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RESEARCH ARTICLE

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# Do environmental regulations and technological innovation enhance environmental well-being in sub-Saharan Africa?

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## Abstract

We investigate the regulation–technology–environment nexus in sub-Saharan Africa (SSA), one of the world's most rapidly growing regions. Using a comprehensive panel dataset consisting of 32 countries from 2000 to 2022, we find that stronger environmental regulations and technological innovation enhance environmental well-being. Moreover, we identify that stronger environmental regulations positively affect pro-environment innovation. Finally, we present clear evidence for a dynamic and non-linear regulation–technology–environment relationship, ruling out one-size-fits-all policy approaches to environmental well-being. Our results remain robust to different estimators, measurements, and sample selections.

**KEYWORDS**
environmental regulations, environmental well-being, sub-Saharan Africa, technological innovation

## 1 | INTRODUCTION

Following the First Industrial Revolution in the 1700s, unprecedented environmental degradation has led to regular occurrences of extreme weather events and natural disasters (Doytch & Narayan, 2016; IPCC, 2023). This degradation, in turn, carries profound implications for consumption behaviors, production patterns, and health outcomes. The urgency of halting and reversing this concerning trend has been a priority on many governments' agenda. Although there are multiple causes of this trend, there is no doubt that unrestrained carbon dioxide ($CO_2$) emissions stand out as the single most significant contributor, accounting for around 76% of total greenhouse gas emissions (IPCC, 2023). To put this into perspective, the current global average concentration of $CO_2$ in the atmosphere is 421 ppm (ppm), which is an increase of over 50% up from 280 ppm during the 10,000 years before the mid-1700s. Given that much of this rise stemmed from the burning of fossil fuels to power economic activities, it has been dubbed by many as human-induced carbon emissions.

The reliance on fossil fuels in developing countries is of particular concern to environmentalists and policymakers. For starters, this reliance compounds the problem by perpetuating excessive carbon emissions that damage the local and global environment (Khan & Hou, 2021). From the outset, promoting renewable energy sources presents a rare opportunity for these countries to transit into a low-carbon future (Appiah et al., 2023; Assi et al., 2021; Musah et al., 2023). However, the successful deployment of renewable energy requires the identification of the right balance of environmental regulations, government institutions, and renewable technology to create a macroeconomy that is conducive to decarbonization. This path to sustainable development is equally vital to individual households not only for achieving energy justice but also for addressing the health concerns brought about by unrestrained carbon emissions (Acheampong & Opoku, 2023; James et al., 2020).

**Abbreviations:** $CO_2$, carbon dioxide; EE, generalized estimating equation; EKC, environmental Kuznets curve; FDI, foreign direct investment; ICT, information and communication technology; OLS, ordinary least square; SSA, sub-Saharan Africa.

Although previous research has highlighted the impact of environmental regulations and technological innovation on environmental well-being, it remains unclear if it is possible at all to decouple one from the other. Moreover, it remains contestable if stronger environmental regulations necessarily enhance environmental well-being at the expense of economic growth. Finally, it remains debatable whether environmental regulations exert a significant impact on technological innovation. Against these backdrops, we propose and examine the following questions: (1) Will stronger environmental regulations necessarily enhance environmental well-being? (2) To what extent does technological innovation influence environmental well-being? and (3) Can stronger environmental regulations be the catalyst for technological innovation? By closing these knowledge gaps, we seek to identify strategies for promoting decarbonization, particularly in the developing world.

To answer these questions, we select sub-Saharan Africa (SSA) as our main unit of analysis not only because there is a lack of empirical literature exploring the interactions between environmental regulations, technological innovation, and environmental well-being in this rapidly growing region but also because of its unique cultural, developmental, and political contexts in shaping the regulation–technology–environment nexus. To date, most studies either examined the impact of renewable energy adaptation on carbon emissions in high- and middle-income countries (see, e.g., Ali et al., 2023; Faisal et al., 2020; Khanna et al., 2019) or the dynamics of renewable and non-renewable energy demands (see, e.g., Adedoyin et al., 2022; Balsalobre-Lorente et al., 2018; Salahuddin et al., 2018). However, a major shortcoming in these strands of literature is that they did not explicitly consider how weak absorptive capacity might have affected the decarbonization path in SSA. Against this backdrop, we approach the regulation–technology–environment nexus by controlling for, among other things, policies and institutions for environmental sustainability, policies for social inclusion, and the imports and exports of information and communication technology (ICT). To the best of our knowledge, there have been no systematic attempts to explore the causal effects of the nexus in this region.

Using comprehensive panel data from 32 SSA countries for the 2000–2022 period, we find that stronger environmental regulations enhance environmental well-being. Specifically, we show that the policies and institutions for environmental sustainability and policies for social inclusion are most effective in reducing carbon emissions and raising renewable energy usage, respectively. However, the environmental benefit of technological innovation is much less clear-cut. For example, we find that the imports of ICT goods raise carbon emissions and renewable energy usage, but the exports of ICT services, for most of the time, reduce carbon emissions. Importantly, we demonstrate that much of the pro-environment technological innovation was forced upon by stronger environmental regulations, providing qualifying support to the Porter and van der Linde (1995) hypothesis. Last, but not least, we attribute the mixed results to the dynamics and nonlinearity of the regulation–technology–environment nexus. Overall, our findings rule out one-size-fits-all approaches to environmental well-being and suggest the need to promulgate environmental regulations that encourage technological innovation.

## 2 | LITERATURE REVIEW

### 2.1 | Environmental well-being and environmental Kuznets curve

In theory, environmental well-being is often defined as the capacity of the environment to sustain ecological balance and provide essential resources for present and future generations (Millennium Ecosystem Assessment, 2005). In practice, enhancing environmental well-being involves minimizing or at least matching carbon emissions with the planet's natural capacity to absorb and sequester. In this state, human-induced carbon emissions do not cause any disparities in the natural carbon cycle and create sustainable ecosystems. Alternatively, environmental well-being can be enhanced by transforming non-renewable energy systems into those powered by solar, wind, hydropower, and geothermal. A successful transformation not only reduces carbon emissions but also preserves environmental capital and ecosystems for future generations. Moreover, this transformation can accelerate economic growth, create green jobs, and promote energy security in the long run.

One of the world's major challenges today is to restore carbon emissions to a level that the environment can comfortably withstand. Given that much of the emissions are man-made, there is hesitancy among policymakers in reducing the emissions level, weary that doing so may put the economy into a protracted recession (Copley, 2022). Historically, this close link between environmental well-being and economic development was first identified by Grossman and Krueger (1995), who coined the term the environmental Kuznets curve (EKC) and hypothesized an inverted U-shaped relationship between environmental degradation and economic development. Although the extant literature, by and large, supports the existence of the EKC, it leaves open the debate on the precise position of the turning point along this nonlinear relationship (Stern, 2004). Empirically, this is because the turning point is directly influenced by factors like industrialization, technology, and urbanization, as well as their indirect interactions with environmental standards, regional coordination, and structural adjustment (see, e.g., Pan et al., 2023; Shen et al., 2023). Take the adoption of stronger environmental standards and renewable energy sources as an example. At the early developmental stage, the government typically pursues economic growth with no environmental oversight by powering the economy with fossil fuels, which are cheap but environmentally unfriendly. However, as the income level continues to climb, the public becomes aware of the adverse environmental and health impacts brought about by the burning of fossil fuels and starts to demand a cleaner environment. As a political response, the government mitigates air pollution by introducing renewable technology and strengthening environmental standards (Saint Akadiri et al., 2019). This effort to decarbonize the economy benefits individuals, society, and the environment, elevating economic sustainability to the forefront of the policy agenda (Shen et al., 2023).

Today, the aspiration for achieving economic sustainability is the strongest in China. As an attempt to strike the right balance between economic growth and environmental sustainability, the government introduced a series of environmental regulations to restrict the expansion of pollution-intensive industries and launched multiple waves of fiscal incentives and concessions to promote the installation of renewable technology (Fan & Hao, 2020; Qiu et al., 2021; Zhang et al., 2014). Although China has only experienced measured successes in balancing economic growth and environmental protection, it has nevertheless shown clear signs of being on the downward slope of the EKC (Pan et al., 2023).

