018). This model is particularly pertinent for analyzing relative efficiency scores derived from DEA analysis, which are constrained between the lower and upper bounds of 0.0 and 1.0, making the Tobit model an indispensable tool for the secondary analysis phase of DEA (Sağlam, 2017a, 2017b). The model is typically expressed through the following linear equation potential (Niu et al., 2018):

$$\boldsymbol{Y_i} = \begin{cases} \boldsymbol{Y_i^* = \beta_0 + \beta_i Z_i + \varepsilon_i \; y_i^* > 0} \\ \boldsymbol{0 \; y_i^* \leq 0} \end{cases} \tag{11}$$

In the context of our study, $\boldsymbol{Y_i}$ denotes the truncated efficiency dependent variable derived from the DEA measurement, while $\boldsymbol{Z_i}$ represents an explanatory variable capturing the factors influencing efficiency. The model incorporates a constant term $\boldsymbol{\beta_0}$, a random variable $\boldsymbol{\beta_i}$ accounting for the association between the explanatory variables $\boldsymbol{Z_i}$ and the latent variables $\boldsymbol{Y_i}$, and a random error term $\boldsymbol{\varepsilon_i}$ following a normal distribution.

4. Results

4.1. Environmental efficiency

The study employed both the DEA-SBM and DEA-EBM methods to calculate environmental efficiency and Fig. 2 provides a visual representation of the environmental efficiency of G20 nations over various years, as determined by DEA-SBM and DEA-EBM methodologies. Utilizing a color gradient—ranging from red to indicate lower efficiency levels to green for higher efficiency—these figures demonstrate the varying degrees of environmental efficiency among the nations, alongside temporal fluctuations observed within both analytical frameworks. Such variations in efficiency levels could potentially be linked to the disparate environmental policies, technological progress, or economic factors specific to each country. Moreover, observable trends, including improvements or declines in efficiency over the assessed period, become apparent for countries. The correspondence in patterns observed across DEA-SBM and DEA-EBM analyses may reflect common underlying determinants of environmental efficiency across the G20. Nonetheless, subtle variances in the color gradation suggest nuanced differences in how each methodology quantifies efficiency. Conducting a comparative analysis facilitates a deeper understanding of the robustness and consistency of these environmental efficiency evaluation methods.

