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Table of Contents

Tables And Figures

To What Extent Does Economic Development Affect Carbon-Dioxide Emissions in Developing Economies?

i: Abstract

This research paper assesses the impact of economic development on CO_2 emissions in China, India and South Africa using time-series data from each country between 1960-2019 on CO_2 Emissions, GDP, Foreign Direct Investment (FDI), Urban Population and the Gini Coefficient in multiple Ordinary Least Squares (OLS) estimators and Vector Autoregression (VAR) Models to find the Granger Causalities. The causality results show a bidirectional causality between CO_2 emissions and GDP, as well as a bidirectional causality between CO_2 emissions and FDI in China and India. A significant unidirectional causality is also found to exist with Urban Population running to CO_2 emissions in India, and a bidirectional causality between CO_2 emissions and the Gini Coefficient in South Africa. The evidence seems to support the Environmental Kuznets Curve (EKC) with a positive relationship between these economic indicators and CO_2 emissions, and reviewed literature confirming that these indicators are likely to cause a reduction in CO_2 emissions in the long run. It can be concluded that the effects are heterogenous across countries and therefore different policies are required across regions, however it is possible to reduce CO_2 emissions without a loss in economic performance through increasing energy efficiency and the encouragement on renewable energies.

1: Introduction

Developing economies today are growing rapidly and will soon become the largest economies in the world. The 5 largest developing economies are the BRICS (Brazil, Russia, India, China and South Africa), and there has been much controversy around the sustainability of their recent growth, with these countries being some of the largest producers of CO_2 emissions. They [47]Kyoto Protocol (2005) set objectives to both developed and developing economies to reduce Carbon Dioxide (CO_2) emissions by an average of eighteen percent compared to the levels in 1990. Whilst BRICS countries signed this protocol, there are still concerns around their emissions compared to their rapid economic growth. The [8]BRICS Summit (2022) in China concluded in a joint commitment to facilitate green and low carbon development where there were agreements to share green technologies and achieve carbon neutrality after they achieve their peak emissions within 30 years.

A study of China, India and South Africa has been chosen for this research, Russia was excluded because there is very limited data on Russia available, making it difficult to obtain accurate results on the relationship between economic growth and CO_2 emissions. Brazil was also excluded because a large percentage of their energy mix is from hydropower due to the Amazon River running through their country. With the minority share of the energy mix being non-renewables, Brazil would be an anomaly in the results and would not provide an accurate representation of a developing economy.

There have been many studies on the causal relationship between GDP and CO_2 emissions in BRICS economies, with BRICS economies representing 42% of the world's GDP according to the [48]UNCTAD (2023), and the relationship between the two theoretically being linear due to the EKC showing the relationship between GDP per-capita and environmental degradation. There are also many studies including the causal relationship between FDI and CO_2 emissions, to identify the pollution haven hypothesis as well as the halo, scale, technical and compositional effects of FDI on an economy – all affecting CO_2 emissions. To emphasis this, BRICS countries received $335 billion of FDI inflow in 2021 according to the [48]UNCTAD (2023).

Urbanisation is also a significant topic of discussion in BRICS countries, with massive urban population growth throughout each country including South Africa – which suffered from low urban populations during Apartheid, with segregated residential areas across urban and rural regions in the country. However, urbanisation has few studies on its relationship with CO_2 emissions – and all studies on this do not include other explanatory variables, highlighting the need to include urbanisation in a study as a key economic indicator alongside others because of its significance in economic development in BRICS countries.

Income inequality in BRICS countries has become an increasingly popular subject, with 50.3% of the rural population in China receiving no access to public benefits, such as public education or healthcare, whilst Brazil and South Africa utilise regressive tax systems based on consumption instead of income according to [35]OXFAM (2013). This indicates the need to include income inequality (Measured using the Gini Coefficient) as an indicator of economic growth in BRICS countries. Much the same as with Urbanisation, there have been few studies on the relationship between CO_2 emissions and the Gini Coefficient alongside other economic indicators.

Therefore, this study will include these variables as economic indicators and assess their relationship with CO_2 emissions within China, India and South Africa to identify whether economic growth can be sustained whilst reducing CO_2 emissions and suggest policies which can achieve this target.

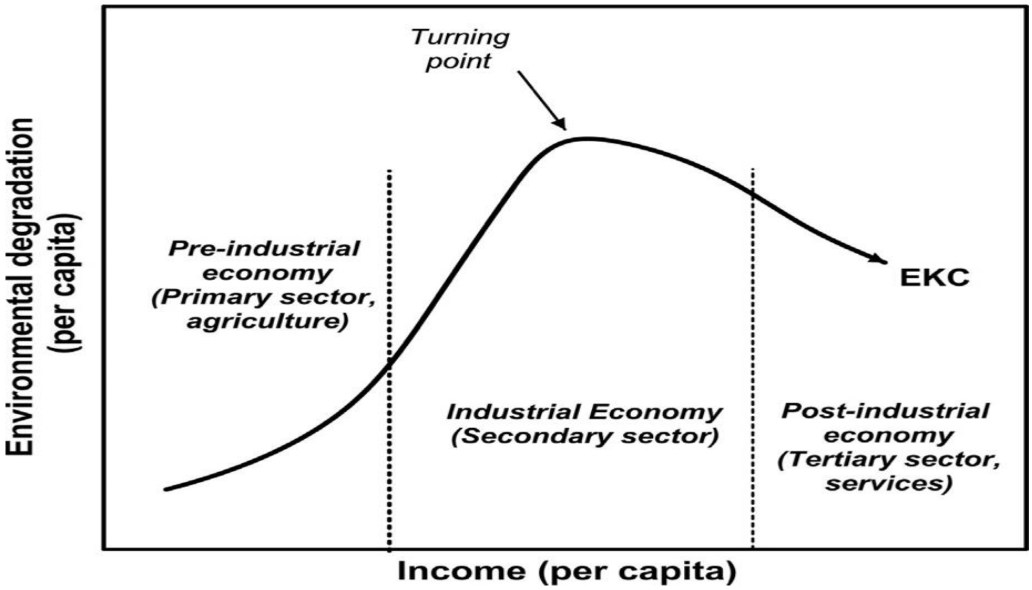
2: Literature Review

2.1: Overview

This review of literature can be divided into six strands of study to give an overview of the topic and explain the relationship between different variables used to explain CO2 emissions, which will ultimately be used in the model created in this study. This review will also highlight how there have been numerous studies on the relevant theories, all finding different conclusions and contradicting each other, showing that there are no "blanket" policies for all countries.

