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Failure to control economic sectoral inefficiencies through policy stringency disrupts environmental performance

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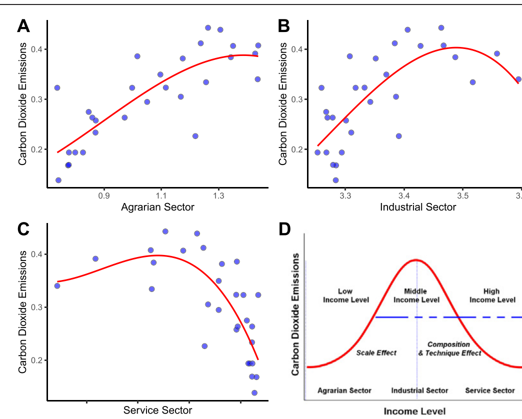
HIGHLIGHTS

- We assess environmental performance–environmental policy stringency nexus while controlling for economic sectoral dynamics.
- We utilize a machine-learning based technique coupled with econometrics to examine pollution effects.
- Long-term maximization of the service sector yield has a mitigation effect on CO_2 emissions.
- We validate the pollution halo hypothesis — implying that FDI inflows are possibly embedded with green growth.

GRAPHICAL ABSTRACT



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ABSTRACT

The developmental agenda of emerging countries often depends heavily on natural resource exploitation — a situation that hampers environmental performance. Hence, maximizing economic sectoral yield while reducing overdependence on fossil fuels and resources is essential to reducing wastage. Here, we assess the economic sectoral impact on emissions while controlling for foreign direct investment and energy utilization from 1990 to 2018. Besides, we investigate the role of environmental policy stringency in ameliorating environmental performance in a carbonized and energy-intensive economy where fossil fuels outweigh renewables. Agrarian, industrial, and energy sector dynamics are found to offshoot CO_2 emissions by 0.12%, 0.14%, and 0.20% whereas service sector productivity declines CO_2 emissions by 0.34%. We observe fossil fuel dominated energy portfolio with limited clean and renewable energy diversification that hinders long-term environmental performance. The validation of the pollution halo hypothesis implies that FDI inflows are possibly embedded with green and abatement technologies that reduce emissions while improving environmental performance. Thus, a comprehensive masterplan on climate change mitigation will comprise sectoral-specific resource investment that maximizes productivity while reducing natural resource exploitation, energy, and carbon-intensity.

1. Introduction

The traditional linear economy poses great danger to achieving environmental sustainability through climate change mitigation. While efforts have been made to shift from linear economy (Sauvé et al., 2016) to sustainable production and consumption — accentuated in the twelfth Sustainable Development Goal (United Nations, 2015), several existing factors limit the global emission reduction efforts. The immediate and underlying determinants of global emissions are reported to include population growth, energy intensity, economic growth, trade, urbanization, industrialization, governance, technology,

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infrastructure, development, consumer behavior, and resource availability (Blanco et al., 2014; Rosa and Dietz, 2012). Besides, economic sectors such as energy, industry, agriculture, forestry, and land use account for ~79.6% of the 49 Gt CO_2 equivalent direct greenhouse gas emissions driven by economic activities (IPCC, 2016). The trilemma between environmental sustainability, economic development, and resource-energy utilization highlights the importance of resource allocation and economic structural adjustment.

While the environmental Kuznets curve (EKC) hypothesis assumes carbonized-economic productivity driven by intense energy and resource utilization in developing economies, decarbonized-economy with energy efficiency through technological innovation (Jordaan et al., 2017) is reported to decline emissions in developed economies (Panayotou, 1993). However, failure to account for economic sectoral and disaggregate energy contribution to global emissions render environmental policies weak. It is acknowledged that no single country operates in one specific economic sector but multiple (agriculture, industry, and services). Hence, using aggregate growth in assessing the popular EKC hypothesis may limit country-specific policy formulation. This implies that the assessment of the various sectoral effects on emissions improve resource allocation with limited carbon and energy intensity (UNEP, 2011). However, previous studies (Arce et al., 2016; López et al., 2018; Steinberger et al., 2012) fail to address these structural adjustments in both economic and energy sector portfolios.

Though several studies assess the effects of domestically generated emissions, very few have examined the impact of transboundary attributed emissions generated through trade (Arce et al., 2016; López et al., 2018; Steinberger et al., 2012). Yet, the role of external funding including foreign direct investment (FDI) — which underpins both pollution haven and halo hypotheses has not been extensively investigated. Pollution haven hypothesis is characterized by natural resource seeking — access and exploitation-based FDI inducing emissions whereas pollution halo is characterized by efficiency-seeking based FDI — boosting technology transfer, innovation, research, and development—hence, decline long-term emission concentrations (Dunning, 1980). Aside immediate and underlying drivers of GHG emissions, several policies, and measures through institutional quality underpin long-term emission standards (Le Quéré et al., 2019). In this regard, proper institutional quality can be assessed by the level of stringency on environmental policies. This also implies that the nature of foreign investment is determined by environmental policy stringency.

Contrary to existing literature, our study presents novel concepts in both spirit and letters. Extant literature appears to focus on aggregate economic productivity and energy demand in assessing emission risks, however, such pathway provides very little knowledge for country-specific policies on environmental sustainability. In considering disaggregate energy namely fossil fuels, clean and renewables––disaggregate economic growth namely agriculture, industry, and services––rather than the usual aggregates — several trends, policies, and measures become evident. In using disaggregates, the magnitude of sectoral-based impact can be quantified and assist in optimal resource investment that maximizes yield while reducing emissions. Second, the rebound effect is reported to affect both direct and indirect emission consequences. However, several studies fail to capture the importance of rebound effects that is evident with socio-economic and environmental factors. The rebound effects are reported to mediate the effectiveness of long-term energy and environmental-related policies and measures. Thus, rebound effects are relatively high in emerging economies (Chakravarty et al., 2013) and require attention — especially with emission reduction modeling in developing countries. We account for possible rebound effects of sectoral economic growth, energy utilization, and foreign direct investment. The impact of transboundary effect through global partnership is examined through foreign direct investment inflows. We assess whether pollution trends that hamper environmental performance are domestically generated or induced by external funding. Here, we model the nonlinear effects of sectoral economic growth, foreign direct investment, and energy utilization. We use innovative accounting technique that graphically projects minimum resource allocation while maximizing yield in one breath and maximum resource investment with limited gains. The different kinds of nonlinear projections demonstrate the importance of considering sectoral economic accounting in environmental policies. We further use stochastic simulation models to project the counterfactual change in environmental performance using the business-as-usual scenario with changes in FDI and environmental policy stringency.

2. Materials & method

The assessment of the proposed hypotheses begins with data identification, selection, and preprocessing. The choice of data series presented in Table 1 for further processing stems from the Sustainable Development indicators and IPCC 5th assessment report on climate change (Blanco et al., 2014; DiSano, 2002). To account for Sustainable Development Goal (SDG) 7 of sustained economic development, we employ both aggregate GDP and sectoral economic contribution namely agrarian, industry, and services. Similarly, to account for clean energy, sustainable industrial productivity, innovation, and responsible production and consumption expounded in SDGs 7, 9, and 12, we employ aggregate energy and disaggregate energy that encompasses both fossil fuels and renewables. To develop conceptual tools for climate change mitigation entailed in SDG 12, we use both carbon dioxide emissions and environmental performance index as target variables (Alhassan et al., 2020). We incorporate environmental policy stringency to account for institutional quality explained in SDG 16. To assess the role of global partnership (SDG 17), we utilize foreign direct investment net inflows as indicator for achieving Sustainable development in developing countries. To control for unevenly spaced data, we utilize the imputation technique presented in Owusu and Sarkodie (2020). Our comprehensive model uses South Africa as a case study with data spanning 1990–2018. South Africa ranks fifth (192 Mt) in terms of global coal consumption (Enerdata, 2019) and the only African country with different economic structure compared to the others in the subregion. The country has a characteristic of an emerging economy with overdependence on fossil fuels and very little attention to clean environment. While foreign direct investment flows to Africa increased by 11% (~US$46 Billion) with slow growth in African countries, South Africa over-doubled its inflows from US$2 Billion to US$5.3 Billion due to resource-seeking investments (UNCTAD, 2019). The over 165.8% growth in FDI to South Africa is alarming and requires attention, owing to the interest of foreign investors in exploiting available natural resources. Hence, South Africa is the only African country among the top 10 FDI (ranks 7th) stock economies after France, Netherlands, the US, UK, China, and Italy.

