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Evidence from the South African Energy Sector on the Impact of Gas Consumption and Technologies on the Environment

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Abstract. Legacy emissions from fossil fuel consumption signify the lasting impact of past carbon dioxide (CO_2) emissions on present-day emissions. Given that the current emission levels are also high; it has become urgent to deal with this crisis. This study aims to examine the effects of gas consumption, legacy CO_2 emissions, energy decoupling, and population on carbon dioxide emissions in South Africa using the modified IPAT identity and the Markov Switching Dynamic Regression analysis. Integrating additional variables into the modified IPAT identity uncovered evidence from the South African energy sector on the impact of gas consumption on the environment. The Markov Switching Dynamic Regression Model (MSDRM) utilised annual data from the South African energy sector from 1966 to 2020, collected from diverse sources. Results indicate that the Gas model's probability (i.e., 0.8475) would persist in high-emissions states over time. The MSDRM results showed that gas consumption suggests a statistically significant negative relationship between gas consumption (–0.0461) and CO_2 emissions, meaning that despite the decrease in CO_2 emissions from using gas, it does not imply instant reversals in the ambient CO_2 as to reduce the overall CO_2, likely contributed from other CO_2-emitting fuels. The MSDRM results showed that legacy CO_2 emissions positively impact (I) current CO_2 emissions and that decoupling (T) leads to increased CO_2 emissions—the latter relationship indicating likely energy rebounding. These findings highlight the need to prioritise interventions and strategies targeting the factors with higher probabilities of contributing to sustained high emissions, which may involve implementing policies to transition away from high-emission sources while exploring alternatives and adopting cleaner energy sources. The results emphasise the challenge of decoupling economic growth from high CO_2 emissions and underscore the importance of sustained efforts to address and mitigate climate change.

Keywords: Gas consumption, energy decoupling, South African energy sector, modified IPAT identity

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Влияние потребления газа и технологий на окружающую среду: опыт энергетического сектора Южной Африки

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Аннотация. Остаточные выбросы от потребления ископаемого топлива свидетельствуют о долгосрочном воздействии прошлых выбросов углекислого газа (CO_2) на современные объемы. Учитывая, что текущие уровни выбросов остаются на высоком уровне, необходимо обращать внимание на накопительный характер данного процесса. Представленное исследование направлено на изучение влияния потребления газа и остаточных выбросов CO_2 на выбросы углекислого газа в Южной Африке с использованием модифицированной идентификации IPAT, а также скрытой модели Маркова. Внедрение дополнительных переменных в модифицированную идентификацию IPAT выявило доказательства влияния потребления газа на окружающую среду в энергетическом секторе Южной Африки. В модели динамической регрессии Маркова (MSDRM) использованы ежегодные данные из энергетического сектора Южной Африки с 1966 по 2020 г., собранные из различных источников. Результаты показывают, что вероятность модели (0,8475) будет сохраняться в состояниях с высокими выбросами с течением времени. Результаты MSDRM показали, что потребление газа указывает на статистически значимую отрицательную связь между потреблением газа (–0,0461) и выбросами CO_2, означающую, что, несмотря на снижение выбросов CO_2 при использовании газа, это не влечет за собой мгновенных обратных изменений в атмосфере. Вероятно, такие изменения вызваны другими источниками выбросов. Результаты MSDRM показали, что остаточные выбросы CO_2 положительно влияют (I) на нынешние выбросы CO_2 и что декаплинг (T) приводит к увеличению выбросов CO_2. Полученные результаты подчеркивают необходимость разработки приоритетных «зеленых» стратегий, направленных на борьбу с источниками с устойчивыми высокими выбросами.

Ключевые слова: потребление газа, энергетический сектор Южной Африки, IPAT

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Introduction

The creation of strategies to reduce disruption and guarantee a smooth integration process is necessary for the effective integration of renewable energy sources (Abas et al., 2015; Benli et al., 2020; Du et al., 2019; Neves, Marques, 2021; Stančin et al., 2020; Zou et al., 2016).

Energy rebound effects occur when an initial boost in energy efficiency is followed by an increase in energy use that returns to pre-involvement levels. These effects are particularly prevalent in places with high levels of energy use (Li R., Li S., 2021). One way to save energy is to replace incandescent lighting with energy-efficient LED fixtures. On the other hand, using more LED bulbs may lead to a greater total energy consumption.