## 2.2 | The regulation–environment nexus

It is a well-established fact that weak environmental regulations are often to the detriment of the environment (Grossman & Krueger, 1995). Compared with their peers under a lax regulatory framework, firms enduring stronger environmental regulations face high compliance cost that reduces competitiveness and profitability (Dechezleprêtre & Sato, 2017; Yang et al., 2023). With this in mind, many developing countries deliberately lowered their environmental standards and promoted it as a favorable locational determinant to attract foreign direct investment (FDI) (List & Co, 2000). This prioritization of economic growth over environmental well-being has resulted in some countries becoming the magnets of pollution-intensive FDI.

To gauge the adverse impact of this ill-conceived priority on the environment, one only needs to consider China's developmental experience. During the early days of economic reform, the government implemented a flexible environmental regime to cater for industrialization and economic growth (Ao et al., 2023). In part, this change was made possible by the low compliance cost of lax environmental regulations that not only fueled the rapid expansion of domestic pollution-intensive industries but also attracted those from the rest of the world. This choice of growing the economy at all costs, including at the cost of the environment, enjoyed unprecedented success by lifting millions of people out of absolute poverty by the end of the 1990s. However, as the country entered the new Millennium, this growth strategy created cumulative damage to society and the environment, particularly in public health concerns over the widespread air and water pollution (Xiao et al., 2020; Xu et al., 2020). Subsequently, the public made repeated demands for a cleaner environment (Li & Taeihagh, 2020; Lu et al., 2020). Bowing to public pressure, the government caved in and launched a series of stronger environmental regulations and sustainable development initiatives. For many pollution-intensive firms, these changes made the compliance cost unbearable and eventually forced their relocation to other countries with lax environmental standards. This tendency for countries to lure FDI by lowering their environmental standards established "safe havens" for pollution-intensive FDI, leading to the so-called pollution havens hypothesis (Eskeland & Harrison, 2003).

The view that environmental regulations constitute a driver for technological innovation can be traced back to Porter and van der Linde (1995), who argued that a tough regulatory framework could compel firms to adopt innovative solutions, which often are not only more productive but also raise corporate competitiveness. For example, the stricter prosecution of environmental regulations by the Chinese government since 2000 ignited the momentum for installing state-of-art technologies that raised both national productivity and international competitiveness (Wang et al., 2019). In this regard, a tough environmental regulatory framework can invite positive changes for pollution-intensive industries, yielding a win-win scenario that combines economic growth and environmental protection (Shen et al., 2023).

## 2.3 | The technology–environment nexus

One of the enduring debates in energy economics is the so-called energy efficiency paradox, which postulates that improving energy efficiency need not necessarily reduce energy consumption; to the contrary, greater energy efficiency can raise energy consumption to the detriment of the environment (see, e.g., Kim & Kim, 2012; Kounetas & Tsekouras, 2008; Linares & Labandeira, 2010). If true, this paradox means that the success in cutting back carbon emissions in a city or country may be offset by the increase in carbon emissions brought about by better energy efficiency from its neighboring locations (Eom et al., 2020; Shen et al., 2023). Given that carbon emissions know no national boundaries, it introduces an added layer of complexity to the already complicated international negotiations on emissions abatement strategies. Indeed, policymakers can avoid this outcome by rolling out renewable technology beyond a single city or country (Zhou et al., 2019). Operationally, it implies that policymakers must strategically install renewable technology in high-emissions areas first before introducing it across the energy network of neighboring areas (Halkos & Tsilika, 2019). At an international level, a global manufacturing powerhouse like China must avoid the pitfall of the energy efficiency paradox by taking the lead on installing renewable technology rather than powering the economy with non-renewable energy sources (Fan & Hao, 2020; Li & Taeihagh, 2020).

The rise to prominence of ICT in the 1990s was seen by many as a double-edged sword on the environment. On the one hand, the introduction of ICT per se can increase the demand for non-renewable energy sources to power circuit boards, releasing carbon emissions into the environment (Martins et al., 2019). On the other hand, given that ICT can be used to enhance logistics and production efficiency in areas such as supply chain management, it can reduce the country's energy demand, reducing its overall carbon emissions into the environment (Cho et al., 2007). Empirically, the impact of technological innovation like ICT on environmental well-being remains unclear, but there is mounting evidence that the level of economic development holds sway. For example, Sadorsky (2010) found that ICT raised carbon emissions in emerging economies. Taking this one step further, Salahuddin et al. (2020) showed that ICT reduced carbon emissions in industrialized economies but not in developing economies because of the poor supporting infrastructure needed to fully internalize the benefits of ICT.

### 2.4 | Hypotheses development

The preceding discussion raised three important empirical questions regarding the nature of the regulation–technology–environment nexus. First, will stronger environmental regulations necessarily enhance environmental well-being? Second, can technological innovation enhance environmental well-being? And third, what is the interaction effect, if any, between environmental regulations and technological innovation on environmental well-being? The answers to these questions carry valuable information for policymakers. Specifically, if the answer to the first question is affirmative, it suggests that tightening environmental regulations need not risk an economic slowdown; to the contrary, a strict environmental regulation framework can induce technological innovation that raises corporate competitiveness and economic growth. Meanwhile, if the answer to the second question is affirmative, it indicates that policymakers must embrace technological innovation as a catalyst for achieving sustainable growth. Finally, if the answer to the third question is affirmative, it reveals the unintended benefit of stronger environmental regulations in stimulating pro-environment technological innovation and strengthening national competitiveness. Based on these three related questions, we test the following hypotheses in the context of SSA:

**H1.** Stronger environmental regulations enhance environmental well-being, ceteris paribus.

**H2.** The adaptation of technological innovation enhances environmental well-being, ceteris paribus.

**H3.** Stronger environmental regulations stimulate pro-environment technological innovation, ceteris paribus.

For completeness, we control for several factors based on the EKC that are known to exert influences on the regulation–technology–environment nexus (Abdulqadir, 2023b).

## 3 | RESEARCH DESIGN AND METHODOLOGY

### 3.1 | Benchmark model

To assess whether environmental regulations and technological innovation enhance environmental well-being in SSA, we propose the following benchmark model specification:

$$EW_{it} = \beta_0 + \beta_1 ER_{it} + \beta_2 TI_{it} + \mathbf{CV_{it}}\boldsymbol{\rho}' + \varepsilon_{it} \tag{1}$$

where the subscripts $i$ and $t$ represent country $i$ and year $t$, respectively. $EW_{it}$ denotes the level of environmental well-being, given a specific combination of environmental regulations $(ER_{it})$ and technology innovation $(TI_{it})$. Intuitively, Equation (1) shows how an SSA country effectively converts environmental regulations and renewable technologies as the inputs to enhance environmental well-being as the output. The coefficient $\beta_0$ is the intercept, representing the baseline environmental well-being. Our main coefficients of interest, $\beta_1$ and $\beta_2$, indicate the effect of a change in environmental regulations and technological innovation on environmental well-being, respectively. If both coefficients are positive and statistically significant, it implies the introduction of technological innovation and environmental regulations enhances environmental well-being. $\mathbf{CV_{it}}$ represents a vector of control variables, and $\boldsymbol{\rho}'$ measures the effect of these variables on environmental well-being. Finally, $\varepsilon_{it}$ is the stochastic error term, capturing the effect of unobserved factors on environmental well-being.

In addition to Equation (1), we also consider the interaction effect between environmental regulations and technological innovation $(ER * TI)$ in enhancing environmental well-being in SSA in the following specification (Brambor et al., 2006):

$$EW_{it} = \beta_0 + \beta_1 ER_{it} + \beta_2 TI_{it} + \beta_3 (ER_{it} * TI_{it}) + \mathbf{CV_{it}}\boldsymbol{\rho}' + \varepsilon_{it} \tag{2}$$

Specifically, a positive and statistically significant coefficient $\beta_3$ suggests that stronger environmental regulations stimulate pro-environment technological innovation.

