

Article

The Impact of FinTech on Economic, Environmental and Social Sustainability: Panel Evidence from Emerging Economies

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Abstract

Sustainable development, challenged by the global climate crisis, environmental degradation, and income inequality, requires more than growth-oriented indicators. In this context, the impact of financial innovation (FinTech) on the economic, environmental, and social dimensions of sustainability in emerging economies has been debated. This study empirically identifies the multidimensional effects of FinTech on sustainability across 23 emerging economies from 2011 to 2023. Using 299 observations over a 13-year period, we apply the triple bottom line (TBL) framework. It also tests the moderating role of physical capital accumulation in the relationship between FinTech and economic sustainability using an economic model. Two-way fixed-effects models were constructed for economic, environmental, and social sustainability metrics. A FinTech index derived from Google Trends search frequencies related to artificial intelligence, blockchain, cloud computing, and data technologies, validated through factor analysis and reliability tests, was used as the primary independent variable. To address the identified issues of heteroscedasticity, autocorrelation, and cross-sectional dependence, robust estimates were obtained using Driscoll and Kraay's standard errors. The results indicate that FinTech does not have a statistically significant direct effect on economic or environmental sustainability. However, FinTech is positively associated with social sustainability, and its contribution to economic sustainability becomes significant when sufficient physical capital accumulation is supported. Interaction analysis revealed that the contribution of FinTech to economic sustainability is conditional. The marginal effect is negative at low levels of physical capital accumulation but turns positive as physical capital accumulation increases. The findings indicate that FinTech acts as a lever to strengthen inclusivity under SDGs 1 and 10; however, it does not automatically generate economic or ecological gains for SDGs 7, 9, and 13 unless it is integrated with physical infrastructure investments, green/ESG regulations, green credit quotas, and renewable energy strategies.



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1. Introduction

The growing global climate crisis, environmental degradation, and income inequality clearly demonstrate that sustainable development cannot be achieved through traditional

economic growth indicators alone. Achieving the United Nations Sustainable Development Goals (SDGs) requires the implementation of innovative frameworks to address systemic challenges globally [1,2]. In recent years, financial technology (FinTech) has emerged as a key transformative actor in the quest for innovation.

Although these terms are often used interchangeably in the literature, the conceptual framework of this study identifies a distinct hierarchy of causality among financial digitalization, FinTech, and financial innovation. In this context, financial digitalization refers to a macro-level transformation process (ecosystem) driven by advancements in information and communication technology [3]. FinTech, on the other hand, represents specific technological tools such as artificial intelligence, blockchain, and big data that have emerged on this digital infrastructure [4]. The integration of these tools with the traditional financial system drives contemporary financial innovation and is utilized to support sustainable development by generating new business models, such as crowdfunding, green bond integration, and mobile wallets [5]. Thus, this analysis positions FinTech as a key driver and analytical proxy for structural financial innovation in developing countries.

Therefore, the integration of big data analytics, artificial intelligence, cloud computing, and blockchain technology into the financial ecosystem offers significant opportunities to minimize transaction costs, accelerate capital allocation toward environmentally sustainable projects, and integrate historically marginalized populations who have been excluded from the economic system [5,6]. However, the outcomes of digitalization in developing countries are not as seamless and linear as assumed. While FinTech has the capacity to facilitate rapid socio-economic progress, it can also become a complex equation with unpredictable outcomes owing to the environmental burdens imposed by energy-intensive digital infrastructure [7,8].

However, existing studies frequently oversimplify the complex nature of FinTech's impact by confining analyses to one-dimensional indicators of sustainability. Many studies oversimplify the complex relationships related to sustainability by confining discussions of digitalization solely to carbon emissions or by limiting the assessment of FinTech's impact on traditional control variables [9,10]. In contrast, sustainability is a multifaceted process in which environmental protection, social equity, and economic progress are achieved simultaneously [11]. A critical flaw in the literature is characterizing FinTech's impact on these three pillars in emerging economies as being automatically beneficial. This study aims to empirically assess the effects of FinTech on sustainability through a multidimensional framework to address the identified research gap.

The theoretical foundation of this study is built on a framework that is directly integrated with the study's empirical design. The decision to test sustainability using three separate econometric models—economic (GDP), environmental (ecological footprint), and social (human development index)—rather than a single-dimensional metric, is a direct reflection of the triple bottom line (TBL) theory [11,12]. Our expectations regarding the environmental model are grounded in ecological modernization theory [13], which argues that digital innovations can reduce ecological pressures, whereas the economic model draws its conceptual framework from the technology–organization–environment (TOE) framework [14]. The TOE model argues that financial technologies alone are insufficient for FinTech to create a sustainable advantage at the macro level; rather, they must be integrated with a country's physical infrastructure capacity. For this reason, in the empirical design of our study, gross fixed capital formation (GFC) has been elevated beyond the role of a simple control variable and integrated into the model as a critical structural moderator (interaction variable) that must be overcome for FinTech to generate economic sustainability. Thus, the abstract conceptual debates in the literature are, for the first time, translated into an

empirical framework using robust panel data techniques that filter out asymmetric shocks and cross-sectional dependence.

The triple bottom line (TBL) framework, which forms the theoretical foundation of this study, provides a conceptual basis and systematically links the study's empirical research models to the United Nations 2030 Agenda and the Sustainable Development Goals (SDGs) [15]. In particular, the economic sustainability model (GDP) developed in this study is directly aligned with the Decent Work and Economic Growth (SDG 8) and Industry, Innovation and Infrastructure (SDG 9) goals. The social sustainability model, measured using the human development index (HDI), represents the macroeconomic dimensions of the goals of No Poverty (SDG 1), Quality Education (SDG 4), and Reduced Inequalities (SDG 10). The ecological footprint (EF) model for environmental sustainability empirically assesses progress toward the goals of Affordable and Clean Energy (SDG 7), Responsible Consumption and Production (SDG 12), and Climate Action (SDG 13). This comprehensive integration of the SDGs transforms the study's findings from a purely academic discussion into a framework that can be translated into actionable policies by global policymakers.

The original contribution of this study lies in translating conceptual debates in the literature into an empirical framework based on 299 observations over a 13-year period (2011–2023) across 23 emerging economies by constructing three distinct core models using GDP for economic sustainability, the ecological footprint for environmental sustainability, and the human development index for social sustainability, and employing robust panel data techniques centered on cross-sectional dependence (CSD). While FinTech reduces transaction costs in emerging economies, digitalization that is not supported by sufficient physical capital infrastructure and industrial investments carries the risk of fueling consumption rather than production. Therefore, we incorporated *gfc* into the model as a critical structural threshold (moderator) that must be overcome for FinTech to generate economic sustainability. This study contributes to the literature in three ways. First, an integrated multidimensional analysis of economic, environmental, and social sustainability was conducted using the TBL framework. Second, evidence is provided from emerging economies. Third, the moderating role of physical capital accumulation is examined.