Modelling environmental impact (*I*), i.e., carbon emissions due to population (*P*), affluence (*A*), and technology (*T*), using the IPAT identity ($I = PAT$) can help quantify GHG emissions and the factors driving them (Chertow, 2000; Pham et al., 2020; Skånberg and Svenfelt, 2022). This model, however, is limited in that it does not account for every element that could impact the environment. More advanced models that get around these restrictions and provide a deeper understanding of the variables influencing the environment have been created and made available.

Technological innovation significantly boosts economic growth, competitiveness, and value creation while addressing long-standing challenges like the health impacts of climate change, unsustainable economic expansion, and an ageing society. The research offers a theoretical understanding of the correlations between independent variables—population growth, consumption trends, and time-series trends of specific indicators—and CO_2 emissions. The following have made a significant contribution to research. First, the methodological approach is the basis of the contribution. The study offers a novel effect assessment formula by providing a modified version of the IPAT identity. This identity allows additional and natural logarithm-converted variables to be incorporated into the model (Gujarati, 2004). Regression analyses that include a lagged dependent variable can capture persistence and dynamics in generating data (Wooldridge, 2010). It enables the relationship between the dependent variable's previous values and its current value to be captured (Gujarati, 2004), which can provide more precise results than considering only contemporaneous variables (Wooldridge, 2010), commonly employed in economics and other disciplines, and it can improve the goodness of fit of the model.

Furthermore, the study uses a technology variable that Data Envelopment Analysis acquired to estimate energy decoupling (DEA). The predicted DEA technology score considers South Africa's CO_2 emissions and GDP per capita. Finding and measuring the effects of this variable is crucial as technology capabilities have made it possible to address several persistent problems. The third contribution of the research deals with endogeneity issues by employing a residual inclusion approach on Kaya identity variables utilising the MSDRM. The Kaya identity formula captures four variables—the human population, GDP per capita, energy intensity (per unit of GDP), and carbon intensity. These determine the overall emissions of greenhouse gases (per unit of energy consumed).

Finally, utilising the modified version of the IPAT identity, the study reveals how structural breaks in CO_2 emission data can be quantified using Markov-Switching Dynamic Regression Models (MSDRM). Since the current state of the data-generating process (DGP) is unknown, these models calculate the likelihood of various unobserved states of the DGP. Therefore, this study aims to examine the effects of gas consumption, legacy CO_2 emissions, energy decoupling, and population on carbon dioxide emissions in South Africa using the modified IPAT identity and the Markov Switching Dynamic Regression analysis.

Exploring the Impact of Energy Decoupling in South Africa

Decoupling has become more significant as a strategy for resolving the problem of excessive carbon dioxide (CO_2) emissions since it isolates economic expansion from resource consumption and environmental degradation. Numerous studies, particularly in South Africa, have looked at the relationship between population growth, decoupling, and the use of fossil fuels in relation to CO_2 emissions.

Hubacek et al. (2021) demonstrated that, as the majority of wealthy countries have shown, it is possible to fully decouple GDP from production-based emissions. A promising development that some countries have managed to achieve is complete decoupling. CO_2 emissions are released into the atmosphere even by nations that are completely disconnected from the environment. Decoupling might not be enough to solve the problems that greenhouse gas emissions are causing for the environment. They also point out that decoupling might only be temporary and that the decoupled countries might eventually resume increasing their emissions; as a result, consistent and continuous efforts are needed to keep decoupling trends going.

Data and methods

Conceptual framework

Because of the disproportionate effects of coal, oil, and gas on the environment, it is important to look at the use of each fossil fuel. For example, coal usually creates more CO_2 and local air pollution per unit of energy than other fossil fuel types. Simultaneously, gas has been seen as a good substitute that tackles issues related to environmental effects.

The formula for measuring human impact, the IPAT identity, is shown below.

$$I = P \times A \times T, \tag{1}$$

where: I = impact; P = population; A = affluence; T = technology.

Econometric model

The econometric models specified CO_2 emissions using the extended IPAT model using the MSDRM. The researchers determined the MSDRM for gas consumption. The comprehensive IPAT model allows for additional variables to be included.

A one-input and one-output DEA model — i.e., GDP per capita and CO_2 Emissions, respectively — estimated the technical efficiency for energy decoupling. The estimated technical efficiency denotes technologies used to decouple GDP per capita and CO_2 Emissions. Additionally, the specified model output-orientated DEA and assumed Constant Returns to Scale.

