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Examining the interaction of technology adoption-diffusion and sectoral emission intensity in developing and emerging countries

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ABSTRACT

This study offers a new perspective on the drivers of environmental sustainability for sector level (manufacturing, mining, agriculture, business, trade, and transport) analysis. In this case, country-level sectoral dynamic index for technology adoption and emission intensity were constructed to study the environmental efficiency effect of technology adoption and technology diffusion across tradable and non-tradable sectors by using empirical illustration for 49 developing and emerging countries during 1990–2018 period. By correcting for potential bias arising from endogeneity and cross-border spillover effects via cross-section dependence, results reveal long-term effects of technological changes. Importantly, it is shown that the environmental efficiency effect of technology adoption holds in technology-intensive sectors (i.e manufacturing, mining, agriculture) only at lower capitalization levels, thus establishing a U-shaped nexus of technology adoption and carbon emission. Additionally, it is found that trade networks reduce emission intensities by improving technology diffusion across all the tradable sectors and in transport sector. Moreover, trade alone mitigates carbon intensity across all the sectors while income per capita spur carbon intensity in the tradable sectors. From policy insight, the study identifies the need for stricter policy directives to scale up energy and clean technologies adoption in all sector activities.

1. Introduction

Building on the endogenous technological change theory that technological adoption can promote economic growth, improve energy efficiency and reduce carbon emissions through the substitution of production factors (technical efficiency), this study addresses how changes in the sectoral adoption of technology influence the dynamics of emission intensity across economic sectors. While studies have so far focused on the relationship between overall technological improvement and carbon emission from an aggregate perspective, less is known about their heterogeneous effects from a sectoral perspective. As the development of new and emerging technological breakthrough unfolds, it offers timely opportunities for developing nations to narrow down technological gaps across economic sectors by playing the catching-up effect (Kassouri et al., 2021; World Bank, 2019). Then, it becomes paramount to understand pathways toward a more sustainable structural transformation in emerging and developing economies (EMDEs) given the environmental setback of rapid industrialization.

Several previous papers addressed the relationship between technology and economic growth. For instance (Syrquin, 1988), argued that the process of economic growth can be formally described as the result of capital accumulation and technological change. Following the structuralist perspective of economic growth, Justman and Teubal (1991) emphasized the key role of technological progress in economic growth and of the structural changes that such progress requires. Building on a endogenous technology-driven growth model (Carlaw and Lipsey, 2003), show that technological change is the main trigger of long term economic growth. Overall, these studies established the role of technology change in driving economic growth. At the same time, there has been increasing drive on the close relationship between economic growth and the environment (Grossman and Krueger, 1991). Starting from the direct impact of technology adoption on economic development, theoretically a series of mechanisms through which technology can influence the environment has been advanced in the literature. First, the adoption of technology improves overall work and production efficiency by replacing low-skilled labor force and display a complementary effect on high-skilled labor force (Wadley, 2021). This in turn may reduce the working hours and energy consumption caused by works.

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This can further reduce emission intensity and improve environmental efficiency. However, it is important to know that improvements in production efficiency can also promote industrial output and therefore exacerbate environmental degradation (Shahbaz et al., 2015).

Moreover, by reducing employment in the manufacturing sector (Acemoglu, 1997; Acemoglu et al., 2007), technology can force workers to make disruptive transitions to agriculture and services. The development of technology can lead to the creation of green jobs across sectors (through green agriculture, green technology research and development) which in turn promote green employments while relieving pressure on the environment (Bessen, 2019). Finally, technological innovation is likely to stimulate a transition to sustainable energy systems by providing good solutions for the management and utilization of renewable energy (Altıntaş and Kassouri, 2020; Bilgili et al., 2020). The deployment of renewable energy stemming from technological innovation can effectively curb environmental degradation Olanrewaju et al. (2019); Alola and Saint Akadiri, 2021; Usman et al. (2020). While energy transition and clean technology development are believed to promote energy efficiency and mitigate environmental degradation (Adebayo et al., 2021; Pylaeva et al., 2022; Vaisman et., 2022; Onifade and Alola, 2022). However, the role of technology adoption especially across the sectors of the economy has been sparsely addressed in the literature.