In this study, we measure environmental well-being separately by carbon emissions $(CO2_{it})$ and renewable energy utilization $(REC_{it})$. Meanwhile, we represent environmental regulations separately by the policy for social inclusion $(PSI_{it})$ and policy and institutions related to environmental sustainability $(PIES_{it})$ ratings. In terms of technological innovation, we capture it separately by the volume of imported ICT goods $(ICTGI_{it})$ and the volume of ICT services exported $(ICTSE_{it})$. To account for the effect of environmental regulations on technological innovation, we introduce the following interaction terms sequentially to Equation (2): *PIES*ICTGI*, *PIES*ICTSE*, *PFSI*ICTGI*, and *PFSI*ICTSE*. Based on the EKC literature, we also control for the effect of natural resources $(NR_{it})$, population $(POP_{it})$, and economic development $(GDP_{it})$ on environmental well-being.

In terms of the estimation procedure, we start by applying the ordinary least squares (OLS) estimator to Equations (1)–(2), followed by the generalized estimating equation (GEE) estimator, to account for endogeneity, cross-sectional dependence, and unobserved confounding factors (Agresti, 2012). As a robustness check, we re-estimate both equations by the generalized least squares (GLS) estimator, which provides more reliable estimates than its OLS and GEE counterparts, especially when there are heteroscedasticity and autocorrelation in the stochastic error terms (Greene, 2019).

**TABLE 1** Variables, measurements, and sources.

| Variable | Mnemonics | Measurement | Source |
|---|---|---|---|
| Environmental well-being | *CO2* | Carbon emissions (kt) from burning fossil fuels and cement production | WDI |
| | *REC* | The proportion of renewable energy in SSA's total final energy consumption | WDI |
| Environmental regulations | *PIES* | Policy and institutions for environmental sustainability rating (1 = lowest to 6 = highest) | WDI |
| | *PSI* | Policies for social inclusion/equity cluster average (1 = lowest to 6 = highest) | WDI |
| Technological innovation | *ICTGI* | ICT goods imports (% total goods imports) | WDI |
| | *ICTSE* | ICT service exports (BoP, current US$) | WDI |
| Natural resources | *NR* | Total natural resources rents (% of GDP) | WDI |
| Population | *POP* | Total population accounts for the total number of residents, regardless of legal status or citizenship. | WDI |
| Economic development | *GDP* | Gross value added by all resident producers in the economy, plus any product taxes and minus any subsidies not included in the value of the products. | WDI |

For consistency, we collect data on 32 SSA countries for the 2000–2022 period from the World Development Indicators.[1] Table 1 provides the list of variables, measurements, and sources used in our study. For ease of interpretation, we transform all variables into their natural logarithms and provide their summary statistics, correlation coefficient matrix, cointegration tests, cross-sectional dependence test, and panel unit root test in Appendix A (Tables A1, A2, A3, and A4). In general, we conclude that our variables are not highly correlated, cross-sectionally dependent, stationary, and cointegrated.

## 3.2 | SPF model

For a vast area like SSA, it is best described by substantial regional heterogeneity in environmental regulations, technological innovation, and environmental well-being. To accommodate for such heterogeneity, we employ the stochastic production frontier (SPF) model to obtain the efficiency scores of a country in transforming inputs like environmental regulations and technological innovation into environmental well-being as the output. Moreover, this model captures unobserved factors that can affect the technology–regulation–environment nexus in the region. Formally, we can represent the model as follows:

$$EW_{it} = \exp\left(\alpha_i + \beta_1 ER_{it} + \beta_2 TI_{it} + \mathbf{CV_{it}}\boldsymbol{\rho}' + \frac{1}{\mu}\ln[H(Z_{it}\gamma)]u_{it} + \varepsilon_{it}\right) \tag{3}$$

where $H(Z_{it}\gamma)$ is the mean technical efficiency with a range between zero and one. It is a function of $Z_{it}$ and parameterized by the vector $\gamma$, which indicates the efficiency of a country in transforming environmental regulations, technological innovation, and a host of control variables into environmental well-being. The coefficients $\beta_1$, $\beta_2$, and $\boldsymbol{\rho}'$ describe the relationship between an independent variable as the input and environmental well-being as the output in Equation (3). We take the natural logarithm of the mean technical efficiency to ensure that the stochastic error term $(u_{it})$ is symmetrically distributed. We also capture the deviation between the actual and predicted output and the variability in the transformation process beyond the control of our model by using a constant scalar $\mu$ to rescale $u_{it}$. Finally, $\alpha_i$ and $\nu_{it}$ are the country-specific unobserved effect and the unobserved random effect, respectively.

Taking natural log on both sides of Equation (3), we have

$$\ln EW_{it} = \alpha_i + \beta_1 ER_{it} + \beta_2 TI_{it} + \mathbf{CV_{it}}\boldsymbol{\rho}' + \ln[\phi(Z_{it}\gamma)]u_{it} + \tau_{it} \tag{4}$$

where $\tau_{it} = \varepsilon_{it} + \frac{1}{\mu}\ln[\phi(Z_{it}\gamma)](\mu_{it} - \mu)$ and $\mu = E(\mu_{it})$. Next, we subtract the time average of each variable and remove the country-specific effect from the data and within-country variations.

$$\begin{aligned}\ln EW_{it} - \frac{1}{T_i}\sum_{p=1}^{T_i}\ln EW_{ip} = {} & \beta_1\left(ER_{it} - \frac{1}{T_i}\sum_{p=1}^{T_i}ER_{ip}\right) + \beta_2\left(TI_{it} - \frac{1}{T_i}\sum_{p=1}^{T_i}TI_{ip}\right)\\ & + \left(\mathbf{CV_{it}} - \frac{1}{T_i}\sum_{p=1}^{T_i}\mathbf{CV_{ip}}\right)\boldsymbol{\rho}'\\ & + \left(\ln[\phi(Z_{it}\gamma)] - \frac{1}{T_i}\sum_{p=1}^{T_i}\ln[\phi(Z_{ip}\gamma)]\right)\\ & + \left(\tau_{it} - \frac{1}{T_i}\sum_{p=1}^{T_i}\tau_{ip}\right)\end{aligned} \tag{5}$$

We can estimate Equation (6) by minimizing the following sum of square errors with respect to the parameter vector $\theta$ as follows:

[1]The 32 SSA countries included in the same are, in alphabetical order, Benin, Burkina Faso, Burundi, Cape Verde, Cameroon, Comoros, Democratic Republic of Congo, Congo Republic, Cote d'Ivoire, Ethiopia, Gambia, Ghana, Guinea-Bissau, Guinea, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, South Africa, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

$$Q_{NT}(\theta)=\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(\ln\tilde{EW}_{it}-\beta_1\tilde{ER}_{it}-\beta_2\tilde{TI}_{it}-\tilde{\mathbf{CV}}_{\mathbf{it}}\boldsymbol{\rho}'-\ln\left[\frac{\sigma(Z_{it}\gamma)}{\prod_{p=1}^{T_i}\sigma(Z_{ip}\gamma)}\right]\right) \tag{6}$$

where $\theta=(\beta_1,\beta_2,\boldsymbol{\rho}')$ is a $(K\times1)$ parameter vector, which can be estimated by the nonlinear least squares estimator.

### 3.3 | Logistic quantile regression

We conclude our analysis by considering the logistic quantile regression, which accounts for the anticipated probabilities of success related to environmental regulations, technological innovation, and environmental well-being within SSA. Given the substantial heterogeneity in this region, this technique provides information on the regulation–technology–environment nexus in different quantiles of the distribution or thresholds (Abdulqadir, 2021). By assessing the relationships across different quantiles, we capture potential nonlinearities that might affect the nexus (Abdulqadir, 2023a). Specifically, we draw inspiration from Bottai et al. (2010) and propose the following model specification:

$$\Pr(EW_{it}\le q)=\frac{b[\alpha_i(q)+\beta_1(q)ER_{it}+\beta_2(q)TI_{it}+CV_{it}\rho'(q)+\varepsilon_{it}]+a}{1+\exp[\alpha_i(q)+\beta_1(q)TI_{it}+\beta_2(q)ER_{it}+CV_{it}\rho'(q)+\varepsilon_{it}]} \tag{7}$$

where $\Pr(EW_{it}\le q)$ is the probability that environmental well-being is less than or equal to the specified quantile $q$, with the parameters $a$ and $b$ being the lower and higher bound for $q$, respectively. The logistic transformation restricts the predicted probabilities between zero and one. The coefficients $\beta_1,\beta_2$, and $\boldsymbol{\rho}'$ represent the quantile-specific estimates, which capture the effect of environmental regulations, technological innovation, and control variables on the distribution of environmental well-being in SSA.