[25]Kaika and Zervas (2013) studied the concept of the Environmental Kuznets Curve (EKC) in the case of CO2 emissions. They find that "according to the EKC- theory, the process of economic growth is expected to eventually limit the environmental degradation created in the early stages of development". This can be shown in Figure 1, [23]Jalil and Mahmud (2009) that estimates China to be operating in the secondary sector within this graph before the turning point - with China one of the largest contributors of CO2 emissions in the world, whilst setting targets to reduce CO2 emissions. [1]Abdouli et al (2018) and [46]Ummalla and Goyari (2021) also validate the EKC hypothesis for BRICS (Brazil, Russia, India, China and South Africa) economies and place them at various points in the Secondary sector in Figure 1. This would be because GDP per-capita has not risen to the post-industrial level to afford less environmental-degrading goods. [27]Khattak et al (2020) confirm this with their findings, also finding a two-way causality between GDP per-capita and renewable energy consumption in India and South Africa, showing when GDP per-capita rises and reaches the turning point, households will increase usage of renewable energy and reduce environmental degradation. However, [34]Onafowora and Owoye (2014) find contradicting results in their study of African countries (including South Africa), with their conclusion being that the long-run relationship between economic growth and CO2 emissions following and "N-shaped" trajectory.

Figure 1: [15]The Environmental Kuznets Curve



[11]Danish et al (2019) use panel data between 1990 and 2015 sourced from the BRICS countries to employ an Augmented Mean Group algorithm to analyse the nexus between natural resources, renewable energy, economic development, and CO2 emissions – finding a relationship between economic development and CO2 emissions, because as economic growth increases, so does the demand for energy. However, [11]Danish (2019) only uses GDP and Urbanisation as their indicators for economic growth and does not consider other factors, whereas [17]Grossman and Krueger (1995) use income per-capita as a measure and find no evidence of [11]Danishs's (2019) conclusions. [11]Danish (2019) also uses a small sample size for their data, if they were to use a longer time-period and use time series data for each BRICS country it would help validate their results, especially if they only include two measures for economic growth. However, it is understood that there is limited economic data for BRICS countries, especially Russia for this analysis. This can be supported by [50]Yang et al (2017), who studied the EKC hypothesis in Russia and only included data from 1998-2013. Their study also had the same conclusions and confirmed the existence of an EKC in Russia. [12]Dong et al (2018) also find the same conclusions in their study of 128 countries between 1990-2014

using data from World Bank and confirm a positive and significant influence from economic growth on CO_2 emissions.

2.2: Gross Domestic Product (GDP)

GDP is the most common indicator for economic growth because it simply shows the size of the economy, this is relevant towards EKC as the size of the economy paints a picture of which sector a country lies in Figure 1. The data for GDP in BRICS countries is also widely available. [10]Cowan et al (2014) examine the causal link between GDP and CO2 among other variables in BRICS countries. They used data between 1990-2010, and results varied by country. They find a bidirectional causality in Russia, a one-way causality in South Africa with GDP causing CO2 emissions, and the opposite in Brazil. [13]Erdoğan, and Gedikli (2019) conducted similar analysis using a larger time-period, using a fully modified OLS approach and found a bidirectional relationship between the same variables. [15]Fu et al (2021) found the same results using their combination of multiple econometric models such as a DOLS, whilst [30]Li et al (2022) found a one-way relationship between GDP and CO2 emissions using an ARDL model with data from BRICS countries between 2000 and 2019. However, one study that contradicts studies on the relationship between GDP and CO2 emissions is that of [4]Azevedo and Campos (2018) whose study on the volume of CO2 emissions using a lag of these emissions and with GDP between 1980-2011, finding mixed results and that this type of analysis must be used country-by-country – further highlighting the fact that there cannot be a blanket policy in developing economies to reduce CO2 emissions.

One of the seminal papers in this area of study is that of [28]Kraft and Kraft (1978), who studied the causal relationship between Gross National Product (GNP) and energy, and therefore CO2 emissions. They used a Sims Causality Test and found a one-way link running from GNP to energy. This paper however, may not produce the most accurate results because it uses data post-World War 2 (Between 1947-1974), where economies are recovering from the shocks of the war and Great Depression. Keeping this in mind, a Sims Causality Test requires a much larger sample size as they include more regressors due to the inclusion of leading terms – this leads to a larger loss of degrees of freedom and could skew results. The main conclusion from this study is that energy conservation would be an effective policy because according to [28]Kraft (1978)'s results, there is no adverse effect on economic growth. [43]Sözen and Arcaklioglu (2007) argue that GDP is a more effective indicator of economic growth than GNP as GDP excludes income from abroad and focuses on the domestic economy, this could argue as another downfall in [28]Kraft (1978)'s study. [24]Joshua and Bekun (2020) revisit [28]Kraft (1978)'s study using the case of Nigeria using data from 1970-2017 and find a unidirectional Toda-Yamamoto causality running from pollutant emissions to GDP, this is supported by [2]Akadiri et al (2019) who run the same model for South Africa, and found significant results in environmental quality causing GDP and real income per-capita, which is likely because according to their findings, 15% of South Africa's GDP is the energy sector, with coal accounting for 70% of primary energy.

[44]Tiwari (2011) uses a Structural Vector Autoregressive (SVAR) Approach to analyse the relationship between economic growth and CO2 emissions in India, they found that a positive shock on GDP had a significant positive impact on CO2 emissions. They conclude that the India government need to focus on creating demand-side policies that complement renewable energy sources to develop the economy sustainably and limit the environmental damage the economy causes before it reaches the turning point in Figure 1. [44]Tiwari (2011)'s study also found their variables to be non-stationary, therefore the first differences were used to ensure stationarity, also no cointegration was detected – Whilst this had to be implemented to ensure the model is not spurious, first-order differencing leads to the inability to make a unique long-run solution. [22]Inumula and Deeppa (2017) also used a VAR model in their study of India and encountered the same problem in the need for first-order differencing, however they only studied the short-term forecasting for CO2 emissions. They concluded that if GDP per-capita in India

rose by 10%, then CO_2 emissions would rise by 1.4%. They also conclude that in the long-run, GDP is limited in explaining CO_2 emissions.