The methodological framework of this study was designed to account for the fragile and interdependent nature of emerging economies in the face of macroeconomic shocks. The modified Wald, Wooldridge, and Pesaran CD diagnostic tests applied to the dataset confirmed the presence of heteroscedasticity, first-order autocorrelation, and cross-sectional dependence in the time series. To overcome these structural issues and obtain reliable estimators, the standard-error two-way fixed effects approach proposed by Driscoll and Kraay (1998) was adopted [16]. The remainder of the study is structured as follows. Section 2 presents the literature review and hypothesis development; Section 3 explains the dataset and methodology; Section 4 presents the empirical results; Section 5 discusses the findings; and the final section concludes the study with results and policy implications.

2. Literature Review

The literature examining the relationship between FinTech and sustainability is grounded in intense theoretical debate that reflects the complex nature of technological innovations. Drawing inspiration from innovation diffusion and ecological modernization theories, the “technological optimism” movement portrays FinTech as a revolutionary catalyst that enhances environmental quality [1]. Studies from this perspective provide strong evidence of how green bonds, crowdfunding, and blockchain-enabled smart contracts provide low-cost lifelines to clean energy projects [17]. Macroeconomic analyses conducted in BRICS, G20, and other developing regions indicate that digital finance enhances op-

erational efficiency, promotes green innovation, and reduces carbon footprints [8,18,19]. According to optimists, digital finance not only democratizes access to environmental information but also ensures long-term value creation by elevating the environmental, social, and governance (ESG) performance of financial actors [20].

However, in recent years, the shadows cast over this optimistic picture have become increasingly evident. A growing number of researchers, by shining a light on the dark side of the industry, emphasize that FinTech incurs significant ecological and economic costs. The staggering electricity consumption of data centers that power blockchain networks and cryptocurrency mining is triggering a veritable “carbon curse” in developing countries that still rely on fossil fuels (coal and natural gas) for their energy [7,10]. Moreover, in the absence of effective environmental policies and green regulations, the ease of accessing credit through digital channels fuels direct raw material consumption rather than green investments, leading to a dangerous rebound effect by weakening the ecological carrying capacity [21,22]. Regarding the environmental footprint (EF), the reducing effect of green investments is offset by the increasing effect resulting from electronic waste (e-waste) and consumption growth caused by the shortening of the product life cycle, which often results in a statistically neutral (insignificant) overall ecological impact [23,24]. The insignificance of the FinTech coefficient in our environmental model aligns perfectly with the argument of mutually offsetting opposing effects in the literature.

While these environmental debates and economic uncertainties persist, the social dimension of sustainability is gaining firmer ground. The academic literature is in rare agreement that FinTech’s greatest promise in the social sphere is financial inclusion [3]. The integration of rural communities, women, and low-income groups, who lack access to the traditional banking system, into the financial system via smartphones, mobile wallets, and microcredit platforms is revolutionizing the fight against poverty [25]. Empirical studies by Demir et al. [26] and Ghouse et al. [27] conclusively demonstrate that digital integration directly contributes positively to a country’s human development index (HDI), eliminates information asymmetry, and mitigates income inequality [28]. The finding of high significance at the 1% level for FinTech in our study’s social model once again confirms the unique power of digital finance in creating social equality of opportunity.

Researchers have pointed to methodological limitations to explain why FinTech acts as a social savior in emerging countries while falling short in terms of environmental and economic sustainability. Many studies rely on first-generation estimators that overlook how vulnerable emerging countries are to macroeconomic shocks or the cross-sectional dependence (CSD) among them [29,30]. However, from an economic sustainability perspective, even if digital finance reduces transaction costs, the primary drivers of industrializing economies remain fixed capital investments and labor force dynamics [31,32]. The fact that a wave of digitalization unsupported by physical production capacity and structural institutional quality cannot make a radical difference in economic sustainability [33] has been fully illuminated through the robust (Driscoll and Kraay’s) methodological framework used in this study. This multidimensional literature synthesis, conducted within the TBL framework, empirically demonstrates that FinTech acts as a social lever but, for economic sustainability, must be integrated with structural reforms and physical capital investments, and for green transition, must be integrated with renewable energy strategies. In light of this theoretical and empirical background, the methodological design of our study focuses on the following central research question: What was the impact of financial technology on sustainability in 23 emerging economies during 2011–2023? The hypotheses developed to address this question are as follows:

- H1.** *FinTech has a positive and significant impact on economic sustainability.*
- H2.** *FinTech has a positive and significant impact on environmental sustainability.*
- H3.** *FinTech has a positive and significant impact on social sustainability.*
- H4.** *Physical capital accumulation plays a positive and significant moderating role in the relationship between FinTech and economic sustainability.*

3. Materials and Methods

The sample consisted of 23 emerging economies observed from 2011 to 2023. Countries were selected based on two criteria: first, they were commonly classified as emerging or developing market economies in the international economic literature and major global economic databases; and second, balanced and consistent data were required for all variables included in the analysis, including the FinTech index, sustainability indicators, and control variables.

Although the sample included countries with diverse economic structures and development levels, such diversity is characteristic of the emerging economy group. Moreover, the use of a two-way fixed effects estimator controls for unobserved time-invariant country-specific characteristics, including institutional quality, cultural factors, regulatory frameworks, and structural economic differences. Therefore, the estimated coefficients primarily reflect within-country variations over time rather than cross-country differences.

Nevertheless, the findings should be interpreted within the context of the selected emerging economies and should not be generalized to all developing or advanced economies without caution.

In the present study, however, the MSCI classification was adopted to maintain comparability, and the dependent variables were defined as gross domestic product (GDP) to capture economic sustainability, ecological footprint to measure environmental sustainability, and the human development index (HDI) to represent social sustainability [34,35].