Table 1
Data description.

Abbreviation	Variable	Unit
AGRARIAN	Agriculture	% of GDP
CO_2	CO_2 emissions	kg per 2010 US$ of GDP
ENERGY	Energy use	kg of oil equivalent per capita
ENVPER	Environmental Performance Index	Index
ENVPS	Environmental Policy Stringency	Index
FDI	Foreign direct investment net inflows	BoP, current US$
FOSSIL	Fossil fuel energy consumption	% of total final energy consumption
GDP	Economic growth	Current US$
INDUSTRY	Industry	% of GDP
RENCONS	Renewable energy consumption	% of total final energy consumption
SERVICES	Services	% of GDP

2.1. Hypothesization

We utilize the FreeViz explorative analysis technique to construct optimal research hypotheses through the nexus pattern of variables depicted in Fig. 1. The FreeViz technique employed herein is used to develop hypotheses based on evidential relationships revealed between classes and characteristics, interactions, and intra-class information of similarities between important variables. Contrary to the principal component analysis that creates projections, the FreeViz algorithm improves linear projections via gradient optimization technique that classifies variables based on relationships and patterns using visualizations (Demšar et al., 2007). Hence, the FreeViz algorithm is a useful explorative analysis tool for hypothesization of highly dimensional data series. It can be observed from the initial position of multivariate visualization that higher levels of CO_2 emissions (indicated by yellow colored-square legend) have strong association with energy, industry, services, and agrarian [Fig. 1(A)]. In contrast, FDI, environmental policy stringency and environmental performance index have relatively weak correlation with CO_2 emissions (indicated by blue colored-square legend). While we find almost all the hypotheses of the FreeViz explorative analysis corroborating existing theories, the linkage between average levels of CO_2 emissions and the neutrality between GDP, renewable energy consumption, and fossil fuels call for more vigorous analysis. Thus, we apply the random optimization procedure to improve the initial position of the sampled variables. Subsequently, we find a strong correlation between high levels of CO_2 emissions, fossil fuels, industry, and agrarian whereas lower levels of CO_2 emissions are attributed to energy, GDP, and environmental policy stringency [Fig. 1(B)]. Besides, a negative or neutral effect is observed running from FDI, renewable energy, services, and environmental performance index to CO_2 emissions. The questions emanating from the explorative analysis include:

(1) What is the sectoral contribution to CO_2 emissions while accounting for inflows, economic development, and energy consumption? (Hypothesized from Appendix B)
(2) What accounts for the strong affinity between renewables and CO_2 emissions while controlling for the dominance of fossil fuel and sustained economic growth? (Hypothesized from Appendix C)
(3) How does the interplay of disaggregate energy mix and economic development affect environmental performance? (Hypothesized from Appendix D)
(4) Does environmental policy stringency ameliorate environmental performance in a carbonized and energy-intensive economy where fossil fuels outweigh renewables? (Hypothesized from Appendix E)

Thus, the questions distilled from FreeViz multivariate visualization of CO_2 emissions and environmental performance require answers that form our a priori expectations for further empirical assessment.

2.2. Model construction

Following the FreeViz explorative analysis technique, we use the novel Kernel Regularized Least Squares (KRLS) estimation method to investigate the hypothesis of the study. KRLS is a machine learning algorithm drawn from an independent identically distributed data with Gaussian kernel — i.e. partly positive definite and symmetric function of inputs mapped onto actual-valued output, hence, measures the resemblance between two input patterns (Ferwerda et al., 2017). The target (CO_2 emissions and environmental performance) functions are fitted with Gaussian kernels, where each input pattern is centered, corresponding weight scaled and summed up. Next, regularization is applied to optimize the tradeoff between fit approximation and complexities of the model by the imposition of a penalty (Tihonov, 1963). To avoid over-parametrization, an optimal regularization boundary is automatically selected by the minimization of leave-one-out errors of the sum of squares (Hastie et al., 2009). The pointwise partial derivatives of CO_2 emissions and environmental performance are derived from the input variables namely agriculture, energy use, environmental policy stringency, FDI inflows, fossil fuels, economic growth, industry, renewables, and services—to examine the pointwise marginal effects of the input variables.

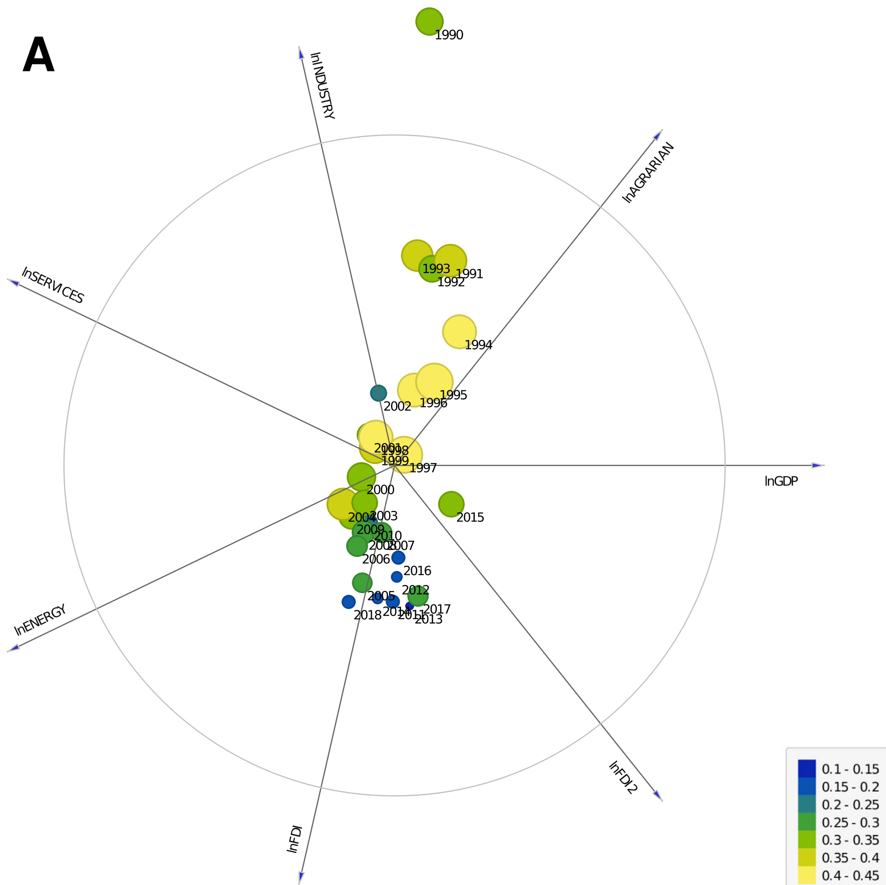
The KRLS estimator is used to derive hypothesis testing, pointwise average marginal effects, formation of confidence interval, and choose an optimal bandwidth automatically for the Gaussian kernel––leading to unbiased, consistent, and normally distributed fitted values with asymptotic characteristics (Hainmueller and Hazlett, 2014).

To improve the complexity of the estimated model — i.e., nonlinearity and interactive effects, we paired the estimated pointwise marginal effects with the independent variables to assess potential statistical significance for inclusion in subsequent analysis. For instance, a statistically significant nexus between pointwise marginal effect of a regressor and target variable signifies nonlinearity whereas a strong relationship between pointwise marginal effect of a regressor and another regressor denotes interaction. In such a situation, re-estimation of the machine-based learning algorithm is executed to include the newly identified additional variables to improve the model's complexity.