Therefore, the main goal of this paper is to investigate the technology-emission intensity nexus across aggregate economic sectors: (a) the tradable sector, which includes manufacturing, mining, and agriculture; (b) the non-tradable sectors, which include transport, commercial activities, and trade services. For the empirical application, this study considers a sample of 49 EMDEs over the period 1990–2018. Based on the current state of the literature, two hypotheses have been put forward: (i) drawing on a perspective of technology heterogeneity among sectors; it is expected that technology-intensive sectors become more environment-efficient than others, which is consistent with the environmental efficiency effect of technology. The rationale behind this hypothesis is that technological development can improve industrialization and help push the upgrading of the energy structure (Su and Fan, 2022; You and Zhang, 2022). (ii) Inspired by Bin and Jianmao (2000), bilateral trade networks among countries is considered to identify technology diffusion by introducing an interaction term between trade and technology. In this light, the hypothesis that strong trade networks among countries can improve the diffusion of technology needed to mitigate CO_2 emission intensity is tested. Previous studies have confirmed that enhancing cross-border diffusion of new technologies is critical to address environmental problems in developing countries (Bayer and Urpelainen, 2013; Dechezleprêtre et al., 2015). Our paper offers research on the above hypotheses.

Moreover, the research innovation of this paper and the contribution to the literature can be viewed from these distinct aspects. Previous contributions mainly rely on input-output approach to generate emission intensity from a single country perspective (Khan et al., 2020; Majumdar and Kar, 2017). But the current attempt contributes to the literature by providing for the first time a comprehensive measure of emission intensity from the perspective of technology adoption alongside other related indicators for a panel of 49 developing and emerging economies. Importantly, selected African countries are employed as a panel of developing economies for a robustness purpose. The justification for using selected African states is not only because of the fast pace of increasing access to the internet across the continent, but also because the continent still lags far behind other continents in term of technological advancements. Furthermore, this study is approached from a rare perspective of sectoral-based approach by using the value-added dataset to assess the sectoral decarbonization effects of technology adoption. In subsequent section 2, the related literature is discussed which further highlights the existing gap. Following the literature section is section 3 where the data and the empirical strategy of the study are detailed. The discussion of the empirical results with policy significance and the conclusion of the study are highlighted in section 4 and 5 respectively.

2. Brief literature review

Although there has been different argument to both the economic advantages of technology adoption and the assumption about the decision agents (Alola et al., 2021; Chen and Ma, 2021; Fang and Ma, 2021), however, its relationship with environmental indicators such as greenhouse gas (GHG) emissions is well-documented in the literature.

For instance, Lu et al. (2022) investigated whether technology adoption and democracy play any moderating role in the nexus of carbon emission and liberalisation in the panel of 35 Organisation for Economic Cooperation and Development (OECD) countries over the time 1970–2019. The study utilised the interaction of trade policy and democracy (i.e trade policy*democracy) to account for technology adoption and suggests that higher value 'trade policy*democracy' signifies higher rate of technology adoption. Consequently, by using the econometric approaches (fixed-effect and Quantile Regression for Panel Data (QRPD)), the study established that democracy mitigates carbon emission while trade liberalisation spur carbon emission. Importantly, Lu et al. (2022) found that technology adoption (i.e trade policy*democracy) spur carbon emission in the panel of OECD countries. In the work of Mohareb and Kennedy (2014), the case of a developed world city such as the Greater Toronto Area was considered to examine whether technological change is capable of mitigating GHG emission by 80 percent. The study used emissions from the residential buildings, light duty passenger vehicles, and institutional or commercial buildings to establish that higher technology adoption is insufficient at providing 80 percent mitigation of GHG emission by 2050.

Furthermore, electric power utilization and high-technology exports were employed as indicators of technology adoption alongside the technology innovation indicators in the study of Su et al. (2021). While considering the case of the Brazil, Russia, India, China, and South Africa (BRICS) economies, the study found that carbon emission is positively driven by electric power utilization and high-technology exports in BRICS countries. However, there is a relief from the findings, as it further revealed that both technology innovation and technology adoption exhibits inverted U-shaped relationship with carbon emission. On the contrary, a more desirable result was put forward in the study of Hammond et al. (2020). The study investigated the appropriate approach to mitigate GHG emissions (as to attain the 80 percent GHG emissions reduction by 2050) by using the freight sector in Canada as a reference case. While the study revealed that both standards and carbon pricing (which are current scenarios in Canada) and implementation of individual policy are insufficient measures to achieving the 2050 sector GHG emission reduction targets. But, as noted by Hammond et al. (2020), policy combination of technology adoption involving the stringent the use of zero-emissions vehicle and low-carbon fuel standard could help to attain the 80 percent reduction in sector GHG emissions by 2050.