Data sources for the variables

The annual data for South Africa were acquired from different sources, covering the different annual periods. Table 1 shows the attributes of the other variables utilised in the research.

Table 1

Data sources for the variables

Variables	Unit	Variable period	Source
Carbon dioxide Emissions Per Capita	Annual production-based emissions of CO_2, measured in tonnes.	1750–2020	(Andrew, Peters, 2021; Project, 2021)
Gas consumption	Fossil fuel consumption is given in terawatt-hour equivalents (TWh).	1960–2020	www.BP.com
Population	Population	1950–2021	https://population.un.org/wpp/
GDP per capita	GDP at purchaser's prices is the sum of gross value added by all resident producers in the country plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without deductions for the depreciation of fabricated assets or the depletion and degradation of natural resources.	1960–2020	https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators
Technology	A Data envelopment analysis fractional score is estimated to capture the technologies in use for efficiency for energy decoupling.		See GDP per capita and CO_2 Emissions.

Source: Andrew, Peters, 2021; Project, 2021. Retrieved 24 December, 2023, from www.bp.com; https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators

Econometric estimation in the extended IPAT model

The below specified empirical models calculated the extended CO_2 emissions utilising the modified IPAT identity for gas consumption. This method permits the model to include other variables dealing with econometric problems, i.e., residuals and lagged dependent variables. The equations below illustrate the extended IPAT identity relationship, and the definitions of the variables are in Appendix.

Gas consumption model — extended IPAT model:

$$\ln CO_2 emissions = residuals + \ln totalpopulation + \ln gasconsumption + \\ + \ln decouplete + \text{Lag.}\ln CO_2 emissions. \quad (2)$$

Regression analysis frequently uses lagged dependent variables, as is common in many research fields. To properly characterise the underlying relationship between the independent and dependent variables, researchers can consider time-varying autocorrelation and persistence in the data by using lag-dependent variables, which capture the historical effect of the dependent variable on itself (Gujarati, 2004). By accounting for previous values of the dependent variable, which may be correlated with the independent variables as well as the error term, a lagged dependent variable can be included in the regression analysis to improve the accuracy of the coefficient estimates and the overall goodness of fit of the model (Wooldridge, 2010).

The natural logarithms of the original IPAT identity variables, the estimated residual to account for anticipated endogeneity, and the dependent variable's lagged variable are all used in the second econometric estimation. Natural logarithms help change the expression of the multiplicative form of the IPAT and allow for the introduction of other variables in the model. Endogeneity issues will likely arise due to the nature of the dependent and independent variables. The former measures CO_2 Emissions, and the latter estimates technology using CO_2 Emissions. Variables that introduce endogeneity are Endogenous Explanatory Variables (EEVs). A Control Function (CF) solves the problem of such EEVs in both linear and nonlinear models (Wooldridge, 2015). A lagged value or a previous value of a dependent variable (i.e., Lag.ln CO_2emissions) is reliable as a proxy variable. An outcome of the dependent variable from an earlier period can be a valuable proxy for various omitted factors or variables.

The Markov switching dynamic regression modelling

Markov chains are statistical models that use a set of probabilities determined by past events to represent a series of future events. The Markov switching dynamic regression model (MSDRM) quantifies these stages or states in the data, which also calculates the likelihood that the series will change states (Hamilton, 1989). For example, p11 represents the probability that the series is in State 1 at time t and remains in State 1 at time $t + 1$. P12 represents the probability that the series is in State

1 at time t and transitions to State 2 at time *t*+1. Dynamic regression models are used to model high-frequency data and allow for quick adjustment after the process changes state.

Results
Determining structural breaks in CO_2 emissions

The swald test determined if there were any structural breaks in the CO_2 emissions data. The null hypothesis of this test states that there is no structural break. A statistically significant *p*-value of 0.0000 was obtained, showing a break in 1990 that resulted in two states of CO_2 emissions. With the results of this estimation test for structural breaks, the MSDRM seeks to quantify these two states. The following graphical illustrations show the structural breaks in CO_2 over time (Figures 1, 2).