2.3: Foreign Direct Investment (FDI)

Foreign Direct Investment (FDI) is important to an economy because it leads to higher economic output and creates jobs, reducing unemployment. FDI also leads to the pollution haven hypothesis where foreign firms move their production to countries with less strict environmental laws, large amounts of natural resources and cheaper labour. This hypothesis is particularly prevalent in developing economies.

[3]Apergis et al (2023) revisits the pollution hypothesis using BRICS countries, with data on FDI inflows between 1993-2012 from eleven OECD countries. They find that FDI from certain countries such as the UK or Denmark increased CO_2 emissions in BRICS counties, whereas inflows from countries such as France reduced CO_2 emissions – supporting the pollution halo hypothesis. They concluded that the country doing the investing is important in determining the environmental outcome in the BRICS country. [45]Udi et al (2020) also studied the effects of FDI on GDP and CO_2 emissions in South Africa using data from 1970-2018 in a ARDL model. They found a unidirectional causality running from FDI to industrialisation; this potentially supports the EKC theory where, as a country industrialises, they move up the curve in Figure 1 in the industrial economy section, therefore increasing environmental degradation.

[36]Pao and Tsai (2011) have one of the key research papers on the study of economic growth and CO_2 emissions in BRICS countries because they include FDI as one of their variables. They use panel data from BRICS countries except Russia between 1980-2007 and find evidence supporting the pollution haven hypothesis and the scale and halo effects, finding a strong two-way causality between FDI and CO_2 emissions. This is supported by the research of [20]He et al (2020) who find strong causal relationships between FDI and CO_2 emissions in

every BRICS country except South Africa, using their ARDL model. This could be due to South Africa receiving considerably less FDI than other BRICS countries, and therefore not enough data being available to make the same econometric conclusion. [39]Rafique et al (2020) contradict these findings using their AMG estimator to find a statistically significant negative relationship between FDI and CO_2 emissions in the long run. However, they use a shorter time-period of between 1990-2017 which would lead to different findings to other papers. They also employ a Dumitrescu and Hurlin panel causality test and find a one-way causality between FDI and CO_2 emissions. [29]Lee et al (2021) also find a positive relationship between FDI (Inflows and Outflows) and CO_2 emissions, supporting the pollution haven hypothesis. They also place emphasis on the need for sustainable domestic policies from BRICS countries in attracting FDI to encourage the halo effect. This could be achieved through further industrialisation so there is cleaner technology throughout industries so that investment will benefit the environment.

[38]Ping and Shah (2023) use data from 2000-2019 and find a positive relationship between FDI and CO_2 emissions in the long-run, but not in the short-run. This could be explained by their data only being from the 21st century which will bring different results to many other studies. However, this could be beneficial as it eliminates the effects of big historical events such as Russia transitioning out of capitalism following the Cold War, or South Africa following the abolition of Apartheid in 1994 which would skew economic indicators. [33]Ngarava's study (2021) supports this, using data from 1993-2020 on various macroeconomic variables, including FDI to study their relationship with CO_2 emissions in South Africa. Their study starts as Apartheid is ending and they also find a long-run relationship with CO_2 emissions, but not in the short-run. Again, this is likely to be due to the lack of FDI in South Africa over the years so that there is no immediate significant impact.

[56]Xie, Wang and Cong (2020) studied the effects of FDI on CO_2 emissions in BRICS countries using a panel smooth transition regression model with data from

2005-2014. They found that increasing FDI leads directly to an increase in CO_2 emissions, but also that increasing FDI could also reduce the CO_2 emissions through the spill-over effect following economic growth, confirming both the pollution haven and halo hypotheses. They also find that this effect has significant regional heterogeneity, once again the need for region-specific policies to reduce CO_2 emissions. This paper also focuses on FDI as the only explanatory variable, which is great for assessing the effects of FDI on CO_2 emissions – but it does not solely explain CO_2 emissions, including additional variables such as GDP or renewable energy consumption and a larger sample size would validate the econometric results further.

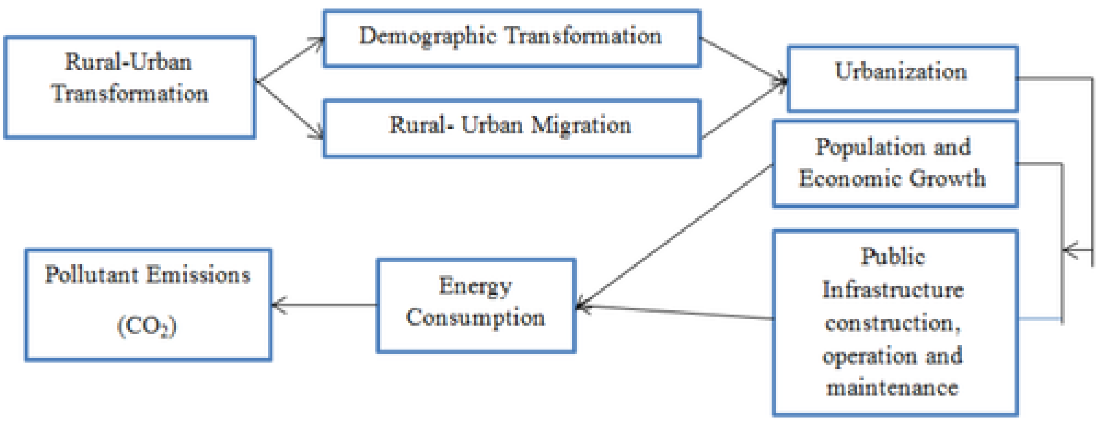
Further theory that can tie in FDI to Figure 1 is that of the scale, technical and compositional effects on an economy following FDI. FDI in the short run can lead to the scale effect where production increases, ceteris paribus – leading to an increase in CO_2 emissions. This can be depicted in Figure 1 where environmental degradation increases up until the turning point. However, FDI could contribute to reducing CO_2 emissions in the long run through the technical effect and the scale effect. The technical effect is where there is a technological spill over from foreign technologies being used in the economy and leads to low carbon technologies being adopted throughout the economy. The compositional effect is where the industrial structure of the economy changes following FDI into lower carbon emitting industries. These effects can be depicted in Figure 1 as the fall in environmental degradation after the turning point. [18]Hao et al (2020) studied the effects of both outward and inward FDI on the environmental quality of China, they found that all three effects are significant for China in both outward and inward FDI.