Moreover, Lasisi et al. (2022) and Pylaeva et al. (2022) are another two distinct studies in the context of the current investigation. Specifically, the case of selected economies i.e., Austria, Denmark, Finland, France, Germany, Netherland, Spain, and Sweden, the leading eco-innovation countries were considered in the period 1990–2020. By using the econometric approach of method of moments quantile regression alongside Granger causality approach, the study reveals that environmental technologies spur economic growth when other factors such as environmental-related technological innovations and oil consumption are controlled. Additionally, with or without the moderating effect of environmental technologies, it is observed that oil consumption also promotes economic growth in the examined panel of eco-innovation countries. Contrarily, a disservice effect of environmental-related technological innovations is observed as economic growth is hindered by increase in the development of environmental-related technological innovations. Similar to Lasisi et al. (2022) but more business-related, Pylaeva et al. (2022) found that implementation of technological development by small and medium enterprises (SMEs) enhances gross profit and asset management as it causes a decline in resource costs of production. Meanwhile, the drivers of environmental-related indicators have been studied under different framework in the literature (Bekun et al., 2019; Anser et al., 2021; Umar et al., 2021).

3. Data and estimation strategy

To study the technology-emission intensity nexus over the stipulated period 1990–2018 for the listed countries (see Table A1), the dataset real GDP per capita, capital stock, and population were obtained from the Penn World Table version 10.0 database. Additionally, total CO_2 emissions was obtained from World Development Indicators. The value-added data of agriculture, manufacturing, mining, trade services, transport services, and business services were retrieved from the Economic Transformation database by (de Vries et al., 2021) and bilateral trade data from World Trade Organization database by (Monteiro, 2020). Specifically, Table 1 provides a description of the dataset. Additionally, Figs. 1 and 2 show that technology adoption and emission intensities display upward trends over our sample period, with higher levels of emission intensity in the transport and mining sectors. The statistical properties of the dataset are displayed in appendix alongside the cross-sectional dependency (CSD) test in Tables 2 and 3 respectively. From the descriptive statistics, it shows that control variable 'Trade' has the highest deviation from the mean followed by emission intensity in the mining sector and emission intensity in the manufacturing sector. Moreover, there is evidence of cross-sectional dependence as illustrated by the result displayed in Table 3.

3.1. Estimation strategy

Given the priori information from the CSD test, the investigation proceeds to employ the advantage of cross-sectional autoregressive distributed lag (CS-ARDL) approach because of its appropriateness. Importantly, the CS-ARDL is found to be appropriate in examining dataset with mixed order of integration, at least not more than I (1). Additionally, this estimation technique offers long-run elasticity for the relationship between the regressor and regressed. Moreover, in the literature, there are other advantages that are associated with the choice of the CS-ARDL, such as robustness to potential bias arising from endogeneity and cross-border spillover effects (cross-section dependence) and heterogeneity across countries. However, one of the key limitations of this estimation approach is in the aspect of heterogeneous slope specifications. Specifically, long-run coefficient estimates with CS-ARDL could be sensitive to outlier estimates of the long-run effects for individual countries (Chudik and Pesaran, 2015).

Nevertheless, to examine the long-run effects of technology on emission intensity, the CS-ARDL approach is considered appropriate, thus its implementation follows this model:

Table 1
Variable description.

Variable	Description
Capital stock	Capital stock at constant 2017 national prices (in mil. 2017US$)
Labor	Number of persons engaged (thousands)
CO_2 emissions	Total CO_2 emissions (metric tons per capita)
Real GDP per capita	Real GDP at constant 2017 national prices (in mil. 2017US$)
Population	Population (in millions)
Value added	Gross value added at constant 2015 prices (millions, local currency)
Trade	Domestic trade flows are computed as the difference between gross output and exports of manufacturing goods

$$\Delta E_{ijt} = \alpha_i + \sum_{l=1}^{P} \gamma_{il} \Delta E_{ijt-l} + \sum_{l=0}^{P} \varnothing_{il} \Delta X_{ijt-l} + \sum_{l=0}^{Q} a_{il} \overline{\Delta E_{it-l}} + \sum_{l=0}^{Q} b_{il} \overline{X_{it-l}} + v_{ijt} \tag{1}$$