In this study, the FinTech index was employed as an independent variable in all three models to examine the impact of FinTech investment on sustainability. To enable a multidimensional analysis of the effects of FinTech, the dataset was expanded, and the index was constructed using Google Trends data based on four structural themes closely associated with FinTech: artificial intelligence, blockchain, cloud computing, and data mining. Rather than using specific keywords, these concepts were searched and analyzed as Google Trends “Topics”. This approach offers a significant advantage for cross-country analyses because Google Trends aggregates searches related to the same concept across different languages and search terms. Consequently, although the topics were initially identified using English terminology, searches conducted in each country’s native language were also incorporated into the analysis using Google’s topic classification system. As a result, the index captures countries’ relative interest in and attention to FinTech-related technologies more comprehensively and accurately. Therefore, the use of topic-based searches provides a more robust and internationally comparable measure than conventional keyword-based searches. This approach captures countries’ relative interest in and attention to FinTech-related technologies through normalized search frequencies obtained from Google Trends. Exploratory factor analysis was applied to assess the coherence of the index, and all keywords were assigned equal weights in the aggregation process, following the precedent established in the literature [36]. The exploratory factor analysis results provide evidence consistent with the construct validity of the index. To enhance transparency and replicability, this study provides detailed information on the operationalization process,

including the weighting scheme, normalization procedures, and factor analysis outputs. This comprehensive documentation allows for replication and enables readers to assess the robustness of the index.

A key methodological aspect of this study is the construction and validation of the FinTech index. While Google Trends data primarily capture search interest rather than the direct adoption or implementation of financial technologies, such indicators can serve as proxies for societal awareness and attention to FinTech-related themes. Interest in concepts such as blockchain or artificial intelligence may, at times, reflect speculative curiosity or media coverage rather than productive integration into financial services, raising potential concerns regarding construct validity. To address this issue, this study explicitly acknowledges these limitations and situates the index within the broader literature on FinTech measurement. Despite their constraints, search-based indicators can provide valuable macro-level insights into FinTech dynamics across countries, as highlighted by the challenges of quantifying FinTech diffusion in the literature [37]. Accordingly, the FinTech index should be interpreted as a proxy for FinTech-related technological awareness and diffusion dynamics rather than as a direct measure of FinTech market activity or direct adoption. This distinction is crucial for interpreting observed associations.

To assess the construct validity of the FinTech index, an exploratory factor analysis (EFA) was conducted. Prior to factor extraction, the suitability of the data was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. Reliability was further assessed using Cronbach’s alpha. The factor analysis results indicate that the selected indicators adequately capture a common latent FinTech dimension.

Reliability was examined using Cronbach’s alpha, and the obtained coefficient was found to be close to the threshold commonly accepted in the literature. Several studies suggest that Cronbach’s alpha values of 0.60 or higher are sufficient to establish scale reliability [38]. As shown in Table 1, the calculated coefficient of approximately 0.697 indicates that the measurement instrument meets the reliability requirements and is therefore statistically sound.

Table 1. Reliability statistics.

Cronbach’s Alpha	No. of Items
0.697	4

Prior to factor analysis, the suitability of the dataset was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. As shown in Table 2, the KMO value of 0.756 demonstrates acceptable sampling adequacy, although higher values would indicate stronger suitability for factor analysis. Bartlett’s test yielded a statistically significant result ($p = 0.0 < 0.05$), confirming that sufficient correlations exist among the variables.

Table 2. The KMO and Bartlett’s tests.

Kaiser–Meyer–Olkin Measure of Sampling Adequacy.		0.756
Bartlett’s test of sphericity	Approx. chi-square	123.906
	df	6
	Sig.	0.000

Overall, these findings demonstrate that the dataset is appropriate for factor analysis and that the constructed indices are based on a reliable and valid statistical basis.

Although Google Trends data do not directly measure FinTech transactions, investment volumes, or adoption rates, they provide a comparable and consistently available

cross-country indicator of FinTech-related technology attention and diffusion over time. Accordingly, the FinTech index should be interpreted as a proxy for FinTech-related technological diffusion, rather than as a direct measure of FinTech market activity.

However, the control variables were tailored to the specific dependent variable in each model. In the first model, which examines economic sustainability, the variables that typically influence GDP are gross fixed capital (gfc), labor force participation rate (lfp), foreign direct investment (fdi), and trade openness (trade). In the second model, which examines environmental sustainability, the control variables are GDP per capita (gdppc), CO₂ emissions (co2), renewable energy consumption (rec), and trade openness (trade). Finally, in the third model, which calculates social sustainability, GDP per capita (gdppc), the global innovation index (gii), the globalization index (gi), and the economic freedom index (efi) are included as control variables in the model. The expansion of the scope of variables demonstrates that FinTech creates multidimensional impacts not limited to financial and human development, but also through investment, trade, energy, and institutional factors. Descriptions of all variables used in the study and the data sources are presented in Table 3.

Table 3. Variable description and sources.

Variable	Symbol	Definition	Source
Gross Domestic Product (constant 2015 US\$)	gdp	GDP refers to the gross domestic product in constant 2015 US\$	World Development Indicators (WDI) database, World Bank
Ecological Footprint per person	ef	Ecological footprint per person refers to biologically productive areas required to provide everything they consume	Global Footprint Network (GFN)
Human Development Index	hdi	The HDI is a summary measure of average achievement across three dimensions (health, education, and living standards).	United Nations Development Program (UNDP)
FinTech	fintech	Fintech refers to the integration of digital technologies such as artificial intelligence, blockchain, cloud computing, and data analytics into financial services, aiming to enhance efficiency, accessibility, and innovation in the financial system	Authors' Calculation
Gross Fixed Capital Formation (constant 2015 US\$)	gfc	GFC refers to acquisitions of produced assets for fixed capital formation, inventories, or valuables.	World Development Indicators (WDI) database, World Bank
Labor Force Participation Rate (% of total 15+)	lfp	LFP refers to the proportion of the population aged 15 and older that is economically active	World Development Indicators (WDI) database, World Bank
Foreign Direct Investment (net inflows % of GDP)	fdi	FDI refers to the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor.	World Development Indicators (WDI) database, World Bank
Trade Openness (% of GDP)	trade	Trade refers to the sum of exports and imports of goods and services, expressed as a percentage of GDP.	World Development Indicators (WDI) database, World Bank
Gross Domestic Product per Capita (constant 2015 US\$)	gdppc	GDPPC refers to GDP divided by the mid-year total population.	World Development Indicators (WDI) database, World Bank

Table 3. Cont.