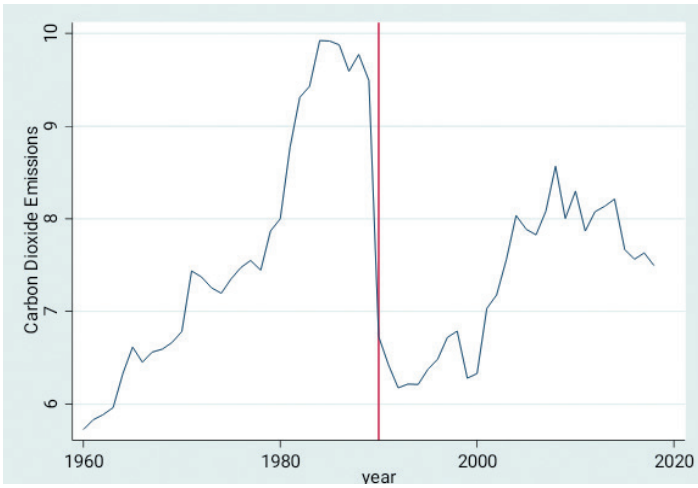

Figure 1. Carbon dioxide emissions in South Africa, 1960–2020
Source: compiled by the authors.

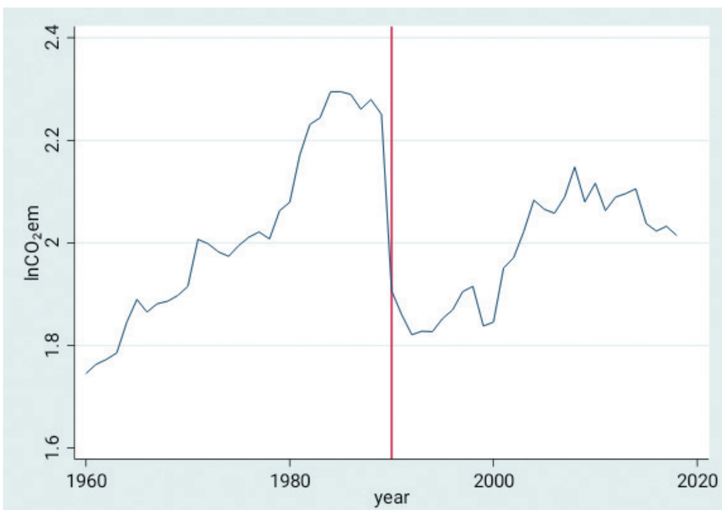

Figure 2. Carbon Dioxide emissions plotted using the natural logarithm of the data
Source: compiled by the authors.

The IPAT summary data are shown in Table 2. Input and output variables for calculating the energy decoupling technical efficiency are also displayed in the table. The previously established pattern for CO_2 emissions indicates a fundamental break, with rising emissions in the second regime. The political situation in South Africa, which affected industrial activities before and after independence in 1994, may cause the pattern.

Table 2

Summary statistics of IPAT variables

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2 Emissions	59	7.497467	1.136301	5.727223	9.922518
Total Population	61	3.35e+07	1.55e+07	2391309	5.86e+07
Gas Consumption (TWh)	56	15.78599	16.58234	0	44.10787
GDP per capita	61	3195.873	2119.326	443.0099	8007.477
Energy decoupling TE	59	0.3345763	0.2769669	0.076	1
ln CO_2em	59	2.00366	0.1478537	1.745231	2.294807
lnGDP per capita	61	7.784901	0.8385268	6.093592	8.988131
lnTotPop	61	17.13301	0.7704493	14.68735	17.88553

Notes: ln CO_2em = natural logarithm of CO_2 emissions; lnGDP per capita = natural logarithm of GDP per capita; lnTotPop = natural logarithm of the total population.
Source: authors' calculation.

Residuals prediction

According to the study, a good model for residual prediction is the Kaya identity. Using the MSDRM to estimate the parameter estimates of the natural logarithms for the identity, residual prediction was the next step in the data-generating process for the residuals (Table 3). The predicted values are the same metric as the model's dependent variable. Before obtaining these estimation results, it was necessary to remedy multicollinearity. Estimating a linear regression model allowed for multicollinearity diagnostics and the variables with high variance inflation factors (VIFs), thereby excluding variables with these high VIFs. The predicted residuals serve as a control for endogeneity in the final model estimating CO_2 emissions. An increase of 1 % in LNGDPPERCAPITA and LNPOPHISTORICALESTIMATES variables causes a –0.1948 % decrease and a 1.3170 % increase in emissions.