where $E_{ijt} = \frac{CE_{it}}{VA_{ijt}}$ represents emission intensity as proposed by Randers (2012), i.e. total carbon emission (CE) per unit of value-added (VA) in sector i of country j in year t. X_{ijt} is a vector of explanatory variables, including technology adoption measured by the capital (k_{jt}) labor (L_{ijt}) ratio ($\frac{k_{jt}}{L_{ijt}}$) as suggested in Majumdar and Kar (2017); real GDP per capita; population, and trade among countries. $\overline{E_{it}}$ and $\overline{X_{it}}$ are the cross-section averages of E_{ijt} and X_{ijt}. The Schwarz criterion were used to select the optimal lag orders (and Q). v_{ijt} is the error term. Building on (Tase, 2019), we measure sectoral dynamics (D_{ijt}) of technology adoption and emission intensity as follows:

$$D_{ijt} = \frac{1}{n} \Sigma_i \left| \pi_{ijt} - \pi_{ijt-1} \right| \tag{2}$$

where π_{ijt} denotes the sector (i) share of emission intensity and technology adoption in the country (j) at time (t). The complete illustration of the CS-ARDL approach is not captured here because of its wide coverage in the literature and for space constraint.

3.1.1. Empirical estimations

To achieve the objective of the study, the CS-ARDL method is applied for different country groups and constructed models (for the main sectors, service sectors, and for interaction term) are categorized as follows.

3.1.1.1. For the main (tradable) sectors. **Model 1a**: Sectoral emission intensity (in manufacturing, mining, agriculture sectors) = f (GDP per capita, population, trade, technology adoption) for entire panel.

Model 1b: Sectoral emission intensity (in manufacturing, mining, agriculture sectors) = f (GDP per capita, population, trade, technology adoption, square of technology adoption) for entire panel.

3.1.1.2. For the (non-tradable) service sectors. **Model 2a:** Sectoral emission intensity (in trade, business, transport services) = f (GDP per capita, population, trade, technology adoption) for entire panel.

Model 2b: Sectoral emission intensity (in trade, business, transport services) = f (GDP per capita, population, trade, technology adoption, square of technology adoption) for entire panel.

3.1.1.3. For the interaction term. **Model 3a:** Sectoral emission intensity (in manufacturing, mining, agriculture, trade, business, transport services) = f (GDP per capita, population, trade, technology adoption, trade*technology adoption) for entire panel.

Model 3b: Sectoral emission intensity (in manufacturing, mining, agriculture, trade, business, transport services) = f (GDP per capita, population, trade, technology adoption, trade*technology adoption) for panel of African countries.

Where in all the aforementioned models, technology adoption is estimated and represented as (K/L), such that the square of technology adoption = (K/L) ˆ2, and technology diffusion is trade*technology adoption = trade*(K/L). Importantly, the study seeks to illustrate whether there is a turning point in the relationship between technology adoption and sectoral emission intensity i.e whether there is a U-shaped or inverted U-shaped relationship between duo.

4. Discussion of the results

The results from the model 1 and 2 (for tradable and non-tradable sectors) are first discussed. From Table 4, especially in Model 1A (without interaction), it is observed that the measure of technology adoption (K/L) shows a negative and significant impact on emission

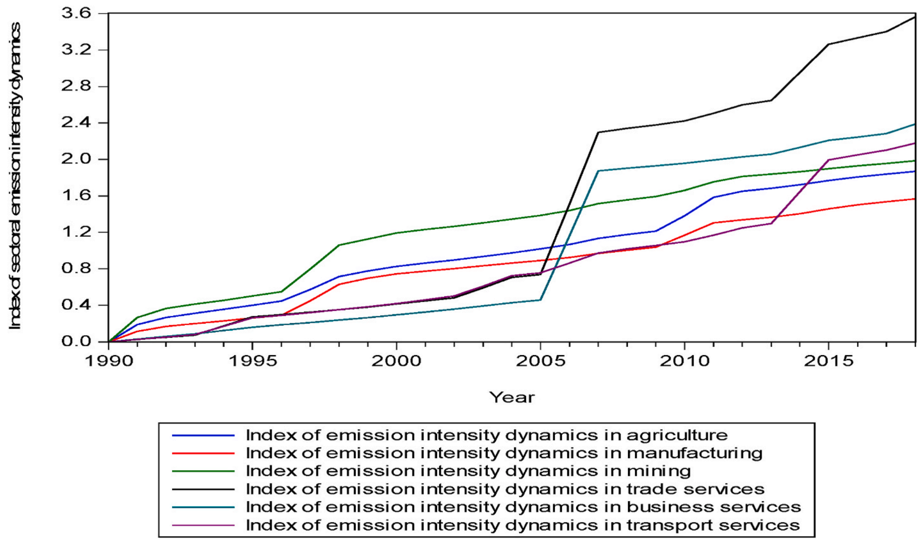

Fig. 1. Evolution of the sectoral emission intensity dynamics.