Variable	Symbol	Definition	Source
CO ₂ Emissions (in tons)	co2	CO ₂ emissions stem from the burning of fossil fuels and the manufacture of cement.	Our World in Data
Renewable Energy Consumption (% of total energy consumption)	rec	REC refers to the share of renewable energy in the total final energy consumption.	World Development Indicators (WDI) database, World Bank
Global Innovation Index	gii	The GII is the most comprehensive guide for measuring the innovation capacity and performance of economies.	World Intellectual Property Organization (WIPO)
Globalization Index	gi	The GI measures the economic, social, and political dimensions of globalization for economies.	Swiss Economic Institute
Index of Economic Freedom	efi	The EFI measures the degree of economic freedom in an economy.	The Heritage Foundation

Logarithmic transformations were applied to the gdp, ef, gfc, gdppc, and co2 time series included in the models to stabilize their variances and normalize their distributions. The descriptive statistics for these series are presented in Table 4. The distributions of the variables subjected to logarithmic transformation were more balanced. Standard deviations were significantly reduced in high-variance variables such as gdp, co2, and gfc.

Table 4. Descriptive statistics.

Variable	N	Mean	Std. Dev.	Min	Max
lngdp	299	26.9314	1.0872	25.3781	30.4995
lnef	299	1.1492	0.6458	−0.1625	2.7991
hdi	299	0.8030	0.0756	0.603	0.94
fintech	299	34.4053	11.7929	6.32	57.1025
lngfc	299	25.6146	1.2006	23.7539	29.6811
lfp	299	62.7998	9.5037	41.626	87.575
fdi	299	2.8446	8.4167	−40.1082	105.6358
trade	299	80.2488	41.4152	23.9344	199.045
lngdppc	299	9.2776	0.8855	7.1558	11.3096
lnco2	299	19.3807	1.2430	17.5129	23.2224
rec	299	15.8843	12.5195	0.01	50
gii	299	38.0294	7.2464	22.7	59.3
gi	299	69.8815	6.9563	58.3011	83.1532
efi	299	64.4548	7.0010	48	79

Table 5 shows the correlation matrix of the variables included in the models. An examination of the correlation matrix revealed strong relationships between certain variables. In particular, a high positive correlation between the lngdp, lngfc, and lnco2 variables was evident. Such a relationship between economic sustainability, capital accumulation, and carbon emissions (particularly in developing countries) can be expected. However, the presence of high positive correlations among variables such as hdi, lngdppc, gi, and efi indicates that they move in the same direction and trigger one another. The presence of high correlations indicates the risk of multicollinearity and highlights the need for careful variable selection. The fact that variables such as fdi and fintech show weak correlations with other variables suggests that the effects of these variables may be indirect rather than linear.

Overall, the correlation matrix highlights the need to assess potential multicollinearity and employ appropriate econometric techniques.

Table 5. Correlation matrix.

Variable	lngdp	lnef	hdi	fintech	lngfc	lfp	fdi	trade	lngdppc	lnco2	rec	gii	gi	efi
lngdp	1.00													
lnef	−0.39 ***	1.00												
hdi	−0.29 ***	0.60 ***	1.00											
fintech	0.06	−0.02	0.11 **	1.00										
lngfc	0.97 ***	−0.31 ***	−0.22 ***	0.01	1.00									
lfp	−0.13 **	0.45 ***	0.20 ***	−0.14 **	−0.04	1.00								
fdi	−0.08	0.00	0.04	0.06	−0.08	−0.04	1.00							
trade	−0.45 ***	0.49 ***	0.54 ***	0.04	−0.38 ***	0.24 ***	0.11 **	1.00						
lngdppc	−0.26 ***	0.78 ***	0.87 ***	−0.01	−0.18 ***	0.45 ***	−0.01	0.49 ***	1.00					
lnco2	0.93 ***	−0.27 ***	−0.34 ***	−0.01	0.91 ***	−0.14 **	−0.11 **	−0.37 ***	−0.26 ***	1.00				
rec	0.18 **	−0.55 ***	−0.47 ***	0.19 ***	0.14 **	−0.13 **	0.07	−0.43 ***	−0.62 ***	−0.01	1.00			
gii	0.25 ***	0.17 ***	0.53 ***	−0.02	0.32 ***	0.10 *	0.04	0.43 ***	0.46 ***	0.22 ***	−0.30 ***	1.00		
gi	−0.48 ***	0.45 ***	0.77 ***	0.17 ***	−0.42 ***	−0.01	0.11 **	0.75 ***	0.58 ***	−0.49 ***	−0.37 ***	0.51 ***	1.00	
efi	−0.43 ***	0.32 ***	0.55 ***	0.01	−0.36 ***	0.40 ***	0.07	0.52 ***	0.49 ***	−0.47 ***	−0.25 ***	0.36 ***	0.56 ***	1.00

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Two-way fixed-effects panel regression models were constructed to examine how financial innovation affects sustainability, considering time-varying and unobservable heterogeneity. This specification controls for country-specific characteristics and common time shocks that could distort the relationship between financial innovation and sustainability. The basic specification models are as follows:

$$\text{lngdp}_{it} = \beta_1 + \beta_2 \text{fintech}_{it} + \beta_3 \text{lngfc}_{it} + \beta_4 \text{lfp}_{it} + \beta_5 \text{fdi}_{it} + \beta_6 \text{trade}_{it} + \mu_{it} + \lambda_{it} + \epsilon_{it} \quad (1)$$

$$\text{lnef}_{it} = \alpha_1 + \alpha_2 \text{fintech}_{it} + \alpha_3 \text{lngdppc}_{it} + \alpha_4 \text{lnco2}_{it} + \alpha_5 \text{rec}_{it} + \alpha_6 \text{trade}_{it} + \mu_{it} + \lambda_{it} + \epsilon_{it} \quad (2)$$

$$\text{hdi}_{it} = \delta_1 + \delta_2 \text{fintech}_{it} + \delta_3 \text{lngdppc}_{it} + \delta_4 \text{gii}_{it} + \delta_5 \text{gi}_{it} + \delta_6 \text{efi}_{it} + \mu_{it} + \lambda_{it} + \epsilon_{it} \quad (3)$$

In the models, gdp is the economic sustainability indicator, lnef is the environmental sustainability indicator, and hdi is the social sustainability indicator; fintech is the financial innovation indicator. The control variables for Model 1 are lngfc, lfp, fdi, and trade; for Model 2, they are lngdppc, lnco2, rec, and trade; and for Model 3, they are lngdppc, gii, gi, and efi. μ_{it} denotes country-specific fixed effects, λ_{it} denotes time-specific fixed effects, and ϵ_{it} denotes the stochastic error term.