Table 3

Markov switching dynamic regression model on Kaya identity

Indicator	Coef.	Std. Err.
LNANNUAL CO_2 EMISSION		
LNGDPPERCAPITA	**–0.1948*****	0.0453
LNPOPHISTORICALESTIMATES	**1.3170*****	0.0319
p11	0.9492	0.0361
p21	0.1420	0.0878

Legend: * p < 1; ** p < 0.05; *** p < 0.01
Sample: 1965–2018; No. of obs = 54; Number of states = 2; Unconditional probabilities: transition AIC = –2.6307; HQIC = –2.5312; SBIC = –2.3728
Log-likelihood = 78.028207
LNANNUAL CO_2EMISSIONS = natural logarithm of annual CO_2 emissions
LNGDPPERCAPITA = natural logarithm of GDP per capita
LNPOPHISTORICALESTIMATES = natural logarithm of the historical population estimates
Source: compiled by the authors.

The table's results display the Markov switching dynamic regression model applied to the Kaya identity. The model examines the relationships between three independent variables and logarithmic annual CO_2 emissions: logarithmic historical population estimates, logarithmic GDP per capita, and residuals from the MSDRM. The results indicate that the coefficients for logarithmic Gross Domestic Product per capita (–0.1948) and logarithmic historical population estimates (1.3170) are statistically significant ($p < 0.01$). The coefficients measure how much logarithmic annual CO_2 emissions would change given a unit change in the independent variables. The coefficients show that logarithmic Gross Domestic Product per capita has a negative relationship with logarithmic annual CO_2 emissions, and logarithmic historical population estimates have a positive relationship with logarithmic annual CO_2 emissions. The table also shows the probabilities of the two states (p11 and p21), which are the transition probabilities from state 1 to state 2 and state 2 to state 1, respectively. The sample used in the analysis covers the period 1965 to 2018, and the number of observations is 54. The model used 2 states, and the evaluation criteria (AIC, HQIC, SBIC) suggest that the model is a good fit. The log-likelihood of the model is 78.028207.

The results in the estimated model

The t-test parameter estimates in the MSDRM show statistically significant relationships. The null hypothesis is that the coefficient estimate of each of the variables equals zero. Therefore, the null hypothesis of these variables is rejected, and it is concluded that the estimated coefficients are not equal to zero.

The proposed results light the relationship between CO_2 emissions and independent factors, such as gas consumption, decoupling efficiency, and lagged CO_2 emissions. The Markov switching dynamic regression model was applied to the extended IPAT framework (Table 4).

Table 4

Markov switching dynamic regression model on extended IPAT: Gas Consumption model

	Natural logarithm of CO_2 emissions
Estimated residuals	**0.149*** **
Natural logarithm of the total population	0.000515
Natural logarithm of decoupling technical efficiency variable	**0.332** **
Lagged natural logarithm of CO_2 emissions	**0.349*** **
Natural logarithm of gas consumption	**–0.0461*** **
State1 constant	**–2.580*** **
State2 constant	**2.774*** **
p11	0.8475
p21	0.1349
Observations	48

p-values in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: compiled by the authors.

The estimated residuals represent unexplained factors affecting gas consumption. After accounting for other model variables, a positive estimate of 0.149*** indicates a statistically significant positive association between gas consumption and unexplained factors. This suggests that the model underestimates emissions when these unaccounted-for elements are present.

The statistically significant positive influence of historical CO_2 emissions on current gas consumption is indicated by the Lagged CO_2 Emissions (0.349*) coefficient. Given that past emissions typically positively impact current consumption, this conclusion emphasises the significance of historical emissions levels when trying to reduce emissions in the future.

Assuming all other factors stay constant, the positive coefficient for decoupling efficiency (0.332)** shows that a rise in the technical efficiency of decoupling is linked to a statistically significant positive influence on gas consumption. This emphasises how crucial it is to cut emissions by disrupting the link between resource consumption and economic growth. Nevertheless, it is important to remember that increasing the usage of decoupling could cause energy to rebound and raise CO_2 emissions.

There is a statistically significant negative correlation between gas consumption and CO_2 emissions, as indicated by the coefficient for the natural logarithm of gas consumption (–0.0461***). In particular, it implies that lower CO_2 emissions are linked to higher gas consumption and vice versa. This inverse relationship suggests a tendency for CO_2 emissions to rise with increasing gas use and decrease with decreasing gas usage.