## 4 | RESULTS

### 4.1 | Benchmark results

Table 2 presents the results for Equation (1) under the OLS, GEE, and GLS estimators. In general, the coefficient on *PIES* in columns (1)–(6) is statistically significant at the 5% level or better, suggesting that stronger policies and institutions for environmental sustainability reduce carbon emissions and raise renewable energy usage in SSA. In

**TABLE 2** The effect of environmental regulations and technological innovation on environmental well-bring, by estimator.

| | OLS (1) *CO2* | GEE (2) *CO2* | GLS (3) *CO2* | OLS (4) *REC* | GEE (5) *REC* | GLS (6) *REC* |
|---|---|---|---|---|---|---|
| *PIES* | −0.509 (0.225) | −0.576** (0.212) | −0.343 (0.243) | 0.322** (0.114) | 0.313** (0.110) | 0.342** (0.130) |
| *PFSI* | −0.966*** (0.257) | −0.899** (0.238) | −0.784*** (0.255) | 0.830** (0.129) | 0.848*** (0.124) | 0.793** (0.143) |
| *ICTGI* | 0.131*** (0.046) | 0.027** (0.045) | 0.434*** (0.034) | 0.043 (0.023) | 0.012** (0.023) | 0.033 (0.010) |
| *ICTSE* | −0.059*** (0.016) | −0.040 (0.015) | −0.023*** (0.098) | −0.021 (0.008) | −0.028 (0.008) | −0.331 (0.009) |
| *NR* | −0.043 (0.035) | 0.011 (0.033) | 0.00 (0.044) | −0.019 (0.017) | −0.035** (0.017) | −0.321 (0.231) |
| *GDP* | 1.134*** (0.035) | −1.265*** (0.035) | 1.1445*** (0.044) | −0.378*** (0.018) | 0.422*** (0.018) | −0.402** (0.020) |
| *POP* | 0.161*** (0.035) | 0.278*** (0.035) | 0.161*** (0.055) | −0.473*** (0.018) | 0.513*** (0.018) | 0.433** (0.034) |
| Constant | −14.014*** (0.370) | −15.506*** (0.379) | −13.045*** (0.035) | 6.223*** (0.186) | 6.705*** (0.194) | 6.242** (0.121) |
| Adjusted-$R^2$ | 0.8632 | | | 0.5632 | | |
| $F(7,705)$ | 635.23 | | | 129.84 | | |
| *p*-value | 0.000 | | | 0.000 | | |
| Wald $\lambda^2(7)$ | | 5100.10 | 4497.09 | | 1021.16 | 919.18 |
| *p*-value | | 0.000 | 0.000 | | 0.000 | 0.000 |
| Number of countries | 32 | 32 | 32 | 32 | 32 | 32 |

*Note*: Cluster-robust standard errors are presented in the parentheses.
***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.

a similar vein, the coefficient on PFSI in columns (1)–(6) is statistically significant at the 5% level or better, indicating that stronger policies for social inclusion reduce carbon emissions and raise renewable energy usage in SSA. The support for policy inclusion aligns with the dimensions of voice and accountability, political stability, and control of corruption (Awosusi et al., 2023; Ganda, 2020; Usman et al., 2022). These factors are considered vital for government effectiveness in policy formulation and implementation, aligning with the pursuit of net-zero greenhouse gas emissions outlined in the Sustainable Development Goals (SDGs). From an economic growth perspective, the study emphasizes the pivotal role of effective policy inclusion in mitigating environmental hazards, drawing on arguments from institutional economics (North, 1990).

In terms of the technology–environment nexus, the coefficient on *ICTGI* in columns (1)–(3) of Table 2 is positive and statistically significant at the 5% level of better, suggesting that the import of ICT goods reduces carbon emissions. This result offers anecdotal evidence rejecting the pollution haven hypothesis in which foreign firms may ship outdated technology to exploit the loopholes in their host countries' weak environmental regulations. Meanwhile, the coefficient on ICTSE in columns (1)–(3) is negative and statistically significant at the 5% level or better, indicating that the export of ICT services reduces carbon emissions and is consistent with the view that technological innovation enhances environmental well-being. Overall, our results lend support to Dehghan Shabani and Shahnazi (2019), who suggest that a positive technology–environment nexus can be driven by the importing of ICT goods that enhance energy efficiency in a digitized economy.

Turning to the first of our control variables in Table 2, the coefficient on *NR* in columns (1)–(6) remains statistically insignificant, suggesting that the availability of natural resources influences neither carbon emissions nor renewable energy usage. In terms of *GDP*, its coefficient in columns (1)–(6) remains statistically significant at the 5% level or better. Specifically, it shows that economic growth reduces carbon emissions and raises renewable energy usage. In general, these results suggest that economic expansion generates greater financial resources and opportunities for investing in environmental protection, renewable energy, and sustainability efforts (Hanif et al., 2019). These results offer partial support for the EKC, where higher income levels can be a catalyst for improving environmental well-being in SSA. Third, the coefficient on *POP* in columns (1)–(3) remains positive and statistically significant at the 5% level or better, suggesting that population growth could cause extensive urban sprawl that requires greater resource consumption and damaging delicate ecosystems. However, it is worth noting that the same coefficient in columns (4)–(6) supports the view that a higher population lowers the establishment cost of distributional networks for renewable energy (Rode et al., 2021).

To put our results in context, we focus on the GLS estimates in columns (3) and (6) of Table 2 on the basis that the OLS (columns 1 and 4) and GEE (columns 2 and 5) estimates can be biased and inconsistent. For starters, the coefficient on *PIES* indicates that a 1% enhancement in *PIES* reduces carbon emissions by 0.34% but raises renewable energy usage by 0.36%. Meanwhile, the coefficient on *PFSI* suggests that a 1% enhancement in *PFSI* reduces carbon emissions by 0.78% but raises renewable energy usage by 0.79%. Together, these results support a positive regulation–environment nexus in SSA. Moreover, the stronger impact of social inclusion policies on environmental well-being could be attributed to the public demand for a cleaner environment, forcing many multinational corporations to introduce environmentally sustainable practices in their facilities (Huang et al., 2022). Second, the coefficient on *ICTGI* shows that a 1% increase in *ICTGI* reduces carbon emissions by 0.43%. This positive technology–environment nexus reveals a shift in SSA away from physical resources to information resources that significantly raise energy efficiency, debunking the so-called energy efficiency paradox (Wang & Zhang, 2020). Meanwhile, the coefficient on *ICTSE* indicates that a 1% increase in *ICTSE* reduces carbon emissions by 0.02%. It is worth noting that although the volume of international trade in ICT might be too low to influence renewable energy usage, the coefficient on *ICTGI* and *ICTSE* paints a picture of a positive technology–environment nexus in SSA (Cotula, 2009). Finally, the coefficient on *GDP* suggests that a 1% increase in *GDP* reduces carbon emissions by 1.68% but raises renewable energy usage by 0.40%. However, the coefficient on *POP* indicates that a 1% increase in *POP* raises carbon emissions and renewable energy usage by 0.16% and 0.06%, respectively. In short, we find strong evidence of a positive regulation–technology–environment nexus in SSA.

## 4.2 | The interaction effect of environmental regulations and technological innovations on environmental well-being

In this section, we examine the Porter and van der Linde (1995) conjecture that stronger environmental regulations catalyze technological innovation in SSA by including an interaction term between environmental regulations and technological innovation in Equation (2). For consistency, we use the GLS estimator to estimate Equation (2) and report the results separately for carbon emissions (columns 1–4) and renewable energy usage (columns 5–8) in Table 3. In general, the coefficient on the interaction terms in columns (2)–(4) is negative and statistically significant at the 5% level or better, suggesting that stronger environmental regulations drive innovation in emissions-reduction technologies. Specifically, the coefficient on *PIES*ICTSE* in column (3) shows that the policies and institutions related to environmental sustainability are most effective for encouraging technological innovation embedded in imported goods. Perhaps this result can be attributed to the firms' effort to install imported energy-efficient equipment in their facilities (Martins et al., 2019). Moreover, the coefficient on *PFSI*ICTGI* (column 2) and *PFSI*ICTSE* (column 4) shows that policy for social inclusion encourages more technological innovation in reducing carbon emissions than the policy and institutions related to environmental sustainability (column 3). In part, this result could reflect the public's sentiment in demanding a clean environment, particularly when this demand can be heard through democratic processes (Nguyen & Le, 2022).