2.4: Urbanisation

[19]Haseeb et al (2017) use panel data from 1990-2014 in a FMOLS model to examine the effects of urbanisation and other variables on CO_2 emissions in every BRICS country. They find that urbanisation has a significant and positive

relationship with CO_2 emissions in every country except for Russia. This can be seen using Figure 2, which shows that as a country develops its urban areas, it attracts rural-urban migration due to better standards of living and more job opportunities. This leads to higher urban population which needs infrastructures such as public transport or general city development, these projects lead to higher CO_2 emissions. This can be seen happening in BRICS countries such as South Africa building new cities such as Nkosi City and the Lanseria Smart City, which attracts rural residents as the benefits of migrating outweigh the costs. [39]Rafique et al (2020)'s supports this with their finding of urbanisation contributing significantly to environmental degradation. [31]Liu et al (2020) also support this theory in their study of the long-term impacts of urbanisation in China, estimating that 333 million people will migrate to urban areas from rural areas by 2050, highlighting the need to make massive improvements in the infrastructure to support this which required energy and explains the movements in Figure 2. They estimate that China will at least double the primary demand for energy throughout this time-period. However, this paper presents no empirical findings and therefore cannot support the statistics presented – but still is effective in presenting the process of urbanisation causing CO_2 emissions.

Figure 2: [11]The Mechanism of Urbanisation on Emissions



One of the seminal articles on urbanisation and CO_2 emissions is from [37]Parikh and Shukla (1995) and was one of the first to discuss the issue using empirical analysis. They find that urbanisation affecting CO_2 is complicated, one of the main points being that the issue depends on the mix of energies consumed – equating to energy being the most important variable in a model when analysing the causal relationship between CO2 emissions and urbanisation. [14]Ehrlich and Holdren (1971) also wrote another key article using an IPAT model to find that population growth leads to a negative impact on the environment and highlights the limitations in policy making to reduce the carbon impact of urbanisation. However, the IPAT model is a conceptual form and cannot determine the size effects of urbanisation. Whilst both articles are crucial in providing context for the relationship between CO2 emissions and urbanisation, neither article has a focus on developing economies and use old data. Therefore, more recent articles which expand on the theories are required for a modern explanation. [40]Raheem and Ogebe (2017) helps this situation with their study on 20 African countries in 1980-2013, expanding on these two articles. They use a pooled mean group to find that urbanisation and industrialisation both directly increase environmental degradation and CO2 emissions. They also found the indirect effects of urbanisation causing CO2 emissions to fall due to the increase in income per-capita, this confirms the EKC hypothesis in Figure 1, where, as incomes increase in the long-term, environmental degradation will fall. [58]Zhu et al (2018) find the same result in their study of BRICS countries and emphasise how we may underestimate the effect of urbanisation on CO2 emissions.

[52]Wang et al (2016) studied the effects of urbanisation on CO2 emissions using a panel of BRICS countries between 1985-2014; they found a long-run cointegrated relationship between the two variables and that urbanisation Granger causes CO2 emissions in the long-run. They conclude that increasing energy efficiency in urban areas is the correct way to reduce this causality, so that the movement in Figure 2 will be less significant. Although this policy could prove problematic in developing economies as it would be costly and could slow down economic growth. The same conclusions are made by [12]Dong et al (2018) whose study focused on population growth and found that the percentage of renewable energy in the energy mix of the country affected the extent to which urbanisation caused CO2 emissions. However, [6]Balsalobre-lorente et al (2018) found in their study of

BRICS countries between 1990-2014 that urbanisation contributes towards reducing carbon emissions, while energy usage is a key driver in CO2 emissions. They conclude that urbanisation can contribute to controlling air pollution in BRICS countries if correct energy policies are introduced.

2.5: Income Inequality (Gini)

Income inequality is a relatively new variable used to explain CO2 emissions. Using Figure 1 we can see that income per-capita has an inverted U relationship with environmental degradation, therefore, income per-capita could be very high for an economy but so could income inequality, meaning that only a few households are able to afford a low-emission lifestyle and CO2 emissions will be higher than expected and the economy may reach the turning point later than the theory suggests. This is particularly relevant in developing economies where such inequality exists. [5]Baloch and Danish (2022) studied the relationship between income inequality and CO2 emissions in BRICS countries over 1994-2018, they found that income inequality does contribute to CO2 emissions in BRICS economies. They suggest that as income distribution becomes more equal, so does the balance of power in BRICS countries, which could lead to more support to fair environmental policies. [58]Zhu et al (2018) also conclude that income inequality has a positive relationship with CO2 emissions, but also find that it is heterogeneous across regions. Their study also finds that the effect depends on energy use, with renewable energies being more widely available and cheaper than previous decades it is possible for low-income households to afford to reduce their CO2 emissions. However, [21]Heerink et al (2001) provide the argument that income inequality and CO2 emissions have a negative relationship in their study of Sub-Saharan Africa. This is because as income inequality rises, it can contradict the effects of the political economy on the environment, and if the political economy is reducing CO2 emissions – then lower income inequality could reverse this. They also conclude that income inequality leads to biased estimates of points in the EKC (Figure 1), similar to the point raised earlier.

[57]Zhao et al (2021) focus on the relationship between just income inequality and CO_2 emissions and found that Russia and South Africa improved in the long run following both a negative and a positive change, but in the other BRICS countries there was a positive relationship between the two variables. And in the short run their income inequality positively impacted CO_2 emissions in Russia, India, and Brazil – concluding that policies must be specific to countries. This highlights the need for developing economies to focus on the environmental quality of economic development, such as a policy of a discriminating tax system between urban and rural areas to reduce income inequality – or a green tax to subsidise environmental products and services, and tax CO_2 heavy products and services. [9]Chen et al (2022) target their research towards the relationship between income inequality and 'Green Growth' using data from 1993-2020 in an ARDL model and find that in the long run they are negatively significant, therefore as income inequality increases, green growth slows down. They find mixed and inconclusive results for the short run estimates across the BRICS countries and conclude that the macroeconomic objective of reducing income inequality whilst reducing environmental degradation can be achieved by a government. These articles are useful towards this research because they give perspectives on policy suggestions to reduce income inequality and CO_2 emissions simultaneously. However, they provide mixed results whilst analysing the same data using different models, indicating that there are no conclusive results in this area. This is likely to be due to a lack of data in BRICS countries because the Gini Coefficient is a very niche economic indicator so it gets reported on less than it already would be in developed economies.