In the Markov switching model, transition probabilities ("p11" and "p21") represent the chance of changing between two states or regimes. If the system is already in State 1, then "p11" (0.8475) indicates an 84.75 per cent probability of remaining in that state. "p21" (0.1349) means that there is a 13.49 per cent probability that State 2 will change to State 1. These transition probabilities describe the dynamics and switching behaviour of the model, providing insight into how changing regimes affect the link between independent variables and emissions as well as changes in the factors influencing CO_2 emissions.

These findings highlight that factors such as historical levels, past CO_2 emissions, and decoupling technical efficiency affect gas usage. The model identifies two separate states with different levels of gas consumption. By enabling the investigation of various states, transitions, and their corresponding impacts on CO_2 emissions, the transition probabilities provide important insights into the dynamics of the model. These results can help formulate practical strategies for emissions reduction and provide insight into the intricate relationship between gas consumption and CO_2 emissions in various circumstances.

Discussion

Reducing the frequency of on-grid power outages is often the main reason for implementing renewable energy technology and other alternative electrical power generation sources. An unstable grid can cause everyday disruptions, negative effects on enterprises, and impediments to socioeconomic progress in many locations (Stančin et al., 2020, Jacal et al., 2022). By investing in alternative power production systems, people and businesses can lessen their need for the grid and offer a more consistent and dependable source of electricity.

Nevertheless, the comparatively greater cost of alternative power generation than on-grid electricity supply is an issue, particularly when fossil fuel-based generators, such as gasoline generators, are utilised (Jacal et al., 2022). The energy production cost can rise dramatically due to these alternative power generation technologies' fuel, maintenance, and operating costs (Stančin et al., 2020). Because of this, many people and companies might find it financially unfeasible to completely switch to these alternatives, which would keep them dependent on fossil fuels to generate electricity.

This reliance impacts the reduction of emissions on fossil fuels. The principal cause of climate change and a major contributor to greenhouse gas emissions is power generation that uses fossil fuels. Even with the environmental risks linked to fossil fuels, some people and companies find it challenging to switch from fossil fuel-based power due to the greater cost of electricity produced by other sources. As a result, there is still a good chance that emissions from the use of fossil fuels will decline.

To get beyond these obstacles and hasten the switch to cleaner energy sources, it is imperative to address the cost and dependability aspects of alternative power generation. Improving the overall reliability and reducing the problem of power outages can be achieved by increasing the stability and efficiency of renewable energy systems, such as wind turbines and solar panels. Governments and legislators can also contribute significantly by putting supportive laws, incentives, and subsidies in place to lessen the financial strain of switching to alternative energy sources.

Reducing reliance on fossil fuels and attaining significant emissions reductions are more likely when these issues are resolved and adopting dependable, affordable alternative power production technologies is encouraged. Switching to cleaner energy sources promotes energy security, resilience, and sustainable economic growth while also assisting in mitigating environmental effects.

Determinants of fossil fuels

The study demonstrates that historical emissions of CO_2 have a large positive impact on current emissions of CO_2 from gas, indicating that the CO_2 buildup in the atmosphere from prior emissions continues to contribute to current emissions. This can probably be explained in multiple ways. The long residence time of CO_2 in the atmosphere of CO_2 in the atmosphere (Granshaw, 2020), the feedback loops associated with climate change (Ripple et al., 2023), and the inertia in transitioning to cleaner energy sources (Gielen et al., 2019) are some of the reasons. Moreover, one factor contributing to the impact of legacy emissions is the resistance to switching to cleaner energy sources. It takes time to replace or phase out fossil fuel-dependent infrastructure, industrial processes, and energy systems, which results in ongoing emissions (Gielen et al., 2019).

A potential way to cut emissions is through energy decoupling, as demonstrated by the positive correlation between energy decoupling and gas CO_2 emissions levels in the estimated empirical model. Findings from earlier studies are consistent with the energy decoupling from CO_2 emissions seen in this investigation (Wang and Su, 2020; Wang, Zhang, 2020; Neves, Marques, 2021; Chovancová, Tej, 2020; Wang, Zhang, 2021). According to the correlation analysis, energy decoupling and CO_2 emissions have a statistically significant positive link. This finding demonstrates how high emissions may be addressed by energy decoupling or the separation of energy consumption from economic growth. Several writers stress switching from fossil fuels to more renewable and sustainable energy sources (Raihan et al., 2022; Lin and Zhu, 2019; Stančin et al., 2020; Gielen et al., 2019). Deploying technologies that enable energy decoupling is another critical step in addressing the root cause of emissions levels.