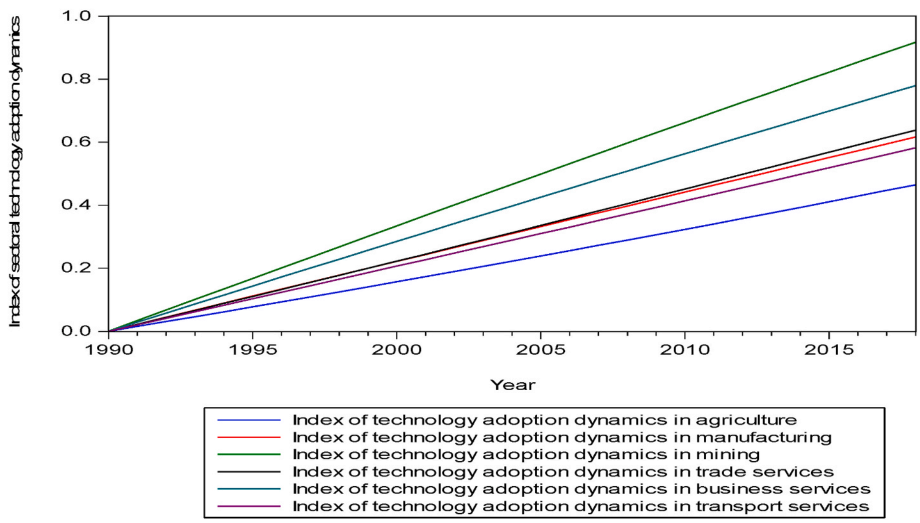

Fig. 2. Evolution of the sectoral technological adoption dynamics.

intensities across tradable economic sectors. In term of the magnitude of the impact, technology adoption shows higher impact in the manufacturing sector and followed by the mining and agriculture sectors. The significance of this desirable observation probably shows that technological change in these sectors is at least driving and achieving carbon emission mitigation, thus conforming with environmental sustainability pursuit. For the non-tradable sectors, insignificant impacts are observed in business and trade services (non-tradable sectors). However, given the interaction terms in Models 1A and 1B in Table 4, there is positive and significant coefficients of the squared terms of (K/L) indicate that a U-shape nexus between technology adoption and emission intensities holds in manufacturing, mining, agriculture, and transport service sectors, suggesting the existence of nonlinearity in the efficiency of technology adoption across tradable sectors as supported in Majumdar and Kar (2017). The implication is that though technology adoption mitigates carbon emission intensity in the tradable sectors (Model 1A), and only the transport services of non-tradable sectors (Model 1B), further escalation of technology adoption to a certain threshold suddenly become a menace to environmental quality. This evidence further louds the position of several studies that technology adoption would probably not or ineffectively drive environmental sustainability (Mohareb and Kennedy, 2014; Lu et al., 2022). Conversely, Su et al., 2021 found an inverted relationship between technology adoption and carbon emission in the BRICS) economies.

Furthermore, the control variables in all regressions generally exhibits expected signs, and when there are not, they are statistically insignificant. For instance, GDP per capita spur carbon emission in the manufacturing sector with elasticity of 21.184 (model 1a with only technology adoption) and in the agricultural sector with elasticity of 0.411 (model 1b with square of technology adoption). Another indicator with a statistically significant impact is trade which mitigate carbon emission in the manufacturing sector with elasticity of 0.005 (model 1a with only technology adoption) and in the agricultural sector with elasticity of 0.004 (model 1b with square of technology adoption). The take-home from previous studies shows that GDP per capita and trade could respectively exert positive and negative effect depending on the circumstance(s) under investigation (Bekun et al., 2019; Usman et al., 2020; Umar et al., 2021). The negative and significant coefficients of the error correction term indicate that our model restore back to long-term equilibrium, giving some indication about the validity of our CS-ARDL model.

The result from the interaction Model (3A) also offer more

Table 2
List of countries and descriptive statistics.