[32]Mahalik et al (2018) studied the linkage between CO_2 emissions and income distribution in every BRICS country except Russia, using data from 1980-2013 in an ARDL model. They found that in the long run, income inequality leads to higher emissions in China, Brazil, and India, whilst it leads to a reduction in emissions in South Africa. This once again contradicts the results from the previous literatures discussed, whilst using the same model. This is likely due to the date range again, by using data from 1980-2013 they include data from South

Africa over the dates of Apartheid ending, as well as excluding the massive recent economic growth in India and China – potentially skewing results.

2.6: Other Variables

The following sub-section in this review of literature will focus on two variables that can also be used to explain CO2 emissions. The first of which is interest rates - lower interest rates would encourage investment in green projects. [15]Fu et al (2021) suggest that BRICS could offer low-interest or interest-free loans for green projects, to incentivise investment. This would not only lead to an increase in GDP, but also lead to environmentally sustainable economic growth and potentially reduce CO2 emissions. This is supported by [16]Fu et al (2023), who highlight that lowering interest rates and increasing the supply of money could lead to excessive economic growth using non-renewable energy, and that green policies should be implemented to ensure this does not happen.

Another variable that is considered in explaining CO2 emissions is renewable energy usage, this variable mitigates the other explanatory variable and is likely to have a negative relationship with CO2 emissions. [27]Khattak et al (2020) confirm in their research that renewable energy consumption mitigates CO2 emissions in BRICS economies. [5]Baloch et al (2022) also finds that renewable energy consumption offsets the effects of income inequality on consumption-based CO2 emissions in BRICS economies.

Table 1: A Summary of the Key Literature

Literature:	Conclusions	Theory	Data	Methodology	Criticisms
[6]Danish et al (2019)	Positive relationship between economic development and CO2 emissions	Testing the EKC hypothesis, also uses production possibility frontier (PPF) with use of natural resources during industrialisation	Panel data from BRICS economies 1990-2015	Uses a Augmented Mean Group algorithm	-Only economic indicators used are GDP and Urbanisation. -Small sample size of 15 years
[19]Kaika and Zervas (2013)	-Studies find that economic growth is not reducing CO2 emissions over time -CO2 emissions are heavily related with economic growth through consuming energy	-EKC hypothesis -Pollution haven hypothesis -Technical and compositional effects -Factors of production -Exhaustion of natural resources, PPF	Did not use data, only reviewed literature	Creates a reduced-form equation to explain the EKC hypothesis, explaining conditions for curve to be an inverted-U shape or inverted N	-Only reviews literature, no methodology -No original conclusions were made, only drew off other studies
[23]Kraft and Kraft (1978)	-Finds a one-way link running from GNP to energy -It is possible to reduce CO2 emissions without hindering economic growth	-Policy making -Embargos and energy crises -Economic crises (Great Depression)	Data from Bureau of mines 1947-1974	Uses a Sims Causality Test	-Does not study developing economies -Sim's test uses a lot of regressors, possibly requires more data -Refers to energy, not directly to CO2 -Only tests unidirectional causality
[35]Pao and Tsai (2011)	-Evidence supporting the pollution haven hypothesis, and the halo and scale effects -two-way causality between FDI and CO2	-Pollution haven and halo -Scale, technical and compositional effects -EKC hypothesis	Panel data from BRICS economies from 1980-2007, except Russia, with data from 1992-2007	-Linear logarithm quadratic form -Panel Cointegration -Granger Causality	-Uses first differences in logarithmic form to ensure data is stationary, this could affect long run predictions

3: Methodology

3.1: OLS Estimators

3.1.1: Data and OLS estimator

The methodology in the report will undertake a positivist position for its analysis, where reality is objective and can be discussed within the report. This position also means that we are independent from the topic and can analyse with a formal and passive voice, whilst testing the hypotheses made in the report.

This report used time series data from 1960-21021, obtained from [53]WorldBank and from accessing [7]The Bloomberg Terminal for [7]CO2 emissions (measured using kilotons(kt)), [53]GDP (measured using US$), [7]Foreign Direct Investment (FDI, measured in US$), [54]Urban Population (Urb, measured in population size) and the [7]Gini Coefficient (Gini, measured using the Gini index) across China, India, and South Africa – 3 of the leading developing economies in the world.

Interest rates were not accepted into this regression, because they influence GDP through encouraging investment and spending, and GDP is considered a more useful macroeconomic variable. Renewable energy consumption was also not accepted as a variable because while crucial in explaining CO2 emissions, renewable energy consumption does not indicate economic growth.

This data was then used to create a linear regression model in the form of an OLS estimator to test the hypothesis the relationship that GDP, FDI, Urb and Gini have with CO2 emissions, and then test for granger causality to assess whether the explanatory variable can be used to forecast GDP. The Ordinary Least Squares (OLS) estimator can be written as follows:

$$CO2 = \alpha + \beta GDP + \beta FDI + \beta Urb + \beta Gini + u$$

3.1.2: Stationarity and Problems with Data

Since the data being used for this regression is time-series, the data must be tested for stationarity. In a stationary timeseries, shocks will be temporary, and the series will revert to the values of its long run mean as the effects disappear. The data used for this regression was tested using the Augmented Dickey-Fuller (ADF) test for unit roots and was concluded as non-stationary. This was expected as the variables being used stay inconsistent over time in developing economies, for example GDP in China has rapidly increased over the time- period used. Because of this, the first differences in the data were taken to use in this regression model.

However, even after this, Urbanisation still tested as non-stationary using the ADF test in China and South Africa. The results can be found in Table 1 within the Appendix, with the ADF test having a null hypothesis on non-stationary.

Another problem with the data used in this regression is that there aren't enough values for the Gini-Coefficient, this is because as these economies are developing, the indicators for income inequality have only been measured in the last 20 years, and at intervals – so in the past this was not being measured at all. To be able to include this explanatory variable in the regression, the missing values for Gini were assumed to be the same as the previous year.