Investing in research and developing new technologies and ideas to help reduce emissions is one possible way to achieve this goal. To lessen the influence on the environment, carbon dioxide emissions from power plants and industrial operations can be captured and stored through the development of carbon capture and storage (CCS) systems. Governments can also encourage companies to use energy-efficient technologies and renewable energy sources, and they can inform the public about ways to use less energy.

A systemic shift in how energy is produced and consumed and technological solutions are also necessary to reduce emissions. This shift may entail adjustments to laws and regulations and consumer behaviour. For instance, governments can enact laws and provide financial incentives to entice companies to use energy-efficient technologies and renewable energy sources. In order to motivate customers to use less energy, they might also offer initiatives for education and awareness.

Energy decoupling, or detaching economic growth from resource consumption and environmental degradation, is important for lowering emissions, as evidenced by the finding that positive decoupling coefficients for gas consumption models imply increased CO_2 emissions.

Remarkably, the natural logarithm of gas consumption shows a statistically significant negative correlation between CO_2 emissions and gas consumption. As a fuel source, switching to gas usage can decrease CO_2 emissions, generally preferred for sustainability and environmental reasons. Reduced emissions might result from using gas at a higher degree of energy efficiency or from using cleaner energy sources. Changing to less efficient or more carbon-intensive energy sources may be why CO_2 emissions rise when gas use falls.

Increases in energy efficiency have decoupled CO_2 emissions from energy consumption, lowering emissions even in the face of rising energy usage (Wang, Su, 2020; Wang, Zhang, 2020; Neves, Marques, 2021; Chovancová, Tej, 2020; Wang, Zhang, 2021), demonstrating that there is a complex relationship between energy use and CO_2 emissions and that other factors like energy efficiency, technology, and policy affect emissions levels. Similarly, cutting CO_2 emissions requires severing the link between economic expansion and CO_2 emissions.

However, the increased use of decoupling to reduce emissions levels shows the presence of energy rebounding. Energy rebounding occurs when a corresponding rise in energy consumption counteracts the benefits of increased energy efficiency. Increased energy efficiency may lead to increased energy use (Li R., Li S., 2021; Sorrell et al., 2020) due to increased travel and greater comfort.

Conclusion

In conclusion, this study has shed important light on the South African energy industry using Markov-Switching Dynamic Regression Models (MSDRM) to quantify structural breaks in CO_2 emission data. The research effectively expanded the use of MSDRM and included other variables by modifying the IPAT identity extension. This produced a new impact assessment formula.

Reducing present emissions and resolving the cumulative legacy emissions over time is crucial since the study's findings also demonstrate the strong positive influence of past CO_2 emissions on current gas emissions. The switch to renewable energy sources and increased energy efficiency are two examples of the required ambitious mitigating measures. The long-term effects of legacy emissions on climate change must be adequately addressed, which requires these steps.

Finally, cooperation with international partners is crucial to address the global problem of reducing emissions levels. Engaging actively in global accords and initiatives, like the Paris Agreement, can offer a framework for curbing global warming and make it easier for countries to share best practices and pool their resources. Countries can effectively and sustainably cut their emissions by cooperating.

In summary, this study greatly advances scientific understanding by applying a modified extension of the IPAT identity and creating a methodology for measuring energy decoupling. The results emphasise the importance of considering historical emissions levels and supporting decoupling to cut CO_2 emissions successfully. These results can be used by stakeholders and policymakers in South Africa and other nations to develop and carry out emission reduction plans that support a more ecologically conscious and sustainable future.

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Appendix

Definition of variables used in equation

Short name of variable	Variable
InCO_2emission	Natural logarithm for CO_2 emissions
Intotalpopulation	Natural logarithm for total population
Ingasconsumption	Natural logarithm for gas consumption
Indecouplete	Natural logarithm for decouplete (i.e., the technical efficiency variable)
Lag.InCO_2emission	The lagged variable for the Natural logarithm for CO_2 emissions

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