To examine the counterfactual change in environmental performance over the next 30 years while accounting for FDI and environmental policy stringency. We predict environmental performance using the average change in growth of FDI (2.12%) and environmental policy stringency (0.07%) based on ceteris paribus analysis using dynamic ARDL simulations algorithm. To apply the dynamic ARDL simulations, several pre-conditions were examined and requirements met. First, data series were first-difference stationary — tested using Phillips-Perron (Phillips and Perron, 1988) and Augmented-Dickey fuller (Dickey and Fuller, 1979) unit root. Second, we adopted an optimal lag structure based on first difference via useful information criteria. Third, the nexus between environmental performance, FDI, and environmental policy stringency was cointegrated with long-run effect — validated using the Pesaran-Shin-Smith bounds test based on surface regression with critical and approximate probability values. A confirmation of the long-run nexus between the sampled series led to the adoption of error correction-based ARDL estimation technique. Thereafter, we applied the dynamic ARDL (Jordan and Philips, 2018) stochastic simulations approach with the selected optimal lag in first-difference. Besides, we utilized a single shock regressor for counterfactual impulse analysis using the specified $\pm$ change (%) along the 20-length scenario at 10-year scenario time for impulse to occur along the horizon based on error correction technique with 5000 stochastic simulations. The parameters stimulated based on the business-as-usual scenario are used in predicting future changes in environmental performance over the time period via stochastic improbability drawn from a zero-mean and variance attributed multivariate-normal distribution. The simulated values are automatically averaged to produce predicted parameters, confidence intervals, and stochastic uncertainties presented in spiked plots.

2.2.1. Model validation

Contrary to traditional linear regression that is extremely vulnerable to misspecification bias, the KRLS estimator is less vulnerable due to an initial flexibility modeling of conditional expectation function and subsequent reporting of parameters as mean derivative of the enhanced fitted model. Second, the optimization of the fitted model with a penalty-attributed to optimal regularization function helps prevent over-fitting. Third, the KRLS estimator controls for complex models with non-additivity, non-linearities, and interaction effects (Hainmueller and Hazlett, 2014). The marginal effects of the estimated models were examined for heterogeneous effects using the pointwise derivatives expressed in percentiles. We observe that all the covariates in the estimated models from 1 to 99 percentiles lack uniform distribution of the marginal effects. Hence, failure to examine heterogeneous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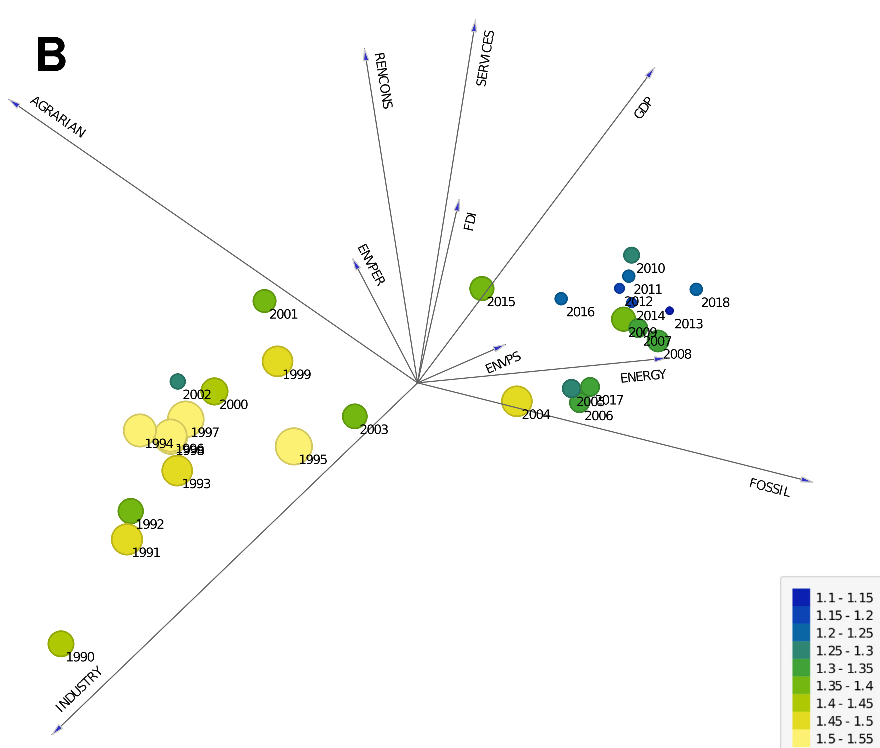
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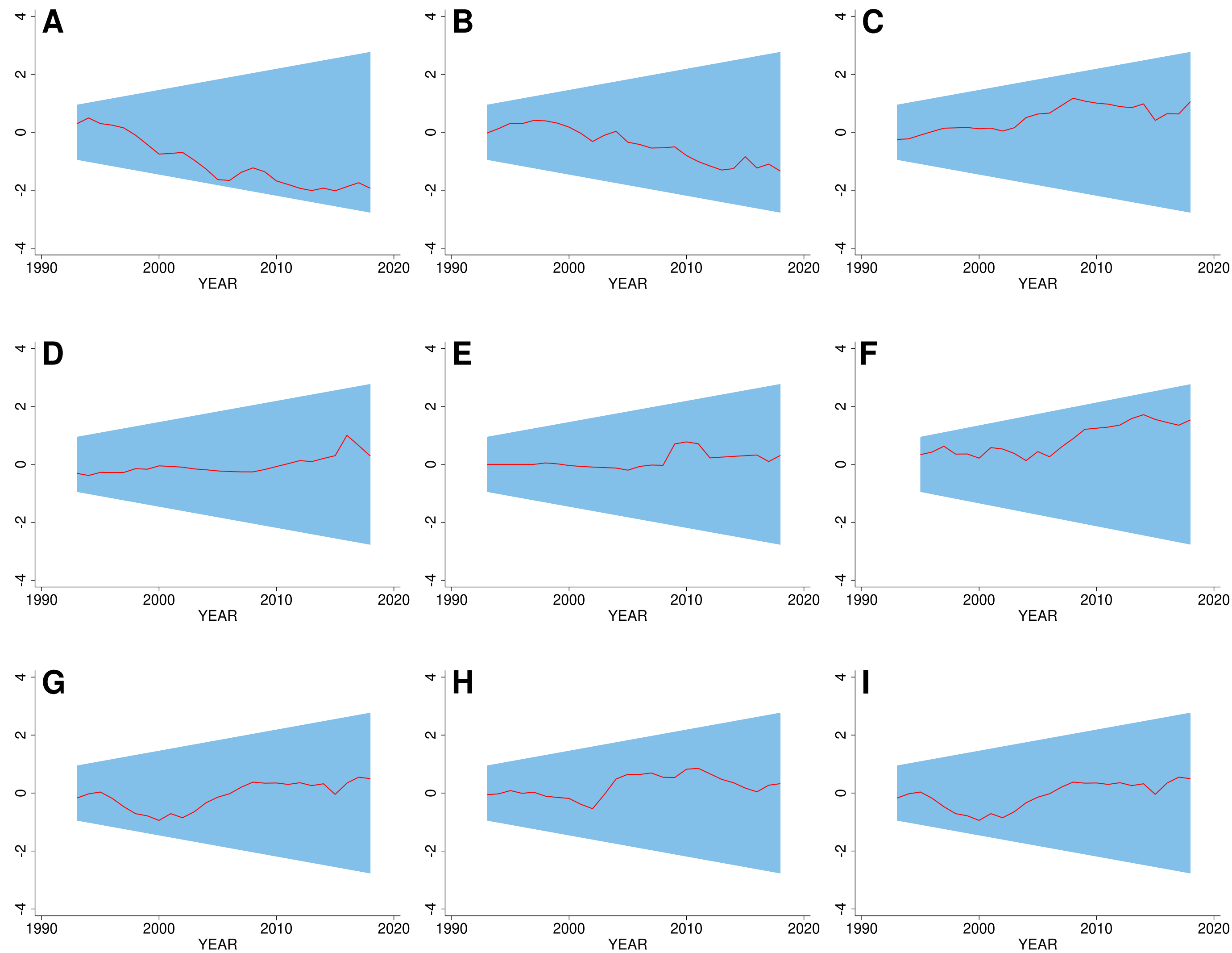

Fig. 2. Recursive CUSUM for stability test: (A) Agrarian Sector (B) CO_2 Emissions (C) Energy Utilization (D) Environmental Performance Index (E) ENVPS (F) FDI (G) Fossil Energy Utilization (H) GDP (I) Industrial Sector.

effects and account for conditional distribution across percentiles leads to biased-statistical inferences and policy formulation. This called for the adoption of average marginal effects rather than the traditional estimation procedure. To confirm the parameter stability of the estimated coefficients of covariates over the period, we adopted the recursive cumulative sum test presented in Fig. 2. We observe that the estimated parameters of covariates are within the 95% confidence band, hence, confirming the time-specific constancy and stability of the models.