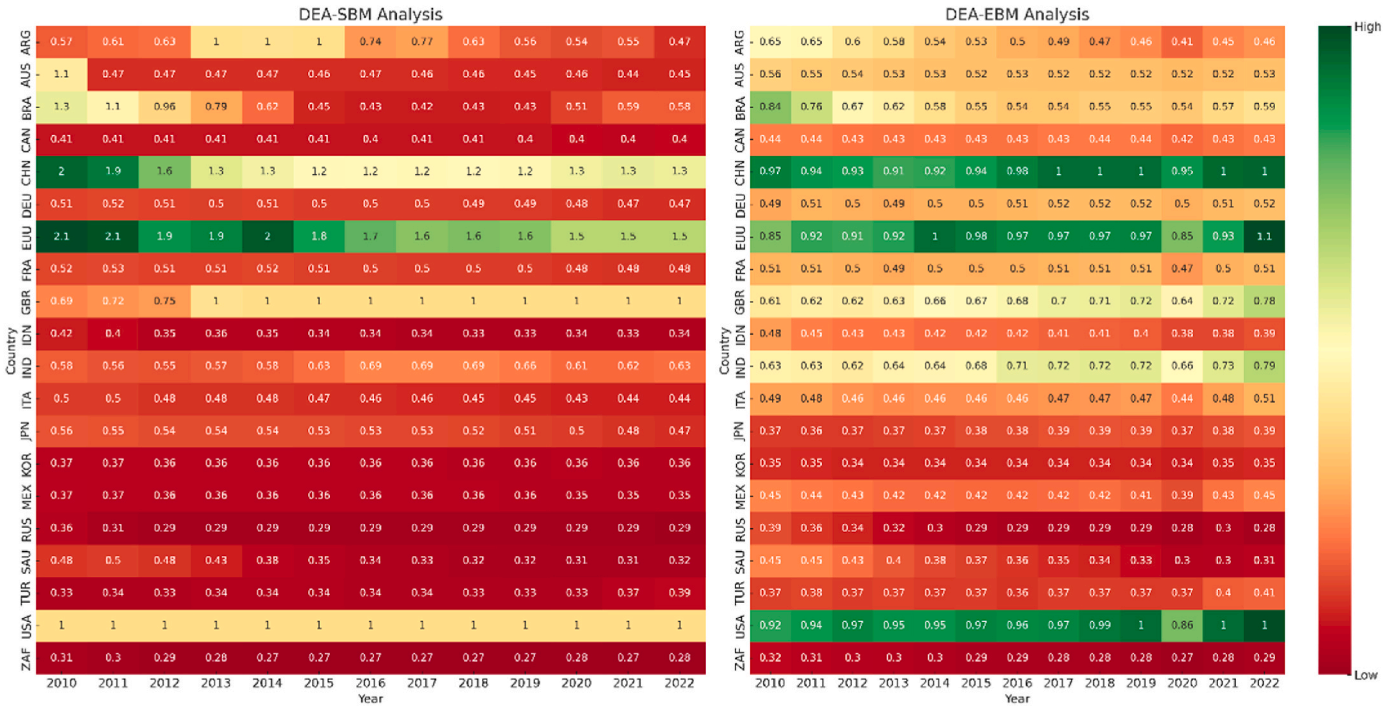

Fig. 2. Environmental efficiency of G20 countries. Note: The figure displays the G20 countries' environmental efficiency scores derived from the DEA-SBM and DEA-EBM analyses.

4.2. Preliminary tests

Recognizing the potential for multicollinearity, denoting heightened interrelations among independent variables that can obfuscate the true outcomes, the research systematically examines the collinearity attributes of the variables as a preemptive strategy. The outcomes, as explained in Table 4, shed light on the variance inflation factor (VIF), a pivotal metric for assessing multicollinearity challenges. The computed mean VIF for the regression variables is established at 2.65, and notably, all parameter VIFs are below the critical threshold of 10. This substantiates that the study is devoid of multicollinearity concerns, underscoring the reliability and validity of the regression results.

The results from the panel CSD test are methodically outlined in Table 45. The null hypothesis for these assessments asserts cross-sectional independence, implying a lack of cross-sectional dependence among the variables. The outcomes, as systematically documented in Table 5, unequivocally demonstrate that at the panel level, there exists no substantiated evidence of CSD amongst the variables examined.

Table 6 delineates the results of the slope homogeneity test conducted according to the methodology proposed by Pesaran and Yamagata (2008). The null hypothesis, asserting slope homogeneity, remains unchallenged as it cannot be rejected based on the test outcomes. This confirmation underscores the consistent homogeneity observed in estimating the relationships between Fintech and environmental efficiency across the diverse spectrum of G20 countries.

The application of unit root tests constitutes an essential econometric technique to validate the robustness of the primary regression analysis. In the present research, a suite of unit root tests was utilized, including Fisher-ADF, Fisher-PP as outlined by Maddala and Wu (1999), LLC as delineated by Levin et al. (2002), and the tests developed by Im et al. (2003). The underlying null hypothesis for these tests assumes the presence of a unit root, suggesting data non-stationarity. The findings, detailed in Table 7, uniformly refute the null hypothesis across all variables when adjusted for first differences at a significance threshold of 1%. This conclusive evidence confirms the stationarity of the variable sequences, highlighting the data's stability and laying a robust

Table 4
Multicollinearity test.