Because of these problems, 9 OLS Estimators were created. 3 for each country to exclude Gini and Urbanisation separately, to identify if removing either of these variables significantly affected the results or not by making the models more parsimonious.

3.1.3: Heteroskedasticity

The OLS estimator has several assumptions, that if violated cause the model to be an invalid. Therefore, these assumptions must be tested for.

One of these assumptions is that the random errors are homoskedastic, where $var(u_i) = \sigma^2$. This means that the error term has a constant variance and therefore an equal spread. If this assumption is violated and the random errors are heteroskedastic, then the betas are unbiased and consistent because the explanatory variables are not correlated with the error term. Heteroskedasticity also causes the OLS estimator to underestimate the variances and standard errors, meaning that the t and F-statistics and will be higher than expected. Heteroskedasticity can be detected by using the Breusch-Pagan LM test and the Whites test, which both have a null hypothesis of homoskedasticity.

Using Table 2 from the Appendix we can see that all the OLS estimators used rejected the null for both tests and detected heteroskedasticity, except India (when all variables were used). This had to be corrected for using White's Standard Errors to provide a more accurate estimate.

3.1.4: Autocorrelation

The next assumption to be tested for is that there is no serial or autocorrelation in the regression models. This can be expressed as Cov(ut, us) = 0. If this assumption is violated then the estimators would still be unbiased and consistent (because these do not depend on this assumption), however the estimators would be inefficient and will no longer be BLUE (Best Linear Unbiased Estimator). Also, the variances of the coefficients in the regression will be biased and inconsistent which would invalidate any hypothesis testing used.

The Durbin-Watson test can be used to detect the presence of serial correlation, and the Breusch-Godfrey LM test and Durbin's h test can be used to detect autocorrelation within the model. Using table 3 in the appendix, we can see that there was no serial or autocorrelation in the OLS estimators except for China after removing urbanisation as a variable – showing that whilst the data for urbanisation in China was non-stationary, taking it out of the regression did not benefit the estimator.

3.1.5: Multicollinearity

Another assumption of the OLS estimator that needed to be tested for is that the sample values of the explanatory variables have no exact, linear relationships, which are known as multicollinearity. If perfect multicollinearity exists within the variables, then the regression coefficient will be indeterminant, but if imperfect multicollinearity exists within the variables – then the variances, and therefore the standard errors will be larger than if the equation did not have multicollinearity. Estimating the Variance Inflation Factor (VIF) can be used to detect any correlation between the explanatory variables, a value of 10 would be considered as a high presence of multicollinearity. Table 4 in the Appendix shows the results of VIF on the OLS estimators, using this we can see that all values are below 2 and therefore there is no evidence of problematic multicollinearity within the variables.

3.1.6: Misspecification

The OLS estimators were also tested for misspecification, this can affect the whole model and covers whether the correct explanatory variables are being used, or whether the model has the correct specification, and the relationships are linear or not. The Ramsey RESET test was used to detect general misspecification, this has a null hypothesis of correct specification. Using Table 5 in the Appendix, we can see that the only times the null hypothesis was rejected was when Urbanisation was excluded – highlighting once again that whilst the data was non-stationary, including it in the regression is beneficial.

3.1.7: Granger Causality Results and Discussion

Causality is used to find whether a variable can be used to predict (and cause) another. Granger causality is useful in determining this, by using the data on a variable X's history to assess if that can be used as a predictor for variable Y. Each OLS used the Granger Test for causality, and the results can be found in Table 6 in the Appendix. The summary of these tests is also found in Table 2. We can see that removing Urbanisation and Gini as variables had no impact on causalities in the findings.

Table 2: A summary of Granger Causality Test Results using OLS

Variable Causality On CO2 by Country	China	India	South Africa
GDP	No Causality	Weak Causality	No Causality
FDI	Significant Causality	Strong Causality	No Causality
Urb	No Causality	Significant Causality	No Causality
Gini	No Causality	Strong Causality	Significant Causality

From these results it is clear in China, that FDI has a very strong causality towards CO2 with a 0.1% significance level. This can be explained by foreign companies increasing their investments in developing economies because they are potential pollution havens, [41]Ren et al (2014) also discuss this in their findings, which show that FDI and CO2 have a significant relationship in China. [36]Pao and Tsai (2011) also have similar findings in their studies with a unidirectional causality from FDI to CO2 emissions in their studies on BRICS countries, supporting the pollution haven hypothesis. Using Table 2 we can also see that FDI causes CO2 in India at a 5% significance level, this could be because India is still less developed than China and is receiving less FDI, but still shows significance.

Using Table 2, there is also a significant effect on CO2 emissions from the Gini coefficient in South Africa with a 1% significance level, as well as India with a 5% significance level - signalling that income inequality causes CO2 emissions. [26]Kang (2022) also has the same finding in their study on OECD countries, with economic growth and income inequality unidirectionally causing CO2 emissions. This is supported by [49]Uzar and Eyuboglu (2019) who find a positive and statistically significant nexus between income inequality and CO2 emissions. This could be explained in the case of South Africa through the unemployment rate being so high, with unemployment being at [55]28.8% in 2021 (World Bank), this would explain high Gini values, signalling significant income inequality in the country. With a vast amount of South Africa's population being low or no-income, this leads to the use of non-renewable energies such as coal, oil and gas to power homes, vehicles etc. because they are cheaper, leading to higher CO2 emissions.

Table 2 also shows a 1% significance level in urbanisation causing CO2 emissions in India, this can be explained in developing economies, where the urban population increases rapidly (as seen in the non-stationarity of the data) as there are more job prospects in the cities, leading to more centred energy usage and therefore higher emission. But also, as the population in a city increases, so does the usage of vehicles and transport in the city, and therefore emissions. [42]Shahbaz et al (2016) also find using VECM Granger Causality tests using data from Malaysia, that urbanisation increasing initially reduces CO2 emissions, but after a threshold level they find that CO2 starts to increase as urbanisation increase – showing a U-shaped relationship between the two variables. [51]Wang et al (2013) also find in their studies in China that urbanization is a significant impact factor on CO2 emissions, this however contradicts the findings of the OLS estimators for China in this report.