In this study, Driscoll and Kraay's [16] standard errors, which are robust to the heteroscedasticity, autocorrelation, and cross-sectional dependence observed in panel data, were used. Upon evaluating the data used in the empirical study, this method was applied for the following reasons. First, because the method does not require balanced or long-term panels, it was deemed appropriate, even though the panel used in the study, although balanced, covered a relatively short period of 13 years. Second, it accommodates the arbitrary movements of the cross-sectional and temporal dependence. This is of critical importance, given that developing countries are more exposed to macroeconomic shocks than developed countries. Third, it demonstrates good forecasting performance when the cross-sectional dimension is more moderate than the time dimension. Its strong finite-sample properties have also led to its more frequent use in recent finance and sustainability studies [39].

Before proceeding to Driscoll and Kraay's analysis, the variance inflation factor (VIF) was calculated to assess linear dependence, and Hausman [40] and Mundlak [41] tests were conducted to determine whether to use random or fixed effects. The power of the Hausman test may be weak in cases of small N and the absence of non-global error. Therefore, the choice between fixed effects (FE) and random effects (RE) should be supported by robust criteria and diagnostic testing. According to Hausman, even if the consistency of RE is not rejected, RE becomes inconsistent when there is a correlation among country-level factors in countries that are geographically and economically similar to each other.

Meanwhile, fixed-effect estimators may retain their validity according to the Mundlak test [42]. Following this stage, the modified Wald test [43] was conducted to determine the validity of the homoscedasticity hypothesis, the Wooldridge test was used to detect autocorrelation in the model errors, and the Pesaran CD test [44] was performed to identify the cross-sectional dependence.

4. Results

Table 6 presents the variance inflation factor (VIF), which shows how rapidly variances and covariances increase when the combined effect of predictors on each variable is isolated. According to the results, the VIF value was below 2.1 in all models, and the average VIF values ranged between 1.12 and 1.60. These findings, which fell well below the generally accepted threshold in the literature ($VIF \geq 10$), indicate that there is no serious multicollinearity problem among the independent and control variables included in the models. Given that the standard errors of the coefficients are not inflated and are statistically significant, the models are interpretable and allow for policy implications. Although several macroeconomic variables exhibit relatively high pairwise correlations in Table 5, this outcome is not unexpected, given the close structural relationship between economic growth, capital accumulation, and carbon emissions in emerging economies. Nevertheless, the VIF results indicate that multicollinearity does not pose a serious threat to coefficient estimation, as all values remained substantially below the conventional thresholds.

Table 6. Variance inflation factor (VIF).

Variable	VIF	1/VIF
Economic Model		
fintech	1.04	0.9652
lngfc	1.18	0.8454
lfp	1.10	0.9111
fdi	1.02	0.9767
trade	1.27	0.7865
Mean VIF	1.12	
Environment Model		
fintech	1.08	0.9239
lngdppc	2.00	0.5006
lnco2	1.31	0.7633
rec	2.03	0.4919
trade	1.58	0.6313
Mean VIF	1.60	
Social Model		
fintech	1.07	0.9351
gdppc	1.73	0.5772
gii	1.46	0.6868
gi	2.09	0.4785
efi	1.57	0.6360
Mean VIF	1.58	

Notes: Variance inflation factor (VIF) and tolerance values (1/VIF) for the model's independent and control variables confirm a low risk of multicollinearity.

After determining which variables could be included in the models and interpreted, Hausman and Mundlak tests were applied to determine which model, fixed effects (FE) or random effects (RE), was appropriate. According to the results of the Hausman test, as shown in Table 7, the null hypothesis was rejected for all models. In this case, the fixed effects (FE) model was more consistent than the random effects (RE) model. Based on

the results of the Mundlak test, which was applied due to the robustness approach, a statistically significant correlation was found between the explanatory variables and the unobserved unit effects. In this case, the fundamental assumption of the random effects model was violated, and the necessity of preferring the fixed effects or conditional random effects (CRE) approach was established.

Table 7. Hausman and Mundlak tests.

Test	Chi²	p-Value	Condition
Economic Model			
Hausman Test	247.23	0.0000	FE better than RE (high correlation between unobserved country-specific effects and explanatory variables) Use FE/CRE instead RE
Mundlak Test	117.26	0.0000	
Environment Model			
Hausman Test	30.27	0.0244	Use FE instead RE
Mundlak Test	15.89	0.0072	Use FE/CRE instead RE
Social Model			
Hausman Test	57.43	0.0000	Use FE instead RE
Mundlak Test	29.10	0.000	Use FE/CRE instead RE

Table 8 summarizes the diagnostic test results. According to the results of the modified Wald test, heteroscedasticity was identified in all models. The Wooldridge test revealed first-order autocorrelation in the error terms of the models used. The Pesaran CD test also indicated a weak cross-sectional dependence in some models. The results of the diagnostic tests indicate that the standard errors obtained from the classical fixed-effects estimators are unreliable. Given that the models included in the analysis are second-generation panel models, the estimators were identified using Driscoll and Kraay standard errors, which are robust to heteroscedasticity, autocorrelation, and cross-sectional dependence.

Table 8. Diagnostic test results.

Test	Statistic	<i>p</i> -Value	Condition
Economic Model			
Modified Wald Test	3509.75	0.0000	Heteroscedastic
Wooldridge Test	157.867	0.0000	First-order autocorrelation
Pesaran Test	−1.721	0.0852	Weak cross-sectional dependence
Environment Model			
Modified Wald Test	2150.72	0.0000	Heteroscedastic
Wooldridge Test	2.726	0.0002	First-order autocorrelation
Pesaran Test	−0.957	0.3388	No cross-sectional dependence
Social Model			
Modified Wald Test	1062.45	0.0000	Heteroscedastic
Wooldridge Test	78.844	0.0000	First-order autocorrelation
Pesaran Test	−1.662	0.0965	Weak cross-sectional dependence

The results of Driscoll and Kraay's models are presented in Table 9. The R^2 values, calculated as 0.805, 0.3078, and 0.8010 for the economic, environmental, and social models, respectively, reflect their explanatory power. However, it is important to interpret these values cautiously; in macroeconomic panel models incorporating fixed effects, high R^2 values often capture substantial long-term within-country variation rather than indicating

the model's direct predictive accuracy for out-of-sample observations. Therefore, high R^2 values should not be considered the primary criterion for model validity [43]. The fact that the F-statistic is highly significant for all models ($p < 0.001$) indicates that the explanatory variables have a statistically significant joint effect on the dependent variable, even under Driscoll and Kraay's correction (for heteroscedasticity, autocorrelation, and cross-sectional dependence). A maximum two-period lag was included in the analysis to enhance the robustness of standard errors.

Table 9. Driscoll and Kraay's results.