3. Results & discussion

We discern from Table 2 that FDI inflows observed the highest growth by 2.12% within the 28-year data sample, followed by environmental policy stringency (0.07%), economic growth (0.05%), services (0.01%), energy (0.01%), and disaggregate energy (fossil fuels and renewables) at par with 0.001% change. In contrast, agrarian sector experienced the highest decline in 28 years by 0.02% and trailed closely by industrial sector (0.01%), CO_2 emissions (0.003%), and environmental performance (0.001%). In terms of sectoral contribution to economic growth, we find that services dominate on average by 58.74%, followed by industry (28.93%) and agrarian (2.97%).

3.1. How does sectoral-based economy affect CO_2 emissions?

To answer this question, we adapted the theoretical support of the traditional EKC hypothesis and substituted it with sectoral economic growth namely agrarian, industry, and services (Fig. 3). The EKC hypothesis posits that initial agrarian-based economic development of low-income countries emboldens environmental consequences due to excessive resource extraction and waste generation — a process termed as the scale effect (Panayotou, 1997; Sarkodie and Strezov, 2019). However, it is assumed that as low-income countries migrate to middle-income status catalyzed by a shift from agrarian to industrial economy, increasing level of income to a specific threshold engenders environmental awareness. This leads to environmentally friendly policies that change the composition of the economic structure, resulting

Fig. 1. Multivariate visualization of CO_2 emissions (indicated by legend) versus socioeconomic and environmental indicators: (A) Before FreeViz (B) After the application of FreeViz algorithm. Legend: Yellow colored-square indicates high levels of CO_2 emissions whereas blue colored-square represents low levels of CO_2 emissions.

Table 2
Descriptive statistics of sampled indicators.

Statistic	AGRARIAN	CO_2	ENERGY	ENVPER	ENVPS	FDI	FOSSIL	GDP	INDUSTRY	RENCONS	SERVICES
%Δ	−0.0198	−0.0031	0.0066	−0.0005	0.0724	2.1155	0.0005	0.0502	−0.0119	0.0005	0.0069
Mean	2.9664	1.3605	2570.9870	51.5607	0.6401	3.06E+09	86.3254	2.35E+11	28.9259	17.2006	58.7428
Median	2.8595	1.3811	2518.3330	50.4600	0.4792	1.52E+09	86.5753	2.29E+11	28.0077	17.1072	60.0857
Maximum	4.2150	1.5569	2950.1540	70.5200	1.7500	9.89E+09	88.1487	4.16E+11	36.4069	19.1214	61.3893
Minimum	2.0888	1.1484	2290.6670	44.7300	0.3958	−75,722,412	84.2434	1.15E+11	25.8535	15.5703	50.4671
Std. Dev.	0.7041	0.1196	168.1998	4.4623	0.3684	2.94E+09	1.1119	1.03E+11	2.8775	0.9405	2.7957
Skewness	0.3580	−0.0808	0.4327	2.4048	2.2950	0.7550	−0.3462	0.2807	1.0606	0.2918	−1.3743
Kurtosis	1.8164	1.8735	2.4845	12.6793	6.9182	2.2827	1.9415	1.5117	3.2113	2.1397	4.2948
Jarque-Bera	2.3123	1.5651	1.2261	141.1568	44.0076	3.3767	1.9333	3.0576	5.4905	1.3058	11.1539
Probability	0.3147	0.4572	0.5417	0.0000	0.0000	0.1848	0.3804	0.2168	0.0642	0.5205	0.0038
AGRARIAN	1										
CO_2	0.7834*	1									
ENERGY	−0.4854*	−0.4124*	1								
ENVPER	−0.1564	−0.1791	−0.0992	1							
ENVPS	−0.4199*	−0.3871*	0.4496*	0.1916	1						
FDI	−0.5213*	−0.5351*	0.7037*	−0.059	0.3012	1					
FOSSIL	−0.4917*	−0.5016*	0.7616*	−0.0529	0.3731*	0.5199*	1				
GDP	−0.8803*	−0.7707*	0.6331*	0.0806	0.6076*	0.5528*	0.6873*	1			
INDUSTRY	0.9162*	0.6208*	−0.4955*	−0.0598	−0.3344	−0.5026*	−0.3926*	−0.7678*	1		
RENCONS	0.5581*	0.4456*	−0.7454*	−0.0394	−0.3087	−0.5386*	−0.6659*	−0.6837*	0.4961*	1	
SERVICES	−0.9059*	−0.6041*	0.4490*	0.0544	0.3864*	0.4940*	0.33	0.7454*	−0.9838*	−0.4184*	1

Notes: %Δ denotes the mean relative change from 1990 to 2018 (elaborated in Appendix A). Pearson correlation of sampled indicators based on a 2-tailed test of significance is used.
* Pearson correlation is significant at 5% level.

in a gradual decline of emissions — a process termed as the composition effect. In contrast, high-income countries are characterized by services, modern technologies, innovation, and environmental policy stringency, ensuing in transfer of polluting industries to developing economies. This in effect declines environmental consequences compared to industry sector — a process termed as the technique effect.