Descriptive statistics					
	Obs.	Mean	Std. Dev.	Min	Max
Technology					
Manufacturing	1421	0.195	0.5244	0	4.216
Mining	1421	0.176	0.163	0	0.854
Agriculture	1421	0.145	0.223	0	1.885
Trade	1421	0.102	0.117	0	1.002
Transport	1421	0.089	0.091	0	0.833
Business	1421	0.121	0.129	0	0.902
Emission intensity					
Manufacturing	1421	0.846	2.282	0	18.330
Mining	1421	1.243	3.842	0	31.235
Agriculture	1421	1.015	2.117	0	15.574
Trade	1421	0.289	0.176	0	0.682
Transport	1421	0.289	0.176	0	0.682
Business	1421	0.394	0.235	0	0.901
Control Variables					
real GDP pc	1421	7.766	1.259	5.213	11.019
Population	1421	3.313	1.490	0.054	7.263
Trade	1421	15.001	4.023	1.945	28.3254

interesting perspectives i.e for the entire panel of countries and the panel of African countries. Table 5 shows that the coefficient of the interaction term between capital intensity and trade is negative and statistically significant especially for the tradable sectors at the conventional level. This suggests that the environmental benefits of technology adoption can operate through bilateral trade among countries and especially in the manufacturing, mining, and agricultural sectors. Given that the interaction between trade and technology is an indirect way to capture the diffusion of technology, one might claim that both technology adoption and diffusion significantly contribute to reducing emission intensities. Comparing the results in Tables 4 and 5, although the role of trade also moderate technology adoption to exert a negative impact on carbon emission, the magnitude of the impact in this case is lower compared to the categorical impact of technology adoption. However, the results of the impact of GDP per capita and trade in this scenario is in harmony with the previous models expressed in Table 4.

Moreover, as indicated in the Model 3B above, the interaction term i.e (K/L) *trade (representing technology adoption) is furthermore employed for the case of the African economies. By considering this endeavour as a robustness check, the result is indicated in Table 6. Apart from the results of the impact of GDP per capita and trade that remained unchanged, the impact of technology adoption and diffusion on carbon emission in this context (African economies) is similar to that of the entire panel earlier illustrated. Thus, these results infer that both technology adoption and diffusion are good enough to mitigate carbon emission in the panel of developing, emerging, and African economies. Meanwhile, the summary of the model specification and results are further exemplified in Table A2 (of appendix).

4.1. Policy recommendation

These findings yield new insights and policy implications for EMDEs. The underlying countries can exploit the emission reduction effect of technology adoption while restricting the rebound effect due to extensive technological development. In this light, a more specific recommendations and priority can be given to sectoral characteristics through exploring desirable environmental sustainability role of technological change such as in renewable energy utilization in the manufacturing, mining, and agricultural sectors. Unlike the non-tradable sectors, especially the trade services and business services, policy makers should give more priority to addressing the potential rebound effect in manufacturing, agriculture and mining sectors, and transport sectors. Moreover, promotion of trade activities and trade networks is important, and such could be achieved through improving the adoption of newer technologies vis-a-vis technology diffusion which in turn contribute to the reduction of emission intensities in manufacturing, mining, and agricultural sectors. Specifically, and according to United Nations Environment Programme (UNEP) report, developing economies are positioned to significantly benefit from the diffusion of environmentally sound technologies through global trades in renewable and clean energy technologies (United Nations Environment Programme, 2022). For instance, toward advancing regional clean energy penetration, Ghana's Green Economy and Trade Opportunities Project (GE-TOP) strategy propagates exportation of solar energy (UNEP, 2016). Similarly, this approach of green economy through trade in environmental goods and especially renewable energy have long been operationalized among the South-South economies (UNEP, 2014). Thus, there should be stricter policy directives that compels the scale up of energy and clean technologies adoption in the activities of the examined sectors. From the societal and behavioral perspective, people's consciousness and adoption of environmentally friendly attitudes could turn out to influence the impact of GDP per capita toward improving environmental quality.

5. Conclusion

This study provides additional knowledge on the drivers of environmental sustainability by employing a panel of 49 developing and emerging countries across the globe over 1990–2018. Categorically, appropriate econometric methods were employed such that the roles of technology adoption and diffusion alongside other relevant indicators in mitigating carbon emission were examined. This study is important because it considers the sectoral (tradable and non-tradable) level

Table 3
Cross-section dependency tests.