Variable	Coef.	Std. Err.	T	$p > z$	[%95 Conf. Interval]
Economic Model					
fintech	0.0005	0.0003	1.47	0.166	[−0.0002, 0.0013]
lngfc	0.1847	0.0144	12.82	0.000	[0.1533, 0.2160]
lfp	−0.0055	0.0011	−4.77	0.000	[−0.0081, −0.0030]
fdi	0.0000	0.0001	0.63	0.540	[−0.0001, 0.0002]
trade	−0.0013	0.0004	−3.20	0.008	[−0.0022, −0.0004]
cons	22.4778	0.3242	69.33	0.000	[21.7714, 23.1843]
Prob > F	0.0000				
R^2	0.8005				
Environment Model					
fintech	0.0003	0.0004	0.88	0.399	[−0.0005, 0.0013]
lngdppc	0.1461	0.0560	2.61	0.023	[0.0298, 0.2682]
Inco2	0.2989	0.0611	4.89	0.000	[0.1656, 0.4323]
rec	−0.0027	0.0009	−2.75	0.018	[−0.0048, −0.0005]
trade	−0.0004	0.0003	−1.03	0.325	[−0.0012, 0.0004]
cons	−5.8873	0.7238	−8.13	0.000	[−7.4645, −4.3101]
Prob > F	0.0000				
R^2	0.3078				
Social Model					
fintech	0.0004	0.0000	6.34	0.000	[0.0002, 0.0005]
lngdppc	0.0103	0.0039	2.61	0.023	[0.0017, 0.01896]
gii	0.0007	0.0002	2.62	0.022	[0.0001, 0.0012]
gi	−0.0006	0.0007	−0.83	0.420	[−0.0022, 0.0010]
efi	−0.0000	0.0002	−0.07	0.942	[−0.0006, 0.0005]
cons	0.6842	0.0484	14.13	0.000	[0.5787, 0.7897]
Prob > F	0.0000				
R^2	0.8010				

According to the results of the economic model, the coefficients of the lngfc, lfp, and trade variables were statistically significant at the 1% significance level. However, the coefficients of the fintech and fdi variables were not statistically significant. The coefficients of the economic model were as follows: $\beta_1 = 22.4778$ ($p < 0.01$), $\beta_2 = 0.0005$ (not significant), $\beta_3 = 0.1847$ ($p < 0.01$), $\beta_4 = -0.0055$ ($p < 0.01$), $\beta_5 = 0.0000$ (not significant), and $\beta_6 = -0.0013$ ($p < 0.01$).

According to the results of the environmental model, the coefficient of the Inco2 variable was statistically significant at the 1% level, while the coefficients of the lngdppc and rec variables were statistically significant at the 5% level. However, the coefficients of the fintech and trade variables were not statistically significant. The coefficients of the environmental model can be expressed as follows: $\alpha_1 = -5.8873$ ($p < 0.01$), $\alpha_2 = 0.0003$ (not significant), $\alpha_3 = 0.1461$ ($p < 0.05$), $\alpha_4 = 0.2989$ ($p < 0.01$), $\alpha_5 = -0.0027$ ($p < 0.05$), and $\alpha_6 = -0.0004$ (not significant).

According to the results of the social model, the coefficient of the fintech variable was statistically significant at the 1% level, while the coefficients of the lngdppc and gii variables were statistically significant at the 5% level. However, the coefficients gi and efi were not statistically significant. The coefficients of the social model can be expressed as follows: $\delta_1 = 0.6842$ ($p < 0.01$), $\delta_2 = 0.0004$ ($p < 0.01$), $\delta_3 = 0.0103$ ($p < 0.05$), $\delta_4 = 0.0007$ ($p < 0.05$), $\delta_5 = -0.0006$ (not significant), and $\delta_6 = -0.0000$ (not significant).

According to the panel data results, FinTech does not exert a statistically significant direct effect on economic or environmental sustainability. In contrast, it has a positive and statistically significant association with social sustainability. As discussed below, additional interaction analysis revealed that FinTech contributes to economic sustainability when it is supported by sufficient levels of physical capital accumulation. In this context, it can be stated that financial innovation is an important tool for social development and inclusivity. However, in the environmental model, income growth is positively associated with environmental degradation, whereas the use of renewable energy reduces this effect.

The economic model shows that the most significant and positive effect stems from capital accumulation. Based on this, an interaction model was estimated to determine how capital accumulation shapes the role of financial innovation in economic sustainability. To reduce the problem of multicollinearity in the construction of the term representing the interaction, the variables were mean-centered.

According to the results presented in Table 10, although the standalone effect of the fintech variable was statistically insignificant, as observed in the economic model, the interaction term between fintech and lngfc was positive and significant. This finding indicates that Fintech influences economic sustainability through capital accumulation.

Table 10. Economic interaction model Driscoll and Kraay's results.

Variable	Coef.	Std. Err.	T	$p > z$	[%95 Conf. Interval]
Economic Interaction Model					
cfintech	−0.0005	0.0004	−1.12	0.284	[−0.0015, 0.0005]
clngfc	0.1615	0.0113	14.21	0.000	[0.1367, 0.1863]
cfintech × clngfc	0.0013	0.0001	8.20	0.000	[0.0009, 0.0017]
lfp	−0.0033	0.0007	−4.78	0.000	[−0.0048, −0.0018]
fdi	0.0001	0.0000	2.10	0.058	[−0.0005, 0.0003]
trade	−0.0011	0.0003	−3.42	0.005	[−0.0018, −0.0004]
cons	27.0587	0.0571	473.21	0.000	[26.9341, 27.1833]
Prob > F	0.0000				
R ²	0.8285				

According to the results of the marginal impact analysis presented in Table 11, fintech has a negative and statistically significant effect on economic sustainability at low levels of capital. However, as capital accumulation increases, the effect becomes positive. In particular, the interaction analysis reveals that fintech is positively related to sustainability in economies with high capital accumulation.

Finally, Figure 1 illustrates the marginal effects of fintech on different levels of capital accumulation. The graph shows that as capital accumulation increases, the impact of fintech on economic sustainability changes. It has been established that at low levels of capital accumulation, fintech has a negative effect on economic sustainability; as capital accumulation rises, the effect of fintech increases, and the marginal effect becomes economically positive around one standard deviation above the mean and statistically significant at higher levels of capital accumulation. This finding indicates that the impact of fintech on economic sustainability is conditional and that it does not play a supportive role in fostering sustainability in economies that lack sufficient capital accumulation. In other

words, in emerging countries, digital financial innovations alone do not impact economic sustainability; rather, financial innovation acts as a lever, alongside increases in physical production capacity.