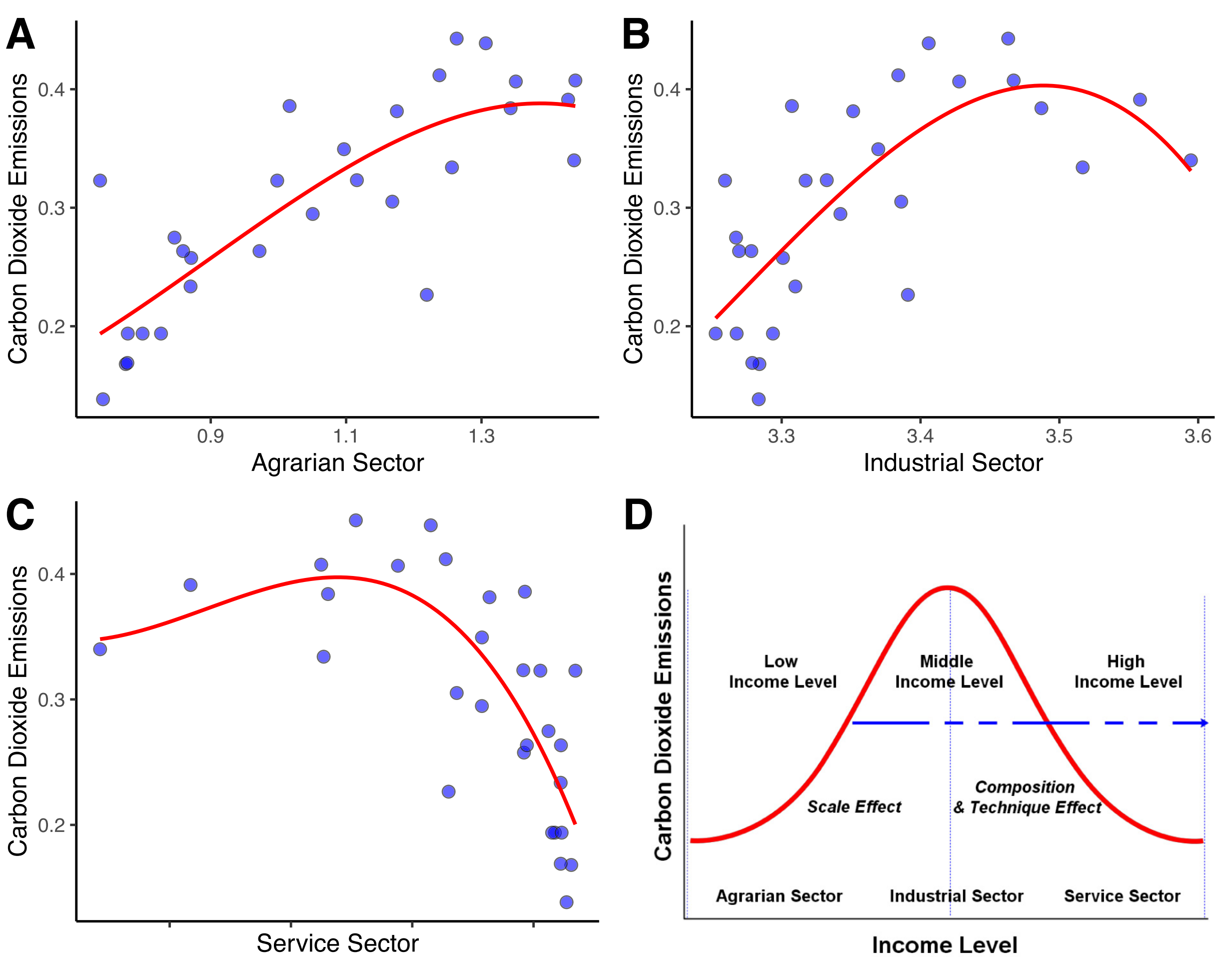

Fig. 3. Schematic representation (A) Trend of CO_2 emissions versus Agrarian sectoral-based economic development (B) Trend of CO_2 emissions versus Industrial sectoral-based economic development (C) Trend of CO_2 emissions versus Service sectoral-based economic development (D) EKC hypothesis showing Income level in CO_2 emissions function.

Table 3
Estimated parameters & pointwise derivatives — economic sectoral accounting.

Percentiles	AGRARIAN	INDUSTRY	SERVICES	ENERGY	FDI	FDI^2
Avg.	0.1207***	0.1367***	−0.3407***	0.1982**	−0.0062***	−0.0002***
	[0.0200]	[0.0477]	[0.0837]	[0.0837]	[0.0020]	[0.0001]
1%	−0.0448***	−0.1854***	−0.7002***	−0.4920**	−0.0159***	−0.0004***
5%	−0.0246***	−0.0476***	−0.6173***	−0.3245**	−0.0154***	−0.0004***
10%	0.0017***	−0.0448***	−0.6092***	−0.2331**	−0.0150***	−0.0004***
25%	0.0652***	0.0604***	−0.5146***	0.0199**	−0.0095***	−0.0003***
50%	0.1372***	0.1649***	−0.3915***	0.2604**	−0.0066***	−0.0002***
75%	0.1730***	0.2264***	−0.2437***	0.4154**	−0.0034***	−0.0001***
90%	0.2369***	0.2807***	0.0171***	0.5191**	0.0015***	0.0000***
95%	0.2375***	0.2853***	0.0296***	0.5236**	0.0061***	0.0001***
99%	0.2597***	0.3112***	0.5541***	0.6306**	0.0074***	0.0002***
Diagnostics	–	–	–	–	–	–
Mean	0.1207	0.1367	−0.3407	0.1982	−0.0062	−0.0002
Std. Dev.	0.0848	0.1205	0.2706	0.2735	0.0056	0.0002
Variance	0.0072	0.0145	0.0732	0.0748	0.0000	0.0000
Skewness	−0.2887	−0.7662	1.4137	−0.7174	0.5617	0.3572
Kurtosis	2.1445	3.0862	5.3290	2.9535	3.2905	2.9220
Lambda	0.8000	–	–	–	–	–
R-square	0.8141	–	–	–	–	–
Looloss	0.8198	–	–	–	–	–
Sigma	6.0000	–	–	–	–	–
Eff. Df	7.3250	–	–	–	–	–
Cointegration	YES[a]	–	–	–	–	–

Notes: [a]The null hypothesis of no cointegration is rejected at 5% significance level by Johansen maximum eigenvalue and Boswijk test for cointegration; [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

While the EKC hypothesis assumes a specific sector across income groups, all three sectoral-based economies practically exist in a country's economic structure but with varying contributions to economic development. Thus, assessment of all sectoral-based economic growth with environmental consequences appears more policy-oriented compared to the traditional framework of the EKC hypothesis. In Fig. 3(A–C), we show that disaggregate economic growth versus CO_2 emissions achieves similar trend as the so-called inverted-U-shaped curve aka EKC hypothesis. On this note, we empirically test the hypothesis with CO_2 emissions as target variable whereas agrarian, industry, and services are regressors while controlling for energy, FDI, and squared of FDI.

We used the general-to-specific reasoning to improve the complexity of the estimated model via KRLS pointwise partial derivatives. Using partial derivatives of covariates generated from economic sectoral accounting, we substituted the derivatives of each covariate in place of CO_2 emissions for subsequent analysis. Regressors that proved significant against specified derivatives qualified for either interaction or nonlinearity. Though the goodness fit test in Table 4 is 79% compared to 81% in Table 3, however, the resulting complex model in Table 4 produces same sign and significance but shows more robust and consistent results. The estimated average marginal effects in Table 3 show that expansion in agrarian, industrial, and energy sector dynamics offshoot CO_2 emissions by 0.12%, 0.14%, and 0.20% ––whereas service sector productivity and growth in FDI reduce CO_2 emissions by 0.34% and 0.01%, respectively. Besides, both linear and second-degree polynomials of FDI are negative and statistically significant at *p-value* < 0.01, thus, confirming the validity of the pollution halo hypothesis (see Table 3). This infers that contrary to arguments of pollution-embedded FDI inflows transferred to developing economies, our empirical analysis shows that the type of FDI inflows to South Africa supports green growth. Meaning that the external funding is possibly embedded with green and abatement technologies such as renewables and clean energy, and green knowledge spillover that underpins circular and green economic growth.

The pointwise derivatives of nonlinear and interactive effects in Table 4 show a negative and significant effect of maximum service productivity ($SERVICES^2$) on CO_2 emissions. This reveals that long-term maximization of the service sector yield has a mitigation effect on CO_2 emissions by 0.012%. We observe that the interaction between energy and agrarian sector (ENERGY×AGRARIAN) — energy and industrial sector (ENERGY×INDUSTRY) escalates CO_2 emissions by ~0.01%, however,

Table 4
Pointwise derivatives of nonlinear and interactive effects — economic sectoral accounting.

CO_2	Avg.	S.E.	t	P > t	P 5	P 50	P 95
$ENERGY^2$	0.0048	0.0036	1.3220	0.2050	−0.0172	0.0032	0.0198
$SERVICES^2$	*−0.0115*	0.0045	−2.5730	*0.0200***	−0.0216	−0.0138	0.0004
ENERGY×AGRARIAN	*0.0064*	0.0010	6.1550	*0.0000****	−0.0011	0.0069	0.0122
ENERGY×SERVICES	−0.0016	0.0035	−0.4440	0.6630	−0.0200	−0.0004	0.0142
AGRARIAN×SERVICES	*0.0125*	0.0021	5.9910	*0.0000****	−0.0017	0.0137	0.0245
AGRARIAN×INDUSTRY	*0.0111*	0.0017	6.6550	*0.0000****	−0.0026	0.0117	0.0218
ENERGY×INDUSTRY	*0.0066*	0.0035	1.8830	*0.0780**	−0.0134	0.0086	0.0195
SERVICES×INDUSTRY	0.0031	0.0130	0.2370	0.8160	−0.0262	0.0072	0.0287
FDI × INDUSTRY	*−0.0004*	0.0002	−2.4000	*0.0290***	−0.0008	−0.0006	0.0005
FDI × SERVICES	*−0.0004*	0.0001	−2.7990	*0.0130***	−0.0007	−0.0005	0.0004
Diagnostics							
Lambda	*0.8000*	Eff. df	*6.5390*	R^2	*0.7859*	Looloss	*0.8465*

Notes: For brevity, individual variables in Table 3 are not reported in this table to avoid repetition. SE denotes standard error, P 5 is the 5th percentile, P 50 is the 50th percentile, and P 95 is the 95th percentile; S.E. represents the standard errors while *, **, *** denote statistical significance at 10%, 5%, and 1% level.

the statistical insignificant interaction effect of energy and services (ENERGY×SERVICES) declines CO_2 emissions. This suggests that energy-intensive agricultural and industrial production exacerbate CO_2 emissions whereas service sector driven energy utilization has no effect on emissions. Similarly, the interaction between agrarian and services — agrarian and industrial sector spurs CO_2 emissions by ~0.01%, however, the interaction effect of FDI and services — FDI and industrial sector declines emissions. This corroborates the existence of pollution halo hypothesis — implying that FDI inflows are possibly embedded with green growth, hence, has CO_2 emissions reduction effect.