3.2: Vector Autoregressive model

3.2.1: Vector Autoregressive Model Estimation

A Vector Autoregressive (VAR) model was also used to analyse this data, this is because all the variables chosen can influence each other, but also because all variables are treated as endogenous and can provide great results in forecasting as it can show the directions of causality. A VAR model includes past values (lags) of the dependent variable as an explanatory variable and uses both to explain the

CO2 = C(1,1)*CO2(-1) + C(1,2)*CO2(-2) + C(1,3)*GDP(-1) + C(1,4)*GDP(-2) + C(1,5)*FDI(-1) + C(1,6)*FDI(-2) + C(1,7)*GINI(-1) + C(1,8)*GINI(-2) + C(1,9)*URB(-1) + C(1,10)*URB(-2)

GDP = C(2,1)*CO2(-1) + C(2,2)*CO2(-2) + C(2,3)*GDP(-1) + C(2,4)*GDP(-2) + C(2,5)*FDI(-1) + C(2,6)*FDI(-2) + C(2,7)*GINI(-1) + C(2,8)*GINI(-2) + C(2,9)*URB(-1) + C(2,10)*URB(-2)

FDI = C(3,1)*CO2(-1) + C(3,2)*CO2(-2) + C(3,3)*GDP(-1) + C(3,4)*GDP(-2) + C(3,5)*FDI(-1) + C(3,6)*FDI(-2) + C(3,7)*GINI(-1) + C(3,8)*GINI(-2) + C(3,9)*URB(-1) + C(3,10)*URB(-2)

GINI = C(4,1)*CO2(-1) + C(4,2)*CO2(-2) + C(4,3)*GDP(-1) + C(4,4)*GDP(-2) + C(4,5)*FDI(-1) + C(4,6)*FDI(-2) + C(4,7)*GINI(-1) + C(4,8)*GINI(-2) + C(4,9)*URB(-1) + C(4,10)*URB(-2)

URB = C(5,1)*CO2(-1) + C(5,2)*CO2(-2) + C(5,3)*GDP(-1) + C(5,4)*GDP(-2) + C(5,5)*FDI(-1) + C(5,6)*FDI(-2) + C(5,7)*GINI(-1) + C(5,8)*GINI(-2) + C(5,9)*URB(-1) + C(5,10)*URB(-2)

other variables. A lag order of 2 was used in this regression to accurately capture the effects of previous years – which is needed as emerging economies have rapid yearly growths. The VAR model is estimated as the following for all 3 models:

3.2.3: Cointegration

If a set of time-series data is found to be non-stationary, first-differences must be used until the data can be found to be stationary. One of the problems with this is that the model can no longer provide a unique long-run solution. The process of cointegration can be used to ensure the process can work to provide long-run solutions - therefore cointegration now becomes the overriding requirement for this VAR model. Cointegration can be tested for using the Engle-Granger approach, this involves taking the residuals from the data at its levels, differencing the data, and then testing the residuals for unit roots using the Augmented Dickey-Fuller test. If the results show stationarity, then cointegration is present and the stochastic trends are similar, therefore the data can be first-differenced and still provide long-run solutions. This was tested for in each VAR model and the results show that the series are cointegrated in all 3 countries as the null hypothesis of non-stationarity is rejected. This is shown in Tables; 10, 11, and 12 within the Appendix.

3.2.4: VAR Model Granger Causality Tests and Discussion

This model was then estimated and used to test for Granger Causality in all 3 countries. The results are shown in Tables 7, 8 and 9 in the Appendix. The highlights are shown in Table 3:

Table 3: VAR Granger Causality Summary

	China	India	South Africa
CO2 and GDP	No causality	Strong bidirectional causality	No causality
CO2 and FDI	Significant bi-directional causality	Very Strong bidirectional causality	No causality
CO2 and Urb	No causality	Significant unidirectional causality on Urb causing CO2	Strong unidirectional causality on CO2 causing Urb
CO2 and Gini	No causality	No causality	Significant bi-directional causality
GDP and FDI	Strong unidirectional causality on FDI causing GDP	Significant bi-directional causality	Weak bidirectional causality
GDP and Urb	Weak unidirectional causality on Urb causing GDP	Significant unidirectional causality on GDP causing Urb	Weak unidirectional causality on GDP causing Urb
GDP and Gini	No causality	No causality	Strong unidirectional causality on GDP causing Gini
FDI and Urb	No causality	No causality	Strong unidirectional causality on FDI causing Urb
FDI and Gini	No causality	No causality	No causality
Urb and Gini	No causality	No causality	No causality

Using Table 3, we can see that CO2 and FDI have a strong bidirectional causality in China and India. This supports the findings from the OLS estimators but also shows how they cause each other, meaning that different policies must be used to fix this issue. We can also see with India a strong bidirectional causality between CO2 and GDP, meaning that GDP is being fuelled by CO2 emissions (most likely from non-renewable energy) – and as GDP increases, therefore so will CO2. This is also shown in the Granger Test results from the OLS estimator, except the VAR results show a stronger significance.

There is also a significant bidirectional causality between CO_2 and Gini in South Africa, which expands on the information found in Table 2 in that both variables cause each other. This is interesting because as explained earlier low or no-income individuals will revert to non-renewable energy because it is cheaper, but also that CO_2 emissions also affect the income inequality in the country, possibly through low income households being affected by increases in energy prices the most – which are caused by rising CO_2 emissions. Therefore a different policy is needed in South Africa, most likely targeted towards employment to fix income inequality.

Table 3 also shows strong unidirectional causalities in both India and South Africa between CO_2 emissions and Urbanisation, with Urbanisation causing CO_2 emissions in India, and the opposite in South Africa. The results from India support the findings from the OLS estimator, however the result from South Africa shows a result that the OLS did not pickup – highlighting the advantage of using a VAR model. This could be from industrialisation in the cities whilst creating new cities, therefore increasing CO_2 emissions, but also creating jobs and attracting urban migration. This can be seen in South Africa with the construction of Nkosi City and the Lanseria Smart City.

The last significant results from Table 3 towards the research question is that there is a strong bidirectional causality between CO_2 emissions and GDP in India, contradicting the OLS estimator for India which shows a weak causality. This could be from non-renewable energies fuelling GDP growth because it is cheaper, then as GDP rises, so does CO_2 emissions. Therefore, a specific policy is needed to resolve this issue, such as taxing non-renewable energies or subsidising renewable energy to achieve cleaner economic growth.