Table 11. Marginal effect analysis results.

c_lngfc	Marginal Effect of cfintech	Std. Err.	z	$p > z $	[%95 Conf. Interval]
−1.5	−0.002571	0.0005	−4.53	0.000	[−0.0036, −0.0014]
−1	−0.00189	0.0005	−3.60	0.000	[−0.0029, −0.0008]
−0.5	−0.00121	0.0004	−2.45	0.014	[−0.0021, −0.0002]
0	−0.0005	0.0004	−1.12	0.262	[−0.0014, 0.0003]
0.5	0.0001	0.0004	0.31	0.754	[−0.0007, 0.0010]
1	0.0008	0.0004	1.72	0.085	[−0.0001, 0.0017]
1.5	0.0015	0.0005	2.99	0.003	[0.0005, 0.0024]

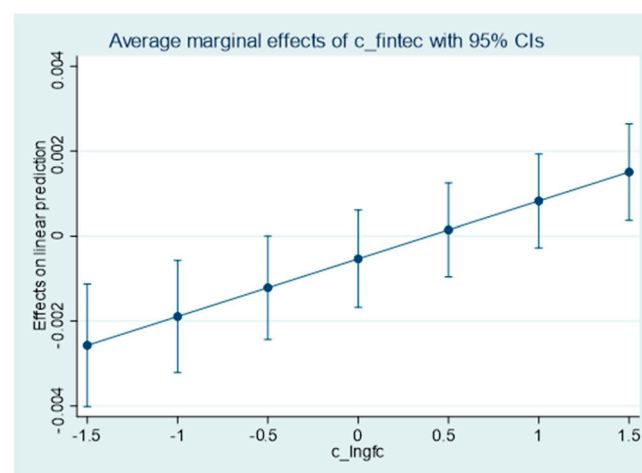


Figure 1. Marginal effect of fintech across lngfc. The figure presents the marginal effect of fintech on economic sustainability at different levels of capital accumulation (mean centered). The vertical bars indicate the 95% confidence intervals based on Driscoll–Kraay’s standard errors.

As a robustness check, all models were re-estimated after excluding the COVID-19 pandemic years (2020–2021). As reported in Appendix A (Table A1), the results remained the same qualitatively. In particular, the interaction between FinTech and physical capital accumulation remained positive and statistically significant, whereas the main findings regarding environmental and social sustainability were preserved.

5. Discussion

The findings of this study empirically refute the technological optimism bias in the literature, demonstrating that FinTech is not an automatic ecological savior but rather an indisputable driver of social inclusion (SDGs 1 and 10). To analyze the various dimensions of the impact of FinTech on sustainability in emerging economies, the Driscoll–Kraay standard-error two-way fixed effects model was employed, yielding findings that challenge the conventional wisdom of technological optimism in the literature. The results show that the effects of FinTech are not automatic or homogeneous but are influenced by different structural mechanisms in economic, environmental, and social contexts. This robust methodological approach, which addresses cross-sectional dependence and asymmetric shocks, reveals that FinTech functions as a strategic catalyst influenced by favorable macroeconomic conditions rather than as a self-contained solution.

The strongest and most robust finding of this study is the social dimension of sustainability. Econometric analyses indicate that FinTech is positively related to the human

development index (HDI) at the 1% significance level. This result empirically validates the financial inclusion argument frequently emphasized in the literature [3]. The inclusion of disadvantaged groups, who lack access to the traditional banking system, into the financial system via mobile wallets and digital platforms helps break down information asymmetry and offers a unique opportunity to fight poverty [2]. These findings are consistent with recent studies demonstrating that digital finance mitigates income distribution inequalities and successfully safeguards the social pillar of the triple bottom line (TBL) in emerging economies [11,26].

However, our findings regarding the economic dimension of sustainability challenge existing assumptions in the literature. At first glance, the negligible direct impact of FinTech on economic sustainability may seem surprising, but the interaction term (*fintechxgfc*) included in the model explains this phenomenon. The finding that the interaction between FinTech and gross fixed capital formation (GFC) is positive and statistically significant, empirically validates the core assumptions of the technology–organization–environment (TOE) framework. The literature also indicates that the mere presence of digital financial applications is insufficient to trigger sustainability in emerging economies. FinTech appears to create a multiplier effect, accelerating economic expansion by reducing the transaction costs, particularly when combined with robust physical production infrastructure and capital investment [14,33]. This finding aligns with the structuralist perspective, which highlights the fundamental roles of fixed capital investments and labor dynamics in facilitating growth in emerging economies.

However, the results obtained in our environmental model shed light on the ongoing dichotomy between technological optimists and pessimists in the FinTech literature. The statistical insignificance of the FinTech coefficient in our environmental model is consistent with the hypothesis in the literature that opposing ecological effects may cancel each other. This paradoxical finding is consistent with the results of Uzar et al. [23]. On the one hand, as argued by the theory of ecological modernization, FinTech exerts a force that reduces the carbon footprint through funding provided for green bonds and clean energy projects. However, on the other hand, the negative effects of the process come into play. The insatiable appetite for fossil fuel-based electricity driven by cryptocurrency mining and massive data centers, coupled with the consumption frenzy fueled by easier access to credit, is weakening the ecological carrying capacity. In this context, the reducing effect of green investments on the environmental footprint is offset by the increasing effect of rising consumption and e-waste, resulting in a neutralized final ecological impact that is statistically insignificant. This finding should not be interpreted as evidence of the absence of environmental effects. Rather, it suggests that the aggregate environmental impact of FinTech reflects the balance of competing, positive, and negative mechanisms operating simultaneously. Therefore, our findings demonstrate that the environmental benefits of FinTech will not yield ecological gains unless they are integrated with robust environmental regulations and renewable energy policies.

6. Conclusions and Policy Implications

This study provides robust evidence of the association between sustainability-focused financial technology and sustainability outcomes. The findings suggest that digital finance plays an asymmetric role in implementing the United Nations 2030 Agenda (SDGs). The strong and meaningful impact of FinTech on the social model confirms its effectiveness in achieving the goals of No Poverty (SDG 1) and Reduced Inequalities (SDG 10) through digital financial inclusion. However, the fact that FinTech is statistically insignificant in the environmental model and can contribute to economic sustainability only when supported by physical fixed capital accumulation indicates that the goals of Climate Action (SDG 13),

Affordable and Clean Energy (SDG 7), and Industry, Innovation, and Infrastructure (SDG 9) cannot be achieved through financial digitalization alone.