Next, we graphically estimated the pointwise marginal effect of derivatives from the optimal and significant candidates (interaction and nonlinearity in Table 4) presented in Fig. 4 with long term policy implications. We observe an inverted-U shape relationship between the marginal effect of industry and agrarian sector—an initial positive sectoral change in industry from low to medium level agrarian productivity and decreases thereafter, reaching the point of maximum agrarian sector yield. This implies that the industrial sector has long-term decreasing marginal returns for high investment in agricultural sector but short-term increasing industrial marginal returns until medium-level agrarian investment. Similarly, the marginal effect of FDI increases with increasing service sector investment but declines to negative after medium to high levels of service sector investment. This indicates that high levels of service sector investment improve internal financing and domestic development but decline external financing, foreign innovation, development assistance, and spillover effects of knowledge, technology, and labor.

The marginal effect of energy rises from negative to positive with corresponding low to high levels of agrarian investment. This implies that long-term agrarian investment increases energy consumption. We observe a U-shaped relationship between the marginal effect of services and agrarian sector. Decreasing marginal return of the service sector is evident between low to medium agrarian investments, however, experiences upturn after reaching the point of minimum agrarian sector yield. This infers that the service sector has long-term positive returns for high investment in the agricultural sector. Next, we examine the long-term association between the marginal effect of services and service sector dynamics. There is evidence of N-shaped relationship, which confirms two different turning points of both maximum and minimum service sector yield — revealing both productive and negative marginal returns. This in effect implies that allocation of resources or investments in only service sector is unhealthy for long-term economic development.

The relationship between the marginal effect of energy and energy consumption reveals a bimodal shape aka M-shape, however, the fit reveals N-shape. We observe two maxima energy sector yields showing

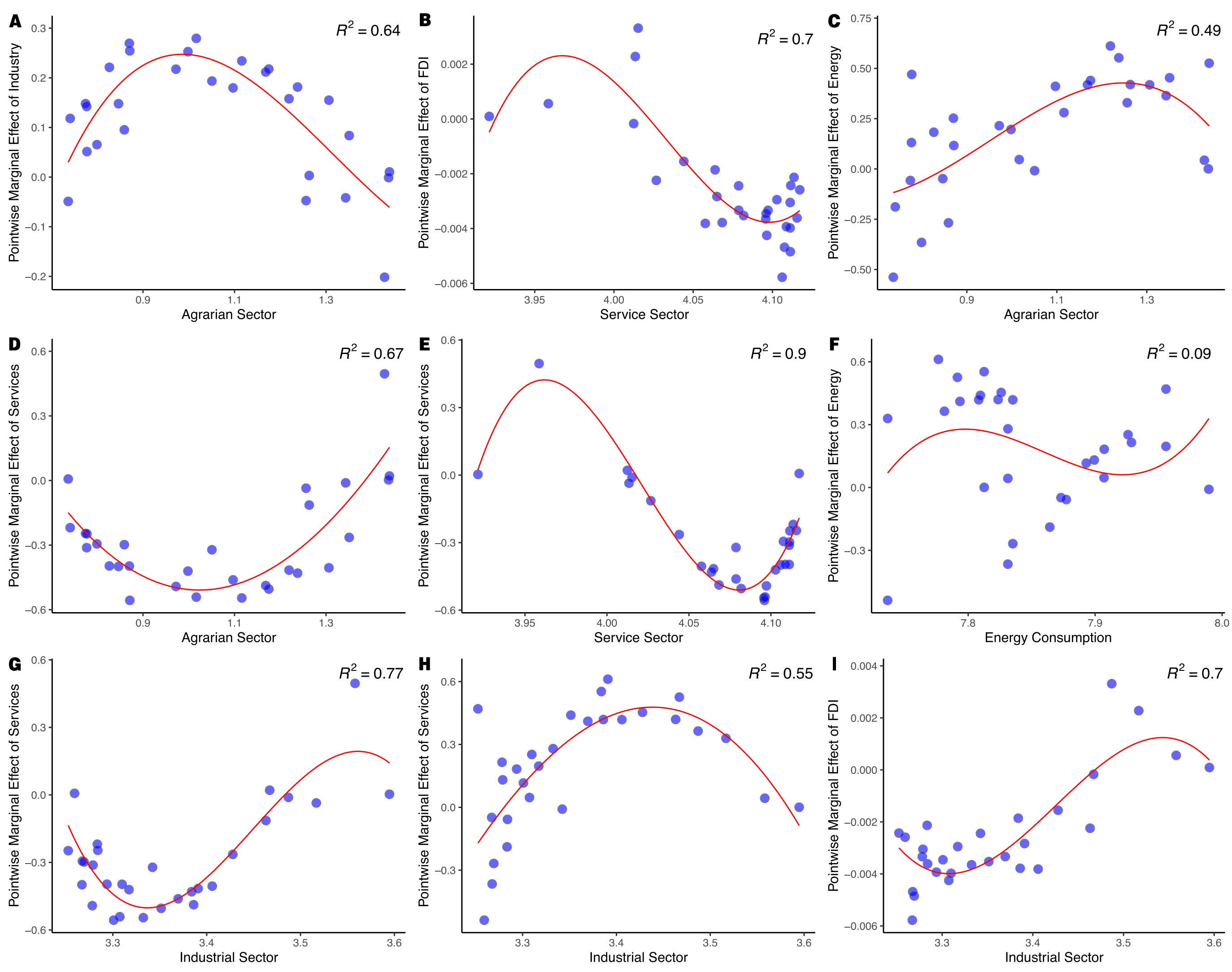

Fig. 4. Pointwise marginal effect of (A) Industry ~ Agrarian sector (B) FDI ~ Service sector (C) Energy ~ Agrarian sector (D) Services ~ Agrarian sector (E) Services ~ Service sector (F) Energy ~ Energy Consumption (G) Services ~ Industrial sector (H) Energy ~ Industrial sector (I) FDI ~ Industrial sector.

increasing marginal returns at two individual points and zero-depression point with decreasing marginal returns. The M-shaped relationship probably reveals the dynamics of disaggregated energy (i.e., fossil fuel and renewable energy) — accentuating the importance of diversification in the energy portfolio. The nexus between the marginal effect of services and industrial sector validates an inversed-N-shaped relationship — revealing an initial negative marginal return (minimum industrial sector yield) before long-term increasing service productivity. Thus, investment in industrial sector has initial recession effects on service sector efficiency but provides long-term opportunities leading to expansion of the service sector.

We confirm an inversed-U-shaped relationship between the marginal effect of energy consumption and the industrial sector. This implies that energy utilization increases at the initial stages of industrial sector production until maximum industrial sector yield is achieved before energy utilization declines with increasing industrial productivity. The relationship between the marginal effect of FDI and industrial sector confirms an elongated uphill-shaped relationship — showing an increasing level of FDI inflows with industrial sector expansion until maximum industrial sector yield is reached before reduction sets in. This further implies that countries with high industrial sector production attract more foreign direct investment inflows. This in effect explains why countries like China, India, among others have high levels of FDI inflows (World Bank, 2020). Concurrently, the nature of FDI namely pollution-halo or pollution-haven is determined by the composition of the industrial sector.