Turning to renewable energy usage, columns (5)–(7) of Table 3 show that although the coefficient on *PFSI*ICTGI* and *PFSI*ICTSE* display the correct expected sign, it is statistically insignificant, indicating that environmental regulations do not encourage technological innovation in SSA. The notable exception is column (8), where the coefficient on *PFSI*ICTSE* is statistically significant at all conventional levels, with a 1% increase in *PFSI*ICTSE* raising renewable energy usage by 0.12%. This result reinforces the pivotal role of the policy for social inclusion in shaping technological innovation pertinent to renewable energy usage (Omri & Bel Hadj, 2020). For policymakers, it means that awarding public credentials based on the use of renewable energy in powering ICT services can be a source of national competitive advantage in the world market (Wang et al., 2019).

Overall, Table 3 shows that environmental regulations can be a powerful catalyst for pro-environment technological innovation in SSA, particularly in terms of reducing carbon emissions. However, it also highlights that environmental regulations may not be the best approach for promoting technological innovation pertaining to the adaptation of renewable energy in the region. In terms of the type of environmental regulations, it suggests that the policy for social inclusion might be a better alternative than the policy and institutions related to environmental sustainability in encouraging technological innovation.

## 4.3 | Robustness checks

### 4.3.1 | SPF model

To check the robustness of our benchmark results, we estimate the SPF model by decomposing technical inefficiency into time-invariant (long-run) inefficiency and time-varying (short-run) inefficiency. To understand this decomposition in the context of environmental well-being, we follow Kumbhakar et al. (2012) and report results for the time-invariant and time-varying inefficiency models in panels A and B of Table 4, respectively. In terms of the time-invariant inefficiency model, the coefficient on *PIES* and *PFSI* in both columns of panel A is statistically significant at the 5% level or better. Specifically, the estimated coefficients suggest that well-designed and enforced environmental regulations reduce carbon emissions and raise renewable

**TABLE 3** The interaction effect of environmental regulations and technological innovation on environmental well-being, by interaction term.

| | *CO2* | | | | *REC* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *PIES*ICTGI* | −0.011<br>(0.036) | | | | 0.820<br>(0.391) | | | |
| *PFSI*ICTGI* | | −0.137***<br>(0.038) | | | | 1.294<br>(0.506) | | |
| *PIES*ICTSE* | | | −0.093***<br>(0.009) | | | | 0.124<br>(0.058) | |
| *PFSI*ICTSE* | | | | −0.026***<br>(0.003) | | | | 0.123***<br>(0.022) |
| *PIES* | 0.569<br>(0.255) | 0.409***<br>(0.087) | 0.439***<br>(0.078) | 0.159***<br>(0.021) | −2.557<br>(1.673) | 0.896***<br>(0.167) | 0.952***<br>(0.167) | 0.899***<br>(0.164) |
| *PFSI* | −1.151***<br>(0.098) | −0.032<br>(0.330) | −1.182***<br>(0.090) | −1.061***<br>(0.091) | −2.135***<br>(0.197) | −7.640***<br>(2.185) | −2.169***<br>(0.200) | −2.245***<br>(0.194) |
| *ICTGI* | 0.002<br>(0.017) | 0.002<br>(0.017) | 0.735***<br>(0.071) | 0.391***<br>(0.080) | 0.080<br>(0.034) | 0.081<br>(0.034) | −0.420<br>(0.233) | 0.111***<br>(0.034) |
| *ICTSE* | −0.041***<br>(0.006) | −0.038***<br>(0.006) | −0.039***<br>(0.006) | 0.043<br>(0.017) | −0.085***<br>(0.012) | −0.085***<br>(0.012) | −0.088***<br>(0.012) | −0.610***<br>(0.095) |
| *NR* | −0.034<br>(0.013) | −0.042***<br>(0.013) | −0.019<br>(0.012) | −0.050***<br>(0.012) | −0.051<br>(0.027) | −0.026<br>(0.030) | −0.062*<br>(0.026) | −0.063<br>(0.025) |
| *GDP* | 0.006<br>(0.021) | 0.011<br>(0.020) | 0.019<br>(0.019) | 0.034<br>(0.020) | 0.621***<br>(0.034) | 0.637***<br>(0.033) | 0.630***<br>(0.033) | 0.604***<br>(0.033) |
| *POP* | 0.418***<br>(0.013) | 0.411***<br>(0.013) | 0.381***<br>(0.013) | 0.369***<br>(0.013) | 0.481***<br>(0.037) | 0.467***<br>(0.037) | 0.480***<br>(0.037) | 0.546***<br>(0.039) |
| Constant | 1.390***<br>(0.396) | 0.212<br>(0.430) | 0.605<br>(0.238) | −1.873***<br>(0.411) | −1.299<br>(2.161) | 1.357<br>(2.808) | −4.897***<br>(0.589) | 3.748***<br>(1.772) |
| Wald $\lambda^2(8)$ | 2250.19 | 2050.23 | 2302.43 | 2400.21 | 2712.50 | 2851.22 | 885.37 | 1054.43 |
| *p*-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note*: Cluster-robust standard errors are presented in the parentheses.
***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.

**TABLE 4** SPF results, by type of inefficiency model.

| | (1) *CO2* | (2) *REC* |
|---|---|---|
| Panel A. Time-invariant inefficiency model (long run) | | |
| *PIES* | −0.576** | 0.310** |
| | (0.212) | (0.109) |
| *PFSI* | −0.899*** | −0.850*** |
| | (0.238) | (0.124) |
| *ICTGI* | 0.027 | −0.009 |
| | (0.046) | (0.024) |
| *ICTSE* | −0.040** | −0.028*** |
| | (0.015) | (0.008) |
| *NR* | −0.011 | −0.036 |
| | (0.034) | (0.017) |
| *GDP* | 1.265*** | −0.427*** |
| | (0.036) | (0.019) |
| *POP* | −0.278*** | 0.518*** |
| | (0.035) | (0.019) |
| Constant | −14.755*** | 6.872*** |
| | (0.513) | (0.210) |
| Wald $\lambda^2(7)$ | 4631.56 | 416.74 |
| *p*-value | 0.000 | 0.000 |
| Panel B. Time-varying inefficiency model (short run) | | |
| *PIES* | −0.316*** | 0.311** |
| | (0.004) | (0.109) |
| *PFSI* | −0.548*** | −0.856*** |
| | (0.005) | (0.124) |
| *ICTGI* | 0.023 | −0.006 |
| | (0.037) | (0.024) |
| *ICTSE* | −0.010*** | −0.029*** |
| | (0.038) | (0.008) |
| *NR* | −0.121*** | −0.036 |
| | (0.047) | (0.017) |
| *GDP* | 1.036*** | −0.426*** |
| | (0.057) | (0.019) |
| *POP* | −0.113*** | 0.517*** |
| | (0.077) | 0.019 |
| Constant | −14.042*** | 6.864*** |
| | (0.087) | (0.210) |
| Wald $\lambda^2(7)$ | 212.83 | 5379.45 |
| *p*-value | 0.000 | 0.000 |

*Note*: Cluster-robust standard errors are presented in the parentheses.
***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.

energy usage. For policymakers, this result reinforces the idea that strong economic institutions and incentives are part and parcel of the decarbonization effort (Bakhsh et al., 2017; Caglar & Mert, 2022; Ren et al., 2021). However, it is worth noting that the coefficient on *PFSI* in column (2) is negative and statistically significant, implying that the policy for social inclusion discourages renewable energy usage. Perhaps this result could reflect the public's hesitancy toward the uncertainties over the reliability and cost of renewable energy sources (Byaro et al., 2022; Kwakwa, 2021; Zhou et al., 2020). In short, these results imply a positive regulation–environment nexus in the long run.