Variable	VIF	1/VIF
lFNTs	1.84	0.542
lFDIg	1.26	0.791
lRD	2.86	0.349
lINDS	1.88	0.530
lTNR	2.05	0.487
lUB	3.43	0.292
lED	5.58	0.179
lTD	1.34	0.744
Mean VIF	2.53	

Notes: VIF, Variance inflation factor; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural resource management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade.

Table 5
Panel cross-sectional dependence tests.

Cross-sectional dependence test	Statistics	P-value
Pesaran test	1.580	0.114
Friedman test	12.679	0.855
Frees test	3.619	0.256

Ho = Cross-sectional independence.

Table 6
Slope Homogeneity test.

	Delta	*p*-value
	−0.683	0.495
adj.	−1.253	0.210

Ho: slope coefficients are homogenous.
Note: The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

Table 7
Results of panel unit root tests.

Variables	LLC		IPS		ADF Fisher Chi-square		PP Fisher Chi-square	
	Level	First difference	Level	First difference	Level	First difference	Level	First difference
ES	−28.980***	12.836***	−23.819***	−11.144***	124.089***	135.655***	99.985***	151.225***
EE	−5.580***	−6.771***	−3.776***	−6.405***	82.772***	111.217***	109.716***	143.965***
lFnTs	−2.371***	−3.299***	−0.677	−2.604***	41.357	81.745***	41.756	107.034***
lFDIg	−8.658***	−16.401***	−6.328***	−12.918***	111.702***	202.572***	120.811***	309.827***
lRD	−3.465***	−9.225***	−1.018	−5.879***	55.916**	102.232***	55.536*	120.286***
lINDS	−3.517***	−8.565***	−0.112	−6.229***	41.437	108.750***	28.514	115.170***
lTNR	−4.274***	−7.432***	−1.205	−5.338***	50.528	95.369***	22.408	74.627***
lUB	−25.745***	−5.156***	−31.269***	−13.223***	125.094***	129.557***	166.650***	128.206***
lED	−5.047***	−12.039***	−0.669	−8.370***	44.425	137.175***	75.576***	214.912***
lTD	−1.933**	−6.748***	−0.286	−7.340***	45.507	125.932***	34.450	89.773***

Ho = Variable has unit root.
Notes: LLC, Levin, Lin, and Chu; IPS, Im, Pesaran and Shin; ADF, Augmented Dickey–Fuller test; PP, Phillips-Perron; ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural Resource Management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade; The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

groundwork for the ensuing primary regression analysis.

In the subsequent phase of preliminary diagnostic tests, the study utilized the Pedroni and Kao cointegration test to ascertain the long-term association among the variables, as proposed by Pedroni (2004) and Kao (1999). These tests leverage distinct parameters, and the outcomes of the cointegration test are meticulously documented in Table 8. The test results unequivocally reject the null hypothesis, providing robust confirmation of the presence of cointegration among the variables under consideration.

4.3. Results of panel regression

4.3.1. Results of direct analysis

Table 9 shows the outcomes of the regression analysis conducted using the panel TOBIT model. The regression analysis reveals that, in the absence of control variables, the coefficient estimates for the interaction between Fintech and SBM-based environmental efficiency (ES) stands at 0.113. When the model is adjusted to include control variables such as research and development, industrialization, natural resource rent, urbanization, economic development, and trade, the coefficient estimate for the relationship between Fintech and SBM-environmental efficiency (ES) adjusts to 0.085. This coefficient maintains statistical significance at the 1% level. Furthermore, the analysis without control variables indicates a coefficient of 0.092 for the interaction between Fintech and EBM-environmental efficiency (EE). Upon incorporating control variables—specifically, research and development, industrialization, natural resource rent, urbanization, economic development, and trade—the coefficient for the Fintech and EBM-environmental efficiency (EE) relationship alters to 0.074. Additionally, variables such as research and development, natural resource rent, and economic development are observed to have a positive influence, whereas urbanization and trade negatively affect both SBM and EBM-environmental efficiency metrics.