Variable	Emission intensity in					
	Manufacturing	Mining	Agriculture	Trade	Business	Transport
CD	128.577*** [0.000]	110.212*** [0.000]	85.755*** [0.000]	158.385*** [0.000]	162.781*** [0.000]	143.413*** [0.000]
	Technology adoption in					
	Manufacturing	Mining	Agriculture	Trade	Business	Transport
CD	37.212*** [0.000]	23.339*** [0.000]	139.015*** [0.000]	22.101*** [0.000]	51.070*** [0.000]	7.436*** [0.000]
	Control variables					
	GDP		Population		Openness	
CD	167.549*** [0.000]		180.199*** [0.000]		6.239*** [0.000]	

Notes: CD stands for the cross-section dependence tests developed by (Chudik and Pesaran, 2013).

Table 4
Long-term effects of technology adoption on emission intensity across sectors.

	(Tradable) Dependent Variable (DV): Emission intensity in					
	Manufacturing	Mining	Agriculture	Manufacturing	Mining	Agriculture
	Model 1A			Model 1B		
Error correction term	−0.308***	−0.208***	−0.244***	−0.125***	−0.200***	−0.276***
	(0.105)	(0.038)	(0.051)	(0.038)	(0.040)	(0.051)
Log GDP per capita	21.184**	0.113	0.456	0.300	4.544	0.411*
	(10.715)	(0.986)	(0.288)	(0.261)	(8.310)	(0.293)
Log population	64.220	−42.873	32.485	−50.252	−104.473	31.010
	(57.669)	(146.751)	(21.749)	(45.618)	(130.66)	(22.284)
Log trade	−0.005*	−0.050	0.002	−0.001	−0.201	−0.004*
	(0.003)	(0.073)	(0.001)	(0.002)	(0.125)	(0.002)
Log K/L	−307.175*	−49.772*	−0.312**	−112.638*	−56.428*	−0.793***
	(178.388)	(28.182)	(0.156)	(60.116)	(33.692)	(0.232)
Log (K/L)ˆ2				9.525*	6.060**	0.056*
				(5.045)	(3.039)	(0.031)
Observations	1173	1173	1177	1132	1173	1177
R-squared	0.56	0.54	0.55	0.53	0.52	0.47
	Trade services	(Non-tradable) DV: Emission intensity				Transport services
		Business services	Transport services	Trade services	Business services	
	Model 2A			Model 2B		
Error correction term	−0.183***	−0.336**	−0.074*	−0.275***	−0.114***	−0.280***
	(0.088)	(0.177)	(0.043)	(0.054)	(0.039)	(0.074)
Log GDP per capita	0.188	7.184*	0.595**	0.454	0.169	1.986
	(0.349)	(4.339)	(0.281)	(0.290)	(0.267)	(1.347)
Log population	6.153	1.233	1.700	8.708	4.820	29.969
	(7.443)	(0.914)	(0.746)	(20.723)	(0.405)	(30.835)
Log trade	−1.696*	−0.015*	−0.483	−0.002	−0.001	−6.32E-04
	(0.958)	(0.008)	(0.558)	(0.003)	(0.001)	(0.001)
Log K/L	0.207	−0.063	−0.119	−1.267*	2.597	−31.257*
	(0.325)	(0.183)	(0.113)	(0.707)	(5.271)	(16.713)
Log (K/L) ˆ2				3.008	−0.175	2.452*
				(2.539)	(0.346)	(1.317)
Observations	1079	1079	1079	1078	1078	1078
R-squared	0.53	0.61	0.66	0.64	0.77	0.43

Note: Standard error are in parenthesis; *** significance at 1%; **significance at 5%; and * significance at 10%.

Table 5
Interaction effects of bilateral trade for overall panel.

	Manufacturing	All sectors: Model 3A (DV: Emission intensity)				Transport services
		Mining	Agriculture	Trade services	Business services	
Error correction term	−0.295***	−0.424**	−0.240**	−0.088*	−0.244***	−0.216***
	(0.107)	(0.185)	(0.051)	(0.046)	(0.042)	(0.066)
Log GDP per capita	0.425	1.049*	0.476*	0.045	0.101	0.240
	(0.462)	(0.585)	(0.280)	(0.180)	(0.477)	(0.433)
Log population	0.545	4.828	−2.204	−0.288	49.942**	19.830
	(0.598)	(4.541)	(5.914)	(0.279)	(25.486)	(21.172)
Log trade	−0.283*	−7.126*	−0.002*	−0.159*	−0.069*	−0.098**
	(0.154)	(3.708)	(0.001)	(0.088)	(0.041)	(0.049)
Log K/L	−0.622**	−14.357**	−0.261**	−0.049	0.077	−0.508***
	(0.291)	(6.961)	(0.119)	(0.050)	(0.196)	(0.193)
Log (K/L) * Log trade	−0.043*	−0.892*	−0.018**	0.007	0.008	−0.001
	(0.024)	(6.961)	(0.008)	(0.007)	(0.005)	(0.000)
Observations	1079	1074	1177	1177	1177	1035
R-squared	0.52	0.46	0.57	0.50	0.62	0.44

Note: Standard error are in parenthesis; *** significance at 1%; **significance at 5%; and * significance at 10%.

carbon emissions in the aforementioned countries.