Turning to the coefficient on *ICTSE* in panel A of Table 4, it is negative and statistically significant at the 5% level of better. Specifically, column (1) shows that a 1% increase in *ICTSE* reduces carbon emissions by 0.04% in SSA. In part, this decarbonization benefit could reflect energy efficiency and technological advancement embedded in the export of ICT services. However, the coefficient of *ICTSE* in column (2) is negative and statistically significant, with a 1% increase in *ICTSE* reducing renewable energy usage by 0.03% in the region. One possible reason could be attributed to the lack of renewable energy infrastructure in the region (Asongu & Le Roux, 2017; Danish et al., 2018). Overall, these results lend support to a positive technology–environment nexus in the long run.

Finally, the coefficient on *GDP* and *POP* in panel A of Table 4 is statistically significant at all conventional levels. In column (1)–(2), the coefficient on *GDP* shows that a 1% increase in *GDP* raises carbon emissions by 1.23% but reduces renewable energy usage by 0.43% in the long run. In general, these mixed results could reflect that higher economic growth might increase the demand for fossil fuels at the expense of renewable energy sources, contributing to a rising level of carbon emissions. Policymakers can avert this worrying trend by continuing the effort to promote sustainable development rather than growing the economy at all costs. Meanwhile, the coefficient on *POP* reports that a 1% increase in *POP* reduces carbon emissions by 0.28% but raises renewable energy usage by 0.52% in the long run. These results are in line with the view that population growth can lower the establishment cost of renewable energy infrastructure and shift the energy demand away from non-renewable energy sources, reducing carbon emissions over time.

For completeness, we also report the time-varying inefficiency results in panel B of Table 4. In theory, these results resemble the short-run dynamics, which must be qualitatively similar to their long-run counterparts reported in panel A (Kumbhakar et al., 2012). A visual inspection of columns (1)–(2) of panel B reveals that all coefficients display the same sign and share similar statistical significance as their counterparts in panel A.

### 4.3.2 | Logistic quantile results

We employ the logistic quantile regressions proposed by Bottai et al. (2010) because it is less sensitive to the presence of extreme values and capable of handling heteroscedasticity across observations. These features are particularly relevant to SSA, which is renowned for substantial regional heterogeneity in its economic development, political system, and cultural diversity that could yield possible nonlinearities in the technology–regulation–environment nexus (Manu et al., 2022). To account for this possibility, we divide our sample into four quantiles (25th, 50th, 75th, and 95th) and report the logistic quantile results in Table 5. In terms of the regulation–environment nexus, the coefficient on *PIES* is negative and statistically significant at the 5% level or better in columns (1)–(2), indicating that a 1% increase in *PIES*

**TABLE 5** Logistic quantile results.

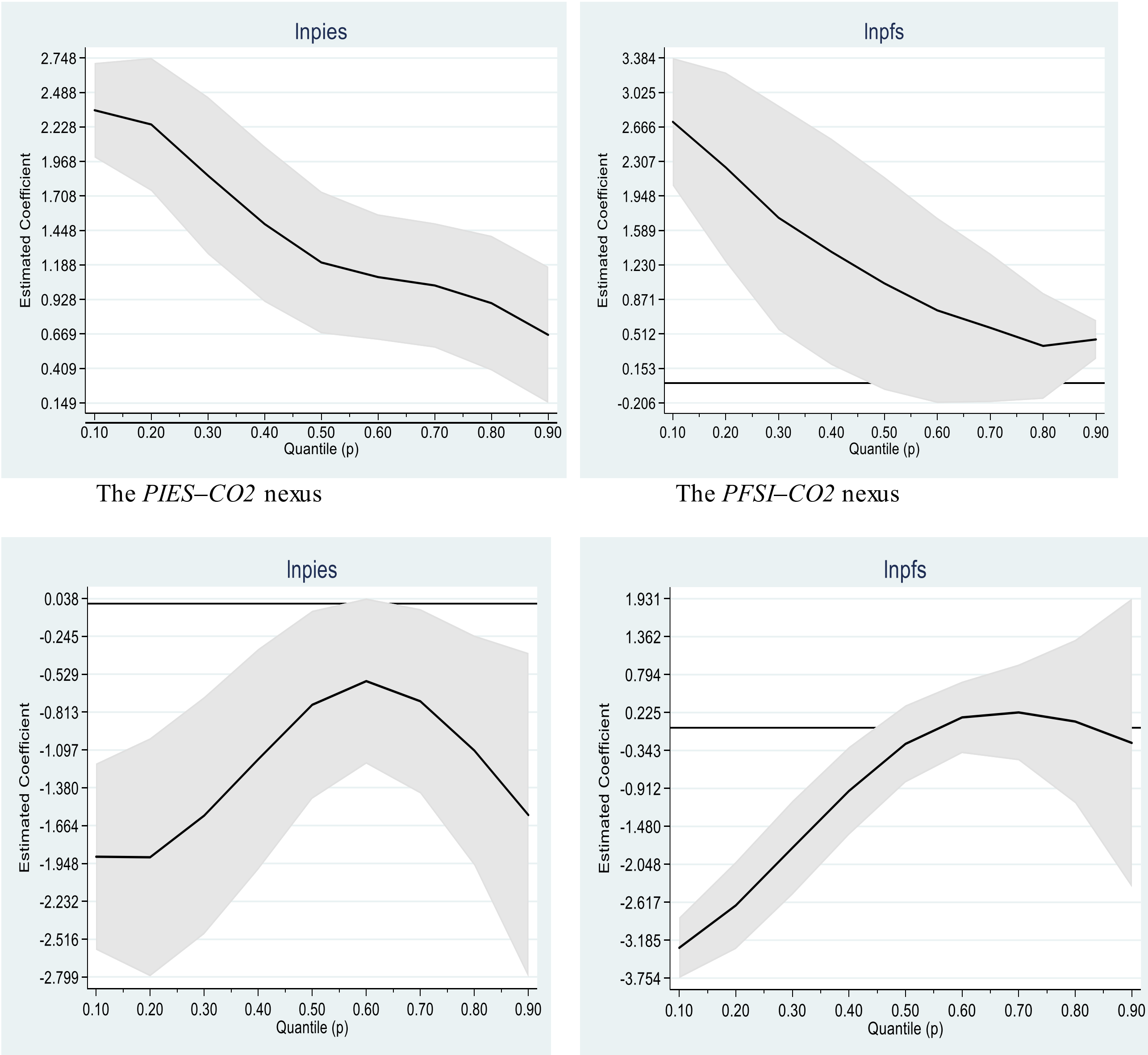
| | CO2 | | | | REC | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | q25 | q50 | q75 | q95 | q25 | q50 | q75 | q95 |
| *PIES* | −0.575*** | −0.356** | 0.017 | −0.839 | −0.191 | −0.768 | 0.010 | −0.957 |
| | (0.174) | (0.122) | (0.152) | (0.478) | (0.439) | (0.352) | (0.325) | (0.375) |
| *PFSI* | −0.479*** | 0.042 | −0.286 | 0.084 | −1.107 | −0.776 | −1.812** | −0.990 |
| | (0.171) | (0.145) | (0.314) | (0.481) | (0.528) | (0.491) | (0.525) | (0.725) |
| *ICTGI* | −0.078*** | −0.073 | 0.058 | 0.163 | 0.118 | 0.321** | 0.289** | 0.023 |
| | (0.037) | (0.030) | (0.047) | (0.105) | (0.103) | (0.081) | (0.095) | (0.162) |
| *ICTSE* | −0.011 | −0.031 | −0.059*** | −0.027 | 0.026 | 0.060 | 0.072** | 0.118 |
| | (0.015) | (0.012) | (0.015) | (0.044) | (0.019) | (0.030) | (0.025) | (0.053) |
| *TNR* | 0.03 | −0.007 | −0.034 | 0.050 | 0.219*** | 0.167 | 0.183** | 0.255 |
| | (0.025) | (0.022) | (0.027) | (0.088) | (0.046) | (0.065) | (0.070) | (0.137) |
| *GDP* | 0.522*** | 0.540*** | 0.663*** | 1.271*** | −1.187*** | −0.746*** | −0.926*** | −0.644** |
| | (0.032) | (0.025) | (0.069) | (0.118) | (0.121) | (0.066) | (0.085) | (0.214) |
| *POP* | 0.013 | −0.032 | −0.157** | −0.5351*** | 1.460*** | 1.179*** | 1.331*** | 1.094*** |
| | (0.036) | (0.019) | (0.054) | (0.111) | (0.100) | (0.054) | (0.103) | (0.226) |
| Constant | −12.607*** | −12.061*** | −11.446*** | −18.6451*** | 6.515*** | 2.259** | 4.959*** | 4.140*** |
| | (0.216) | (0.376) | (0.779) | (1.556) | (1.248) | (0.828) | (0.652) | (0.226) |