Table 8
Results of the cointegration test.

		Statistics	p-value
Pedroni cointegration test	Modified Phillips-Perron t	8.090***	0.000
	Phillips-Perron t	−6.538***	0.000
	Augmented Dickey-Fuller t	−5.040***	0.000
Kao cointegration test	Modified Dickey-Fuller t	−1.470***	0.070
	Dickey-Fuller t	−4.126***	0.000
	Augmented Dickey-Fuller t	−3.017***	0.001
	Unadjusted modified Dickey-Fuller t	−1.547***	0.060
	Unadjusted Dickey-Fuller t	−4.164***	0.000

Ho = No cointegration exists among the variables.
Note: The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

Table 9
Results of Tobit regressions for SBM (ES) and EBM (EE)-Environmental Efficiency.

Variables	ES	ES	EE	EE
	Coef.	Coef.	Coef.	Coef.
lFnTs	0.113***	0.085***	0.092***	0.074***
lRD		0.108***		0.069***
lINDS		0.038		0.059
lTNR		0.021**		0.021***
lUB		−0.371***		−0.430***
lED		0.108***		0.090***
lTD		−0.302***		−0.193***
Constant	0.235***	1.898***	0.250***	1.823***

The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.
Notes: ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural resource management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade.

4.3.2. Results of interaction analysis

To examine whether FDI influences the Fintech-environmental efficiency relationship, the study explored the interaction effect between FDI and Fintech, and the results are displayed in Table 10. The study observed that the combined effect of Fintech and FDI on both SBM and EBM-environmental efficiency is significantly negative. This suggests that Fintech and FDI are complementary hindrances to environmental efficiency. Thus, Fintech companies with foreign investment endorse Fintech, negatively influencing environmental efficiency. As FDI involves focusing on short-term profits, pressure for rapid expansion, and influence from global supply chains prioritizing cost-efficiency over sustainability.

4.4. Robustness checks

To reinforce the reliability of our findings, a two-step Generalized Method of Moments (GMM) regression was implemented, as detailed in Tables 11 and 12. The GMM methodology was selected due to its capability to manage unobserved heteroskedasticity and its resistance to autocorrelation issues (Baum et al., 2003), while also mitigating the risk of omitted variable bias to produce reliable outcomes. Instrumental variables were incorporated in the GMM framework through the

Table 10
Results of Tobit regressions for SBM (ES) and EBM (EE)-Environmental Efficiency.

Variables	ES	ES	EE	EE
	Coef.	Coef.	Coef.	Coef.
lFnTs	0.075***	0.098***	0.063***	0.080***
lFDIg	0.054*	0.106*	0.061***	0.101***
lFnTsXlFDIg		−0.017*		−0.013*
lRD	0.110***	0.112**	0.072***	0.073***
lINDS	0.051	0.054	0.071	0.073
lTNR	0.014	0.014	0.014**	0.013*
lUB	−0.393***	−0.386***	−0.456***	−0.450***
lED	0.0109***	0.108***	0.092***	0.091***
lTD	−0.309***	−0.309***	−0.201***	−0.201***
Constant	1.933***	1.838***	1.864***	1.789***

Notes: ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural resource management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade.
The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

Table 11
Results of GMM robust estimation for SBM (ES) and EBM (EE)-Environmental Efficiency.

Variables	ES	ES	EE	EE
	Coef.	Coef.	Coef.	Coef.
lFnTs	0.096***	0.052***	0.086***	0.044***
lRD		0.173***		0.09**
lINDS		0.073		−0.042
lTNR		0.056***		0.015**
lUB		−0.607***		−0.423***
lED		0.107**		0.058
lTD		−0.281***		−0.122***
Constant	0.298***	2.794***	0.266***	2.233***
AR (1) value	z = 1.14	z = 1.09	z = 0.78	z = 1.07
AR (2) value	z = 2.03	z = 1.87*	z = 1.15	z = −0.20
Hansen test	chi2(21) = 18.83	chi2(16) = 12.22	chi2(21) = 19.87	chi2(16) = 16.61