Drawing on a perspective of technology heterogeneity across economic sectors, there is statistically significant evidence that a U-shaped pattern characterizes the technology-emission nexus across all the tradable sectors (the manufacturing, mining, and agriculture) and the transport sector of the service industry. This result implies that although technology adoption initially provides an environmentally desirable result, but further adoption of technology to a certain threshold can be detrimental to the environment in the long term. Additional findings disclose that trade liberalisation is essential to technology diffusion across tradable sectors (mainly the manufacturing, mining, and agriculture) in each of the entire panel of countries and panel of African countries. Moreover, the result of the other indicators shows that GDP per capita in all the scenarios and across the tradable sectors exacerbate environmental degradation by increasing carbon emission while trade mitigate carbon emission.

Considering the limitation of this study, more sectors could be examined in future study while the roles of several environmental agents especially the non-economic indicators are further examined. This study does not explicitly account for spatial effects in the diffusion of

Table 6
Interaction effects of bilateral trade for African countries.

	Manufacturing	All sectors: Model 3B (DV: Emission intensity)				Transport services
		Mining	Agriculture	Trade services	Business services	
Lagged DV	−0.012**	−0.264***	−0.174**	−0.210**	−0.269***	−0.141**
	(0.006)	(0.081)	(0.073)	(0.105)	(0.071)	(0.064)
Log GDP pc	7.968*	0.178	8.271	3.693*	1.052**	0.016
	(4.462)	(1.089)	(5.605)	(2.157)	(0.532)	(0.910)
Log population	0.714	−1.013	2.783	5.036	0.233	1.853
	(3.526)	(1.262)	(2.114)	(5.239)	(0.359)	(1.303)
Log trade	−1.915***	−0.342*	−1.196**	−0.007**	−0.177**	−0.088*
	(0.587)	(0.184)	(0.533)	(0.003)	(0.085)	(0.051)
Log K/L	0.282***	−0.673*	−0.304*	−0.396**	−0.021*	−0.497*
	(3.536)	(0.367)	(0.179)	(0.197)	(0.117)	(0.288)
Log (K/L) * Log trade	3.763*	−0.040*	−0.002**	0.230	−0.172	−3.768*
	(2.278)	(0.367)	(0.001)	(0.067)	(0.368)	(2.049)
Observations	390	385	435	390	435	472
R-squared	0.44	0.47	0.50	0.52	0.47	0.50

Note: Standard error are in parenthesis; *** significance at 1%; **significance at 5%; and * significance at 10%.

technology. Future studies can adopt spatial econometric techniques to uncover how spatial interdependence among neighboring countries can shift technology diffusion and emission intensity. However, the result of the current study provides policy guidelines for decision makers and stakeholders in the examined sectors.

CRediT authorship contribution statement

Yacouba Kassouri: Data curation, Writing – original draft, Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Andrew Adewale Alola:** Writing – review & editing, Investigation, Visualization, Corresponding.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix

Table A1
List of countries

Argentina, Burkina Faso, Bangladesh, Bolivia, Brazil, Botswana, Chile, China, Cameroon, Colombia, Costa Rica, Ecuador, Egypt, Ethiopia, Ghana, Indonesia, India, Israel, Japan, Kenya, Cambodia, Republic of Korea, Lao People's, Sri Lanka, Lesotho, Morocco, Mexico, Myanmar, Mozambique, Mauritius, Malawi, Malaysia, Namibia, Nigeria, Nepal, Pakistan, Peru, Philippines, Rwanda, Senegal, Singapore, Thailand, Tunisia, Turkey, Tanzania, Uganda, Viet Nam, South Africa, Zambia.

Table A2
Alternative model specifications

Model	Tradable	Non-tradable	linear	Quadratic	Technology adoption	Sample
Model 1a	*		*			Whole sample
Model 1b	*			*		Whole sample
Model 2a		*	*			Whole sample
Model 2b		*		*		Whole sample
Model 3a	*	*			*	Whole sample
Model 3b	*	*			*	African countries

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