*Note*: Cluster-robust standard errors are presented in the parentheses.
***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.

reduces carbon emissions by 0.58% and 0.36% for the 25th and 50th quantiles, respectively. Meanwhile, the coefficient on *PFSI* is negative and statistically significant in columns (1) and (7), with a 1% increase in PFSI reducing carbon emissions by 0.48% in the 25th quantile and renewable energy usage by 1.81% in the 75th quantile. These mixed results suggest that stronger environmental regulations need not necessarily enhance environmental well-being (Lu, 2018; Ren et al., 2021). For policymakers, this result implies nonlinearities in the regulation–environment nexus and highlights the need to constantly revise their environmental regulations over time.

Turning to the technology–environment nexus, the coefficient on *ICTGI* is only negative and statistically significant at all conventional levels in columns (1) but positive and statistically significant at 5% level or better in columns (6)–(7) of Table 5. Specifically, a 1% increase in *ICTGI* reduces carbon emission by 0.08% in the 25th quantile but raises renewable energy usage by 0.32% and 0.29% in the 50th and 75th quantiles. Meanwhile, the coefficient on *ICTSE* is only negative and statistically significant in column (3) and only positive and statistically significant in column (7). Quantitatively, a 1% increase in *ICTSE* reduces carbon emissions by 0.06% but raises renewable energy usage by 0.07% in the 75th quantile. Qualitatively, these figures provide partial support to the argument that technological innovation enhances environmental well-being and national competitiveness in the world market (Shen et al., 2023; Wang et al., 2019). In short, a cursory glance at these results confirms nonlinearities in the technology–environment nexus. For policymakers, these mixed results suggest that the greatest environmental benefits of technological innovation occur at the 75th quantile. Moreover, as a catalyst for renewable energy adaptation, technological innovation is most likely to succeed between the 50th and 75th quantiles (Li & Taeihagh, 2020; Omri & Bel Hadj, 2020).

A useful representation of nonlinearities in the regulation–technology–environment nexus is to follow the change in the magnitude of the estimated coefficient on environmental regulations and technological innovation over quantiles. For example, Figure 1 shows the effect of environmental regulations on environmental well-being in SSA. Specifically, panel A shows that the effect of *PIES* on carbon emissions diminishes at higher quantiles, suggesting that policymakers must carefully calibrate the strength of environmental regulations to avoid potential negative effects at the upper end of the cumulative distribution. Interestingly, panel B shows a rebound effect in the *PFSI–CO2* nexus around the 80th quantile, indicating a trade-off between social inclusion efforts and carbon emissions reduction. Potentially, this effect could reflect the negative influences that energy injustice exerts on decarbonization, particularly when there are multiple competing developmental goals in the country (Duodu et al., 2021; Musah et al., 2020). Meanwhile, panels C and D depict the *PIES–REC* and *PFIS–REC* nexuses. Broadly, it shows that the positive effect of environmental regulations on renewable energy usage peaks around the 50th–60th quantile before waning away. One plausible explanation for this inverted U-shaped relationship could be attributed to the fact that providing financial incentives might be a more effective means than environmental regulations in pushing the economy toward full renewable energy adaptation (Cia Alves et al., 2019). Overall, these trends indicate that policymakers in SSA must take into account the dynamic and nonlinearity of the regulation–environment nexus when designing environmental regulations.




The *PIES–CO2* nexus

The *PFSI–CO2* nexus

The *PIES–REC* nexus

The *PFSI–REC* nexus

**FIGURE 1** The logistic quantile results for the regulation–environment nexus, by quantile.

In a similar vein, Figure 2 depicts the effect of technological innovation on environmental well-being in SSA. Specifically, panel A shows that *ICTGI* reduces carbon emissions before the 50th quantile but raises emissions afterward. In part, this trend could provide anecdotal evidence for the pollution haven hypothesis, whereby the imported technology contributes rather than lessens carbon emissions at the higher quantiles (Wang et al., 2019). In contrast, panel B shows a U-shaped *ICTSE–CO2* nexus, suggesting that technological innovation in ICT exports reduces carbon emissions before reaching the turning point around the 70th quantile, possibly because of the asymmetric increase in energy demand fulfilled by non-renewable energy sources (Cho et al., 2007). Meanwhile, panels C and D show that *ICTGI* and *ICTSE* initially raise renewable energy usage before plateauing out around the 60th quantile. Intuitively, these trends suggest that the technological innovation embedded in the imported ICT goods and exported ICT services strengthens the absorptive capacity of renewable energy, making it an effective catalyst for renewable energy adaptation (Manu et al., 2022). Taken together, this dynamic and nonlinear technology–environment nexus suggests that policymakers in SSA must embrace and invest in technological innovation if their goal is to encourage renewable energy adaptation over time.

## 5 | DISCUSSION AND IMPLICATIONS

We investigated the regulation–technology–environment nexus in SSA for the 2000–2022 period. Using the GLS, SPF, and logistic quantile estimators, we found that policies and institutions geared toward