3.2. Does growth in GDP, renewables, and fossil fuels affect CO_2 emissions and environmental performance?

From a policy viewpoint, accounting for disaggregated energy utilization and economic development is reported to provide useful insights for energy-driven economic policy formulation. We estimated the effect of disaggregate energy utilization and aggregate economic growth on CO_2 emissions and environmental performance. The goodness of fit test for both models is 0.996 and 0.908 — implying that the regressors explain 99.6% of CO_2 emissions and 90.8% of environmental performance. The average marginal effect parameters presented in Table 5 reveal an increase in fossil fuel consumption and economic growth increases CO_2 emissions by 4.13% and 0.13% whereas renewable-based energy consumption declines CO_2 emissions by 0.28%. In contrast, an increase in the average marginal effect of fossil fuels and economic growth declines environmental performance by 6.54% and 0.13% whereas increasing the share of renewables improves environmental performance by 1.51%. This equally reflects the composition and share of fossil fuels and renewables in South Africa's energy portfolio. As of 2019, domestic utilization of coal, oil, natural gas, nuclear energy, and renewables stood at 85.98 Mtoe, 25.26 Mtoe, 0.42 Mtoe, 2.51Mtoe, and 2.80 Mtoe, respectively (BP, 2019). This infers that the share of clean energy technologies (i.e., renewables and nuclear energy) accounts for a mere 4.54% of domestic consumption, hence, corroborating the empirical results. Besides, it amplifies carbon and energy-intensive economic development driven by fossil fuel utilization. Thus, fossil fuel-dominated energy mix with limited diversification from clean and renewable energy technologies is a threat to environmental performance (Sarkodie et al., 2020).

3.3. Does environmental policy stringency ameliorate environmental performance?

Environmental policy stringency plays an essential role in FDI inflows from high-income countries to developing countries, albeit key to environmental sustainability. The composition of the economic sector, energy portfolio, production and consumption, and environmental performance depends on environmental policies and measures. Here, we examined the impact of environmental policy stringency — as a policy measure in enhancing environmental performance in a carbon-embedded and energy-intensive economy where fossil fuel utilization outweighs renewables and clean energy. The estimated model with parameters presented in Table 6 reveals that the regressors explain 99.7% variations in the target variable. Hence, confirming the predictability of disaggregate energy, GDP, environmental policy stringency, and CO_2 emissions in explaining the dynamics of environmental performance. We observe from the average marginal effect that CO_2 emissions, fossil fuel utilization, and economic growth contribute significantly to reducing environmental performance by 1.16%, 0.71%, and 0.25%, respectively. According to the IPCC 5th Assessment report (Blanco et al., 2014), carbon intensity, economic growth, and energy utilization are the immediate drivers of greenhouse gas emissions — implying that these limiting factors disrupt environmental performance, hence, thwarts efforts towards attaining environmental sustainability. Besides, carbon dioxide is the main contributory factor of anthropogenic GHG emissions that hampers environmental sustainability through its long-term degradation effect. In contrast, the expansion of renewable energy and environmental policy stringency improves environmental performance significantly by 1.27% and 0.17%, respectively. Though the adoption of renewable energy technologies is reportedly affected by policy instruments, technological innovation attributable cost, and market failure, however, its climate mitigation, environmental, and health impact reduction effects cannot be underrated (Owusu and Asumadu, 2016). Likewise, diversification of the energy mix with renewable energy

Table 5
Estimated parameters of emissions & environmental performance.

Percentiles	FOSSIL	RENCONS	GDP
Avg. CO_2[a]	4.1261***[a]	−0.2760***[a]	0.1262***[a]
	[0.3140][a]	[0.0669][a]	[0.0144][a]
Avg. ENVPER[b]	−6.5374***[b]	1.5055***[b]	−0.1295**[b]
	[1.3019][b]	[0.2773][b]	[0.0597][b]
5%	−11.8789[a]	−2.5872[a]	−0.4615[a]
	−23.7009[b]	−3.6690[b]	−0.9142[b]
10%	−11.3494[a]	−2.5002[a]	−0.4374[a]
	−21.5267[b]	−3.6073[b]	−0.8176[b]
25%	−0.9686[a]	−0.7759[a]	−0.1601[a]
	−15.1635[b]	−1.4949[b]	−0.5021[b]
50%	6.7879[a]	−0.0395[a]	0.0092[a]
	−3.9549[b]	1.2234[b]	−0.0908[b]
75%	9.9579[a]	0.7130[a]	0.4991[a]
	1.9348[b]	3.8137[b]	0.2281[b]
90%	15.9668[a]	1.5730[a]	0.7254[a]
	5.1049[b]	5.7474[b]	0.5389[b]
95%	17.1760[a]	2.0191[a]	0.7336[a]
	10.7233[b]	7.4852[b]	0.5768[b]
99%	19.1097[a]	2.6240[a]	0.8075[a]
	21.6801[b]	12.0052[b]	0.7226[b]
Diagnostics			
Mean	4.1260[a]	−0.2760[a]	0.1262[a]
	−6.5374[b]	1.5055[b]	−0.1295[b]
Std. Dev.	9.7136[a]	1.6063[a]	0.4271[a]
	11.5228[b]	3.6869[b]	0.4893[b]
Variance	94.3539[a]	2.5801[a]	0.1824[a]
	132.7753[b]	13.5929[b]	0.2394[b]
Skewness	−1.2110[a]	−0.7749[a]	0.0771[a]
	0.2465[b]	0.6848[b]	−0.2700[b]
Kurtosis	5.0804[a]	3.6476[a]	1.8230[a]
	2.5145[b]	3.5128[b]	2.1674[b]
Lambda	0.0010[a/b]	–	–
R-square	0.9956[a]	–	–
	0.9079[b]		
Looloss	1.5330[a]	–	–
	4.7440[b]		
Sigma	3.0000[a/b]	–	–
Eff. df	25.3900[a/b]	–	–
Cointegration	YES[a/b]	–	–

Notes: [a]The null hypothesis of no cointegration is rejected at 5% significance level by Johansen maximum eigenvalue, Banerjee, and Boswijk test for cointegration. [b]Engle-Granger, Johansen, Banerjee and Boswijk test for cointegration reject the null hypothesis of no cointegration at $p < 0.05$; [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

Table 6
Determinants of environmental performance – stringency nexus.

Percentiles	FOSSIL	RENCONS	GDP	ENVPS	CO_2
Avg.	−0.7055**	1.2734***	−0.2482***	0.1706**	−1.1590***
	[0.2861]	[0.0503]	[0.0072]	[0.0120]	[0.0382]
1%	−15.6870**	−3.3078***	−0.6940***	−0.4986**	−7.0334***
5%	−15.3372**	−3.1941***	−0.6402***	−0.4628**	−6.1806***
10%	−7.7055**	−2.3021***	−0.6074***	−0.4547**	−6.0261***
25%	−3.4926**	−1.7096***	−0.4223***	−0.0634**	−1.5521***
50%	0.7298**	0.0726***	−0.2418***	0.2725**	−0.4399***
75%	2.6944**	2.8625***	−0.0464***	0.4111**	0.4333***
90%	4.2148**	9.1763***	0.0743***	0.5679**	1.1827***
95%	4.3682**	9.1873***	0.1798***	0.6544**	1.2164***
99%	4.3850**	9.7176***	0.2686***	0.7349**	2.1911***
Diagnostics	–	–	–	–	–
Mean	−0.7055	1.2734	−0.2482	0.1706	−1.1590
Std. Dev.	5.1857	3.9436	0.2517	0.3600	2.4823
Variance	26.8915	15.5521	0.0633	0.1296	6.1620
Skewness	−1.6271	0.9757	0.0676	−0.5721	−1.1651
Kurtosis	5.2798	2.7248	2.2480	2.1903	3.2518
Lambda	0.0010	–	–	–	–
R-square	0.9970	–	–	–	–
Looloss	5.5240	–	–	–	–
Sigma	5.0000	–	–	–	–
Eff. Df	28.16	–	–	–	–

Notes: [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

technologies is reported to provide opportunities for achieving energy access, energy security, human development, and socio-economic development (Edenhofer et al., 2011; Owusu and Asumadu, 2016; Sarkodie and Adams, 2020). Increasing levels of environmental policy stringency serve two purposes in developed economies — first, it may stimulate emission-reduction technologies, innovation, and research and development, or second, shift polluting industries to developing countries with lax environmental regulations. Environmental policy stringency navigates industrial production efficiency, hence, an important determinant of fossil fuel utilization and pollutant emissions (Johnstone et al., 2017). This explains why the introduction of stringent environmental policies, viz. environmental regulations are reported to escalate industrial and technological innovations, hence, lower pollution abatement costs due to a reduction in emission intensities (Milani, 2017). In contrast, pollution-embedded external financial support — in the form of FDI inflows underscores knowledge spillover, technology, and human capital attributed emissions from foreign countries — which underpins the pollution haven hypothesis. However, our empirical analysis contradicts pollution haven in support of pollution halo hypothesis.