Notes: GMM, Generalized method of moments; ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural resource management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade; AR, autoregressive; The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

utilization of lagged variables on the right-hand side, aligning with the methodology proposed by Arellano and Bond (1991). The appropriateness and the absence of over-identification of the instrumental variables were ascertained using Hansen's test, which validated the use of these variables in both direct and interaction effect analyses. Additionally, the Arellano-Bond tests for first and second-order autocorrelation, AR(1) and AR(2), affirmed the absence of second-order autocorrelation, thereby confirming the consistency of the estimators in our analyses.

4.4.1. *Results of direct analysis*

Table 11 presents the results of the direct analysis using panel GMM robust estimation for SBM (ES) and EBM (EE). The findings suggest that Fintech has a positive impact on both SBM and EBM-EE, signifying significance at a 1% level. This aligns with the results obtained from the Tobit regression. Additionally, research and development, natural resource rent, and economic development exhibit a positive impact, whereas urbanization and trade demonstrate a negative impact on environmental efficiency.

Table 12
Results of GMM robust estimation for SBM (ES) and EBM (EE)-Environmental Efficiency.

Variables	ES	ES	EE	EE
	Coef.	Coef.	Coef.	Coef.
lFnTs	0.007	0.185***	0.022**	0.240**
lFDIg	0.623***	0.636***	0.244***	1.182***
lFnTsXlFDIg		−0.119***		−0.171**
lRD	0.195***	0.092***	0.083***	0.209***
lINDS	0.258***	0.119**	0.083**	0.309***
lTNR	−0.048***	−0.013	−0.007	−0.056***
lUB	−0.537***	−0.482***	−0.543***	−0.449***
lED	0.062	0.086***	0.096***	0.047
lTD	−0.246***	−0.219***	−0.216***	−0.251***
Constant	1.56**	1.324***	2.100***	0.448
AR (1) value	z = −1.06	z = −0.48	z = −3.11***	z = −1.54
AR (2) value	z = −0.97	z = 0.19	z = −1.09	z = 0.98
Hansen test	chi2(15) = 6.83	chi2(14) = 5.06	chi2(15) = 15.00	chi2(14) = 6.36

Notes: GMM, Generalized method of moments; ES, SBM (Slack-Based Measure)-based environmental efficiency; EE, EBM (Epsilon-Based Measure) -based environmental efficiency; lFNTs, Log of Fintech companies; lFDIg, Log of Foreign direct investment; lRD Log of Research and development; lINDS, Log of Industrialization; lTNR, Log of Natural resource management; lUB, Log of Urbanization; lED, Log of Economic development; lTD, Log of Trade; AR, autoregressive; The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively.

4.4.2. *Results of interaction analysis*

Table 12 presents the results of the interaction analysis using panel GMM robust estimation for SBM (ES) and EBM (EE)-environmental efficiency. The findings suggest that the combined effect of Fintech and FDI on both SBM and EBM-environmental efficiency is significantly negative, consistent with the results of the Tobit regression. Additionally, the results indicate that Fintech has a positive impact on both SBM and EBM-Environmental Efficiency, with significance at a 5% level. Furthermore, research and development, industrialization, and economic development exhibit a positive impact, while urbanization, natural resource rent, and trade demonstrate a negative impact on environmental efficiency.