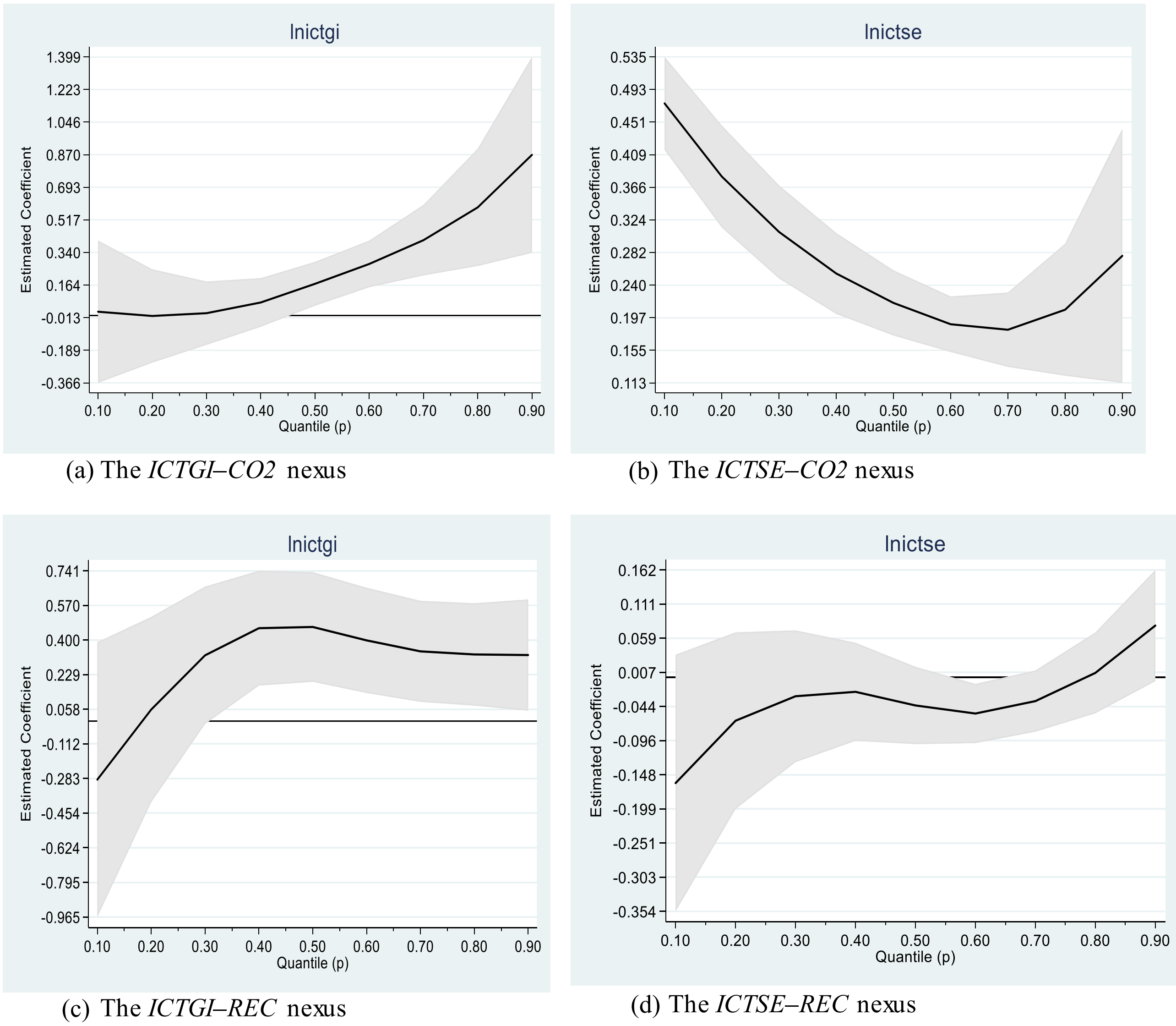



**FIGURE 2** The logistic quantile results for the technology–environment nexus, by quantile.

environmental sustainability enhance environmental well-being. However, we showed that policies aimed at social inclusion did not always exert a positive impact on environmental well-being. In terms of technological innovation, we found that such innovation generally reduces carbon emissions and promotes renewable energy usage. Moreover, we presented evidence that stronger environmental regulations drove technological innovation. Finally, and for the very first time in the extant literature, we showed that the regulation–technology–environment nexus in SSA is dynamic and nonlinear, ruling out one-size-fits-all approaches toward environmental sustainability.

## 5.1 | Theoretical implications

Our findings for SSA aligned with Porter and van der Linde (1995), who posited that a well-designed environmental regulatory framework enhances national competitiveness and environmental well-being. Second, we demonstrated that the regulation–technology–environment nexus is far from uniform in the region, suggesting that contextual factors, such as economic conditions, governance structures, and institutional capacity, matter. Third, we identified the interaction between environmental regulations and technological innovation to be a key driving force behind the nexus, emphasizing the need to formulate pro-innovation environmental regulations. Fourth, we highlighted the absorptive capacity to be a deterministic factor for internalizing the benefits of environmental regulation and technological innovation in the region. Finally, our control variables emphasize that environmental well-being is not solely a regulatory and technological concern but also an economic one.

## 5.2 | Practical implications

Our findings suggest that policymakers should take an interdisciplinary approach to address sustainable development in SSA. For example, over-emphasizing policies for social inclusion might adversely influence environmental well-being, underscoring the complexity of crafting policies that address multiple dimensions of economic well-being while considering potential trade-offs between them. Moreover, the differential impacts of policies and institutions related to environmental sustainability and policies for social inclusion on carbon emissions and renewable energy usage reinforce the need for balanced environmental and social considerations to achieve equitable outcomes. Similarly, our results highlight the import of ICT goods raises carbon emissions and renewable energy usage, but the export of ICT services reduces carbon emissions and renewable energy usage, calling for carefully calibrated industrial upgrading programs that reduce carbon emissions and boost renewable energy adaptation over time.

### 5.3 | Limitations and future research directions

Constrained by data availability, our study focused on SSA. However, it will be interesting for future studies to analyze regional trading blocs, such as the East African Community, the Economic Community of West African States, or the Southern African Development Community. Studies on these blocs can shed light on topical debates like the pollution haven hypothesis and the effect of trade on the turning point of the EKC. Next, given the asymmetric responses to environmental regulations, it will be insightful to examine the regulation–technology–environment nexus by combining firm-level information and geospatial data. Last but not least, mixed-method research like interviews and surveys engaging local communities, policymakers, and stakeholders can provide a better context for the evolution of the regulation–technology–environment nexus.

## CONFLICT OF INTEREST STATEMENT

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.

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## APPENDIX A

**TABLE A1** Summary statistics, by variable.

| Variable | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|
| *CO2* | 7.932 | 1.724 | 3.980 | 13.013 |
| *REC* | 4.168 | 0.486 | 2.044 | 4.588 |
| *PIES* | 1.180 | 0.166 | 0.288 | 1.846 |
| *PFSI* | 1.195 | 0.147 | 0.405 | 1.504 |
| *ICTGI* | 1.196 | 0.547 | −1.167 | 2.509 |
| *ICTSE* | 16.817 | 1.873 | 10.015 | 20.665 |
| *TNR* | 1.952 | 0.749 | 0.205 | 3.896 |
| *GDP* | 22.938 | 1.647 | 18.146 | 27.076 |
| *POP* | 16.236 | 1.525 | 11.876 | 19.202 |

**TABLE A2** The correlation coefficient matrix.

| | *CO2* | *REC* | *PIES* | *PFSI* | *ICTGI* | *ICTSE* | *NR* | *GDP* | Tolerance | VIF |
|---|---|---|---|---|---|---|---|---|---|---|
| *CO2* | 1.000 | | | | | | | | 14.970 | 0.067 |
| *REC* | −0.273 | 1.000 | | | | | | | 4.460 | 0.224 |
| *PIES* | 0.295 | −0.161 | 1.000 | | | | | | 2.610 | 0.383 |
| *PFSI* | 0.224 | −0.241 | 0.748 | 1.000 | | | | | 3.180 | 0.315 |
| *ICTGI* | 0.229 | −0.079 | 0.127 | 0.225 | 1.000 | | | | 1.150 | 0.872 |
| *ICTSE* | 0.514 | −0.168 | 0.184 | 0.252 | 0.241 | 1.000 | | | 1.880 | 0.531 |
| *TNR* | −0.042 | 0.198 | −0.055 | 0.043 | −0.053 | 0.007 | 1.000 | | 1.140 | 0.876 |
| *GDP* | 0.923 | −0.079 | 0.319 | 0.285 | 0.226 | 0.600 | 0.009 | 1.000 | 14.880 | 0.067 |
| *POP* | 0.774 | 0.275 | 0.232 | 0.219 | 0.215 | 0.497 | 0.170 | 0.876 | 13.090 | 0.076 |

**TABLE A3** Cointegration tests.

| | Statistics | Cointegration |
|---|---|---|
| **Kao** | | |
| Modified Dickey–Fuller test | 0.331 | No |
| Dickey–Fuller test | 2.398** | Yes |
| Augmented Dickey–Fuller test | 0.701 | No |
| Unadjusted modified Dickey–Fuller test | 0.596 | No |
| Unadjusted Dickey–Fuller test | 2.621** | Yes |
| **Pedroni** | Statistics | *p*-value |
| Modified Phillips–Perron test | 6.266*** | Yes |
| Phillips–Perron test | −3.439*** | Yes |
| Augmented Dickey–Fuller test | −1.093 | No |

***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.

**TABLE A4** Cross-sectional dependence and unit root tests.

| | Cross-sectional dependence test | | CIPS | |
|---|---|---|---|---|
| | Test statistics | Cross-sectional dependence? | First difference | Stationary? |
| *CO2* | 36.559*** | Yes | −4.178*** | Yes |
| *REC* | 32.137*** | Yes | −3.830*** | Yes |
| *PIES* | 58.7*** | Yes | −3.814*** | Yes |
| *PFSI* | 63.2*** | Yes | −3.918*** | Yes |
| *ICTGI* | 61.7*** | Yes | −5.346*** | Yes |
| *ICTSE* | 54.0*** | Yes | −4.315 *** | Yes |
| *TNR* | 64.7*** | Yes | −4.131*** | Yes |
| *GDP* | 21.7*** | Yes | −5.034*** | Yes |
| *POP* | 1.800* | Yes | −1.328*** | Yes |

***The rejection of the null hypothesis at the 1% level of significance.
**The rejection of the null hypothesis at the 5% level of significance.