To further validate the hypothesis on environmental performance, we plugged in the individualistic and interactive effects of FDI inflows, and environmental policy stringency using the dynamic ARDL simulations and further predicted future shocks in regressors using the

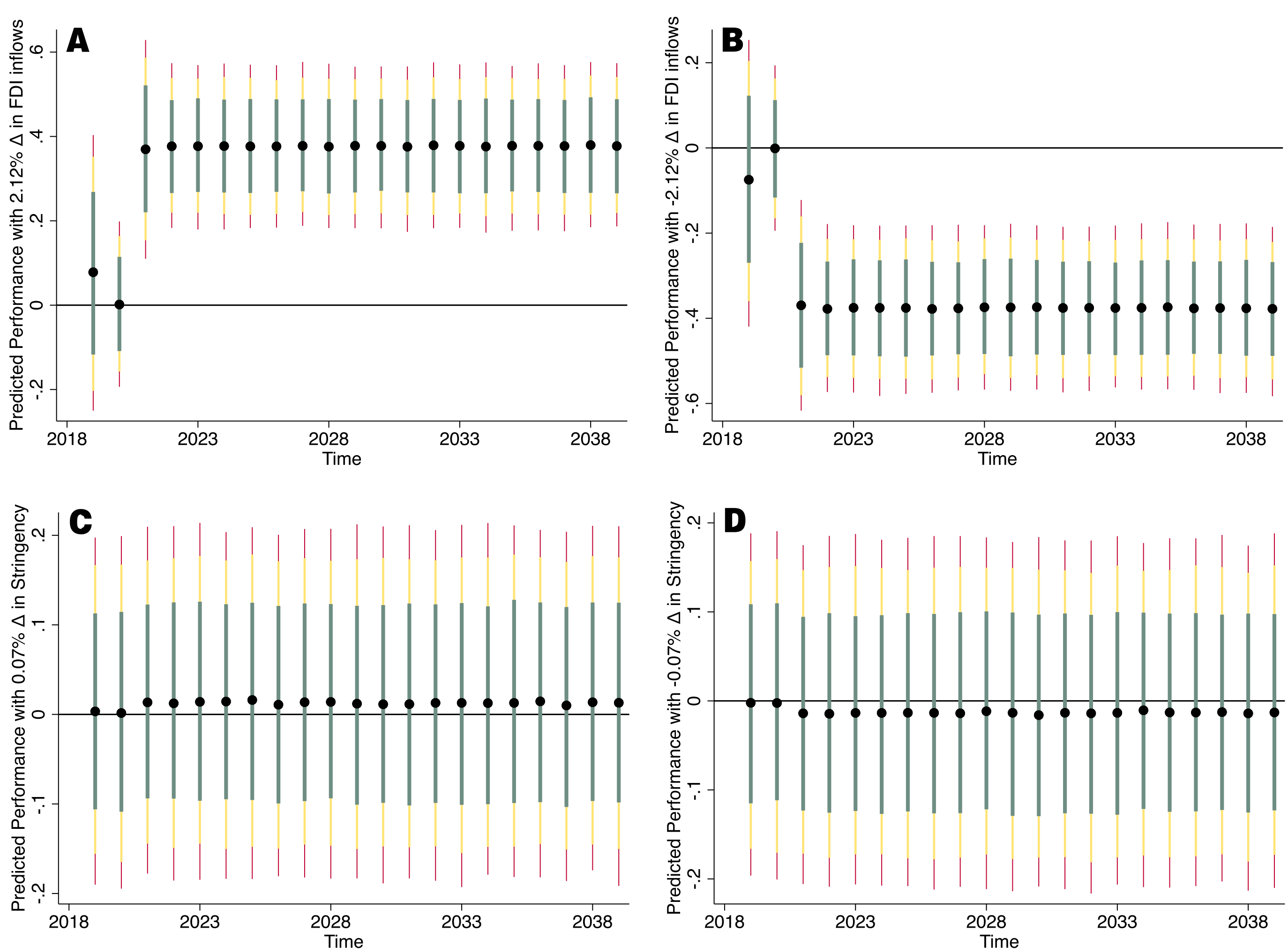

Fig. 5. Predicted Environmental Performance with (A) 2.12% change in FDI inflows (B) −2.12% change in FDI inflows (C) 0.07% change in Environmental Policy Stringency (D) −0.07% change in Environmental Policy Stringency. Legend: cranberry, sand, teal colored-spikes represent 95, 90, and 75% confidence interval.

average change over the 28-year period. We observe a potential long-run association evidenced in the bounds test cointegration results in Appendix F. To examine the response of environmental performance to counterfactual shocks in FDI inflows and environmental policy stringency, we utilized the mean change of historical trends — 2.12% and 0.07%, respectively, and assumed a constancy over the predicted 20-year (2018–2038) horizon. Our predicted parameters are within the 95, 90 and 75% confidence interval represented by cranberry, sand, teal colored-spikes. Using the ceteris paribus analysis, we observe in Fig. 5(A) that 2.12% shock in FDI inflows will increase environmental performance after the 2nd year by ~0.39% and stabilize thereafter. In contrast, −2.12% shock in FDI inflows declines environmental performance by ~0.39% after the 2nd horizon [Fig. 5(B)]. Thus, confirming our initial results in Table 4 that validate the pollution-halo hypothesis. We further observe very little change in the response of environmental performance to ±0.07% shock in environmental policy stringency [Fig. 5 (C–D)]. The lagged (2)-interaction between FDI inflows and stringency (Appendix F) corroborates the position of pollution-halo hypothesis. This implies that the current state of agrarian and industrial-based emissions and poor environmental performance are not imported but domestically generated, hence, environmental policy stringency and FDI inflows are not linked to polluting industries.

4. Conclusion

We investigated the determinants of environmental performance – environmental policy stringency nexus while controlling for economic sectoral dynamics. In summary, we observed that the failure to account for economic sectoral inefficiencies by the institutionalization of environmental policy stringency will disrupt environmental performance. Our case scenario of the assessment of economic-driven emissions revealed that using aggregate economic growth rather than individual economic sectoral input provides little and vague overview for environmental policy formulation, especially in resource allocation. Hence, the assessment of country-specific economic sectoral accounting highlights how linear economy can be shifted towards circular economy by maximizing yield while reducing wastage, environmental pollution, and resource consumption. Our study demonstrated that the allocation of scarce resources should be based on long-term prospects rather than short-term gains. Contrary to the traditional EKC hypothesis, we showed that sectoral-based economic productivity is useful in understanding pollution-reduction policies. Besides, our empirical analysis reveals *when* and *where* to allocate limited natural resources for sustainable economic development while reducing production shortfalls. Thus, at the point of diminishing returns in the service sector, it is advisable to invest, combine, or substitute resources from both agrarian and industrial sectors. Implying that a combination of other sectors like agrarian and industry has long-term productivity. We showed that diversification of the energy portfolio is essential to sustain long-term economic development. Our study revealed that the overdependence on fossil fuels has long-term environmental costs that hinder progress towards the mitigation of climate change and its impacts. The introduction of energy efficiency and decarbonization of economic policies could begin with disaggregation of economic growth rather than the traditional aggregated GDP. This provides opportunity to examine both efficiency and deficiency of the economic structure and incorporate the appropriate policy. Long-term industrial sector production is observed to increase energy efficiency while short-term industrial sector productivity increases energy intensity. This implies that industrial sector production has both escalation and mitigation effects, hence, the introduction of energy conservation and management policies will hamper short-term industrial sector productivity. Our empirical estimation confirmed that foreign direct investment inflows are driven by industrial sector production. Thus, the industrial structure determines the level of external funding, environmental performance, knowledge, and technological spillover. From a policy perspective, increasing the share of renewables while reducing fossil fuels in the energy portfolio declines CO_2 emissions while increasing environmental performance. Political will through the enactment of stringent environmental policies is critical to improving long-term environmental performance.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145603.

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