4.5. *Discussion*

This study assesses the crucial role of Fintech in improving environmental efficiency across G20 nations, highlighting its vital contribution to sustainable economic development. Drawing on evidence from Dong et al. (2024), Li et al. (2024a,b), Xia and Liu (2024), Yang et al. (2024), and Zhang et al. (2024a,b), the research demonstrates how Fintech, through innovations such as digital payments, blockchain, and artificial intelligence, enhances resource management and efficiency. These technological advances not only optimize processes but also channel investments toward environmentally sustainable projects, reinforcing Fintech's key role in fostering environmental stewardship. The study also reveals a positive link between FDI and environmental efficiency within the G20, as shown by the transformative potential of FDI in integrating advanced technologies and green business models, supported by findings from Gao and Zhang (2013), Wu et al. (2023), Yang et al. (2024), and Zhou et al. (2024). These studies collectively highlight FDI's role in promoting environmental efficiency through technology transfers and support for sustainable development initiatives.

However, our research identifies a negative interaction between Fintech and FDI regarding environmental efficiency in G20 countries. This suggests that while individual contributions of Fintech and FDI generally support environmental goals, their combined effects may sometimes undermine these objectives. This negative synergy likely arises from the rapid scale and nature of the investments and technological advances, potentially overwhelming local environmental capacities or shifting focus away from sustainability. Additionally, the research underscores the importance of R&D in advancing environmental efficiency, as evidenced by Safitri et al. (2020), Zhang et al. (2016), and Zhou et al. (2024). R&D plays a critical role in driving sustainable innovations, especially in the renewable energy sector, essential for reducing emissions and enhancing energy efficiency. The positive influence of natural resource rents on environmental efficiency is also noted, with studies from Chen et al. (2022), Khaddage-Soboh et al. (2023), and Li et al. (2024a,b) demonstrating how strategic use of natural resource revenues can foster technological progress and shift practices away from environmental harm.

The study further explores the environmental challenges of urbanization, supported by Ahmad et al. (2021), Liu et al. (2024a,b,c,d), and Yasmeen et al. (2020), which confirm that urban expansion increases energy consumption and carbon emissions, necessitating innovative approaches to sustainable urban planning and waste management. The role of economic development in promoting environmental efficiency is highlighted by Li et al. (2024a,b), pointing to the transition towards cleaner energy sources and the implementation of stringent environmental regulations as key sustainability drivers. Finally, the research investigates into the environmental implications of global supply chains and increased trade, as discussed by Alhassan et al. (2020), Eregha et al. (2023), and Yang et al. (2019). These studies illustrate the complex interactions between economic activities and environmental sustainability, emphasizing the need for a balanced approach that integrates technological, economic, and environmental strategies to support sustainable development. This comprehensive analysis of the interconnections between Fintech, FDI, R&D, urbanization, economic development, trade, and their collective impact on environmental efficiency in the G20 calls for harmonized efforts to ensure technological advancements and economic growth align with environmental sustainability goals.

5. Conclusion and implications

5.1. Conclusion

Fintech has significantly transformed the financial arena globally, with notable advancements in the G20 nations over the last two decades, marked by rich resources, foreign investment appeal, and growth prospects. These countries face climate change challenges and ecological imbalances due to increased demands for resources against the backdrop of reduced biocapacity. The heterogeneity in their technological progress, economic frameworks, sociocultural changes, resource wealth, and ICT infrastructure suggests a complex relationship among Fintech, economic factors, and environmental efficiency. This study investigated into Fintech's impact on environmental efficiency across G20 countries from 2010 to 2022, focusing on FDI's moderating role. Utilizing DEA with SBM and EBM methods, the research underwent extensive data validation processes, including tests for multicollinearity, cross-sectional dependence, and stationarity, followed by Pedroni and Kao cointegration tests to explore long-term relationships. The Tobit regression model, supported by GMM analysis and incorporating variables like R&D, industrialization, and trade, served to investigate the Fintech-environmental efficiency nexus.

The findings reveal that Fintech and FDI independently exert a positive effect on environmental efficiency, underscoring their roles in promoting environmental sustainability. However, an intriguing interaction between Fintech and FDI emerges, showing a negative impact on environmental efficiency. This suggests a complex dynamic where the amalgamation of Fintech with foreign investments, prioritizing short-term gains over sustainability, detracts from environmental goals. The rapid Fintech growth, coupled with insufficiently integrated sustainable practices and a focus on financial returns by foreign investors, culminates in a detrimental effect on environmental efficiency within the G20 context.