Considering these empirical findings, three interrelated policy recommendations are presented for governments and regulatory bodies in developing countries. First, to maximize FinTech's potential for Decent Work and Economic Growth (SDG 8), digital financial investments must be systematically aligned with the real sector's physical capital development. For instance, central banks might consider incentives or prerequisites for FinTech firm licensing that encourage commitment to real sector credit provision (physical production and green technology infrastructure).

Second, central banks and financial institutions should establish green restrictions on credit mechanisms to mitigate the rebound effect associated with environmentally harmful technological development. ESG regulations must be designed to redirect digital financial resources toward projects that support Climate Action (SDG 13) and Responsible Consumption and Production (SDG 12) rather than fossil fuel consumption. To prevent the rebound effect while applying higher reserve ratios to digital consumer loans (personal loans), tax exemptions should be provided for green crowdfunding activities that channel funds toward solar/wind energy projects. Furthermore, the fact that the environmental impact of FinTech remains neutral demonstrates that digital finance does not inherently provide ecological benefits. To address this and achieve Climate Action (SDG 13) goals, regulators must mandate a minimum "Green Credit Quota" in FinTech platforms' loan portfolios and program blockchain-enabled smart contracts to ensure that funds are used exclusively in renewable energy projects.

Third, to make social integration achieved through digital financial services sustainable and to support the achievement of Reduced Inequalities (SDG 10) and No Poverty (SDG 1), financial inclusion policies must be supported by concrete infrastructure and educational initiatives. Policymakers should increase investments in broadband Internet connectivity to bridge the digital divide in rural and disadvantaged areas and subsidize access to smart devices for low-income groups. Additionally, partnerships should be established between FinTech companies and public banks to integrate individuals without a traditional banking history into the system, and low-cost microcredit and digital savings products should be developed using alternative credit scoring mechanisms powered by artificial intelligence and machine learning algorithms. Finally, this technological access must be supported by nationwide digital financial literacy campaigns and safeguarded by robust cybersecurity legal frameworks. This will prevent disadvantaged groups from being exploited due to cyber fraud or algorithmic biases as they integrate into the financial system, ensuring that financial access translates into responsible financial behavior. However, a limitation of this study is the measurement of FinTech using Google Trends data. Although search-based indicators provide a useful proxy for technological attention and diffusion, they do not directly measure FinTech adoption, transaction volumes, or investment activity. Consequently, the positive association identified between the FinTech index and social sustainability should be interpreted as reflecting broader technological awareness and diffusion dynamics, rather than direct evidence of FinTech market activity. Future research may employ alternative indicators based on digital financial service usage, transaction data, or FinTech investment flows. Similarly, although the ecological footprint provides a broader measure of environmental sustainability than carbon emissions alone, future studies may employ alternative indicators, such as carbon intensity, ecological efficiency, greenhouse gas emissions, or renewable energy transition measures, to evaluate the robustness of environmental sustainability outcomes.

Although this study provides robust evidence of the relationship between FinTech and sustainability in emerging economies, it has some limitations. While the analysis employs

Driscoll and Kraay's estimators, which address cross-sectional dependence, the risk of potential bidirectional causality (endogeneity) among the macroeconomic variables should not be entirely disregarded. Despite the empirical framework accounting for unobserved heterogeneity, common temporal effects, heteroskedasticity, autocorrelation, and cross-sectional dependency, the potential for reverse causality remains. Improvements in economic or social sustainability may accelerate FinTech development and technological dissemination. Consequently, while our robust panel data techniques address various challenges, the potential for reverse causality suggests that the reported findings should be interpreted as strong associations, and conclusive causal claims remain limited without further endogeneity-specific methodology. Subsequent research may utilize dynamic panel estimators or instrumental variable methodologies to further mitigate the endogeneity issues.

The findings should be interpreted in the context of the selected emerging economies. Therefore, caution should be exercised when generalizing the results to developing or advanced economies. Future studies are encouraged to test these findings using different data techniques and expand the analysis beyond the 23 countries included here to include comparisons between developed and developing countries (e.g., OECD vs. BRICS). Furthermore, classifying emerging countries based on their technological infrastructure may reveal important thresholds related to the environmental impact of digitalization. In conclusion, this study empirically demonstrates that emerging countries cannot achieve sustainability goals through digitalization alone without structural reforms, robust environmental regulations, and physical infrastructure investments, and encourages policymakers to develop comprehensive strategies that go beyond technological optimism.

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Abbreviations

The following abbreviations are used in this manuscript:

TBL	Triple Bottom Line
SDGs	Sustainable Development Goals
ESG	Environmental, Social and Governance
FinTech	Financial Technology
TOE	Technology–Organization–Environment
GFC	Gross Fixed Capital Formation
HDI	Human Development Index
CSD	Cross-Sectional Dependence
GDP	Gross Domestic Product
LFP	Labor Force Participation Rate
FDI	Foreign Direct Investment
TRADE	Trade Openness

GDPPC	GDP per Capita
CO ₂	CO ₂ Emissions
REC	Renewable Energy Consumption
GII	Global Innovation Index
GI	Globalization Index
EFI	Economic Freedom Index
FE	Fixed Effects
RE	Random Effects
VIF	Variance Inflation Factor
CRE	Conditional Random Effects

Appendix A

Table A1. Robustness check: excluding the COVID-19 years.

Variables	Economic Sustainability	Environmental Sustainability	Social Sustainability	Interaction Model
fintech	0.0003 (0.0014)	0.0003 (0.0010)	0.0003 ** (0.0001)	−0.0008 (0.0013)
lnfgc	0.1873 *** (0.0574)	-	-	0.1705 *** (0.0601)
fintech x lnfgc	-	-	-	0.0013 *** (0.0003)
lngdppc	-	0.1041 (0.1437)	0.0080 (0.0249)	-
lnco2	-	0.3320 *** (0.0995)	-	-
rec	-	−0.0030 (0.0030)	-	-
gii	-	-	0.0008 (0.0007)	-
gi	-	-	−0.0006 (0.0007)	-
efi	-	-	−0.0003 (0.0005)	-
lfp	−0.0067 (0.0055)	-	-	−0.0040 (0.0045)
fdi	0.0001 (0.0001)	-	-	0.0001 (0.0001)
trade	−0.0015 (0.0014)	−0.0001 (0.0006)	-	−0.0012 (0.0014)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	253	253	253	253
Within R ²	0.8169	0.3171	0.8329	0.8415

Notes: Robust standard errors clustered at the country level are in parentheses. The models were estimated after excluding the COVID-19 pandemic years (2020–2021). Country and year fixed effects are included in all specifications of the model. *** $p < 0.01$, ** $p < 0.05$.

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