5.2. Policy implications

The findings from our study offer several practical implications for governments, regulators, private sectors, and international bodies, emphasizing how technology and investment can be strategically utilized to promote environmental sustainability. First, governments and regulators should consider crafting policies that specifically encourage the integration of fintech solutions in sectors with significant environmental impacts. We recommend tax incentives for investors and companies actively engaged in green fintech initiatives. These incentives could include tax credits or deductions for investments in technologies that significantly reduce environmental footprints or enhance energy efficiency within the fintech sector. Such policies could accelerate investment in sustainable fintech solutions by reducing the financial burden on investors and encouraging the industry to adopt greener practices. Furthermore, we suggest the introduction of stricter regulatory frameworks for FDIs that require compliance with environmental performance criteria. These regulations could mandate that all FDI projects in the fintech sector undergo rigorous environmental impact assessments to ensure alignment with national environmental goals. Additionally, these regulations should ensure that any foreign investment contributes positively to the host country's sustainability objectives, potentially deterring investments that could harm environmental standards.

Second, the private sector, particularly companies in the fintech and investment sectors, should focus on developing and funding projects that prioritize environmental efficiency. This involves investing in blockchain technologies that enhance transparency in green supply chains, AI that optimizes energy use, and digital platforms that facilitate carbon trading and renewable energy trading. International bodies and investors need to establish clear guidelines and frameworks for foreign direct investment that prioritize environmental sustainability, supporting cross-border investments in green infrastructure and sustainable projects. Third, there is a need for increased collaboration between government bodies and private companies to ensure that technological innovations align with national and international sustainability agendas. This can be achieved through public-private partnerships that leverage private sector innovation and public sector policy support. Additionally, international organizations should play a more active role in coordinating efforts between countries to standardize environmental efficiency metrics and practices, which could help in creating a global standard that ensures consistency in how fintech and investments impact environmental goals.

Fourth, regulators and governments must develop robust mechanisms to monitor and evaluate the environmental impact of fintech and related investment activities. This can include the use of data analytics and environmental impact assessments to ensure that the actual outcomes align with expected sustainability objectives. Finally, all stakeholders should invest in educational programs and capacity-building initiatives that raise awareness about the benefits of integrating fintech in achieving environmental sustainability. Training programs designed for policymakers, industry leaders, and the workforce can ensure that all parties are equipped with the necessary knowledge and skills to implement and support green fintech solutions effectively. By implementing these practical implications, stakeholders can ensure that technology and investment are harnessed effectively to not only enhance economic growth but also to promote environmental sustainability, creating a balanced approach to development that benefits both the economy and the planet.

This study, while offering insightful findings on the interaction between fintech, FDI, and environmental efficiency in G20 countries, acknowledges several limitations that may affect the generalization of results. The focus on G20 countries limits the applicability of findings to global contexts with differing economic and environmental policies. The study's reliance on available data may not fully capture the complexities of fintech innovations and FDI flows, and the difficulty in isolating the effects of these factors from other economic or policy changes poses challenges in attributing direct impacts on environmental efficiency. Notably, our findings indicate a negative impact when FDI is combined with fintech investments, suggesting potential conflicts or inefficiencies that merit further investigation. Future research should expand to include a broader range of countries and explore the specific conditions under which this negative interaction occurs. Longitudinal studies and advanced econometric models could provide deeper insights into the long-term effects and help isolate fintech and FDI impacts from other variables. Additionally, investigating the types of fintech and regulatory frameworks that optimize FDI's environmental outcomes could offer valuable guidance for enhancing sustainable development goals.

CRediT authorship contribution statement

Myne Uddin: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abu Bakkar Siddik:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhao Yuhuan:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Abubakr Naeem:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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