The VAR results also show other causalities between variables excluding CO_2, whilst do not directly impact CO_2 emissions, they still have an indirect impact.

For example, in India there is a significant unidirectional causality in GDP causing Urbanisation, whilst Urbanisation causes CO2 emissions significantly. And the same can be said in South Africa with GDP causing Gini strongly, whilst Gini and CO2 have a significant bidirectional causality.

3.3 Criticisms and Limitations in Methodology

The first point that may affect the results of this hypothesis testing is that there are limited observations for the Gini Coefficient in the three countries used for data analysis. This is likely because these are developing economies and are still industrialising, therefore a lot of modern measurements have not been used such as the Gini coefficient, and unemployment – which was considered as a variable but there was even less data for it than Gini, so it was decided against. The decision to assume that the gaps in the data were the same as the year before was undertaken to use this as a variable, however this affects the validity of the results.

Another point to make is that urbanisation was found to be non-stationary, even at the first order. This leads to the regression potentially being spurious and invalidate the findings as the long-run mean is not constant.

However, the OLS estimators were run with and without both variables and did not have any negative impacts on the results. In fact, removing Urbanisation actually led to autocorrelation in China and misspecification in all three countries. Therefore, the decision was made to include both variables.

Another weakness in this analysis is that the VAR model could mean a loss of degrees of freedom, with the model including 5 variables in total with 2 lags each – this leads to 10 parameters in each equation within the model, and potentially not enough observations to capture the correct estimation. This could be improved by a larger sample size, which was not available in the data collection for this methodology. Therefore, the findings from this research must be treated with caution – but still show a useful insight in the effects of economic development on CO2 emissions.

It should be stated that GDP was chosen instead of Real GDP because the other variables could be adjusted for inflation. Also, because the size of the economy was desired for this data analysis, and real GDP may show a false picture of the economies chosen – especially during a developing economies growth period where inflation varies so much as economies are more fragile towards shocks.

Possibly the largest limitation within this methodology is that the Engle-Granger test for cointegration was used. The results for this were achieved by creating an OLS estimator, removing the residuals before first differencing the data and testing the residuals for stationarity. This would not be the appropriate test for a VAR model because it does not give the number of cointegrating vectors and if there are any errors in the first step, they are carried into the second step. The more appropriate test would be the Johansen test for multiple equations, and if the test shows that cointegration exists, then a Vector Error Correction Model (VECM) may be used to combine levels and first-differences to provide accurate long-run solutions.

Conclusions And Policy Implications/Recommendations:

This study has attempted to estimate the extent to which economic development affected carbon-dioxide emissions in China, India, and South Africa over the period of 1960-2019, using a review of literature as well as OLS estimators and a Vector Autoregression model. All data series were found to be non-stationary in levels but appeared to be stationary in the first differences except for Urban population. Using the Johansen test, evidence of cointegration was found in all three countries at a 5% significance level. The causality findings were heterogeneous by country but show that each economic indicator had a causal relationship with CO2 emissions. A bidirectional causality was found in India with CO2 emissions and GDP, and two bidirectional causalities were found between CO2 emissions and FDI in China and India. A unidirectional causality was found in South Africa running from Urban Population to CO2 emissions, and a bidirectional causality was found in South Africa between CO2 emissions and income inequality. These results support the EKC hypothesis, but also show that a country may have higher environmental degradation through CO_2 emissions than the EKC suggests through income inequality impeding economic growth by limiting social mobility and earnings potentials - this also leads to a higher percentage of low or no-income households, who rely on non-renewable energies as they have a lower cost, leading to higher CO_2 emissions from outside the top 10% earners in the economy. The causality being bidirectional causes policy making for South Africa to be problematic, the need to reduce income inequality whilst reducing CO_2 emissions could prove expensive. One solution could be to subsidise renewable energies such as solar panel installation so that the lower-income households can afford this. This is also the best renewable energy for South Africa as the country sees a lot of sunlight throughout the year, meaning that it would be very cost-efficient and the total benefits (future savings) would outweigh the total costs sooner than most countries, because the marginal benefits (monthly savings) would be much larger. Another solution would be to reduce income inequality through taxing high emission products higher, but this would affect the lower-income households negatively if their income stays the same. A discriminating tax could prove efficient; by taxing rural areas less than urban areas this could fix income inequality and leave rural households a higher income to afford renewable energies. This would be most efficient if combined with a subsidisation of solar panels.

The results of strong bidirectional causalities between FDI and CO_2 emissions in India and China also support the EKC hypothesis and currently show the scale effect, where production has only increased in both countries and methods of production are yet to change – leading to increased CO_2 emissions. The policies needed for China and India should not aim to reduce FDI, as it can be seen in Table 3 that FDI causes GDP and therefore economic growth. Therefore, the policies must lead to greener investment. This can be achieved through either the technical or the compositional effect. The technical effect can be achieved through the introduction of cleaner technologies, using either subsidisation or negotiating trade deals for green technology with developed economies such as the USA or the UK. Trade deals are the more effective policies, as developing economies such as India and China have an abundance of natural resources which would benefit other nations.

Results in India from both the OLS estimator and VAR model show a unidirectional causality running from Urbanisation to CO2 emissions and Urbanisation only causing GDP in China. These results show the need to reduce Urbanisation to reduce CO2 emissions, however we can see from various literature such as [6]Balsalobre-lorente et al (2018) that Urbanisation is important for economic development, and can even lead to a reduction in CO2 emissions in the long run. This means that the policies needed for BRICS economies should be centred around urban energy usage instead of urban population. If the economy switched to renewables or lower-CO2 emission energies in urban areas, then there is a massive opportunity to convert a larger proportion of the population to a lower CO2 emission lifestyle. This is because as rural households migrate to urban areas, they are moving to a better infrastructure which can reduce their carbon footprint. This can be seen in South Africa with the construction of smart cities to reduce emissions and using Table 2, we can see a unidirectional causality in South Africa running from CO2 emissions to Urban Population.

The final conclusion and policy idea is that of a bidirectional causality in India between GDP and CO2 emissions. This, alongside literature such as [44]Tiwari (2011), we can see that demand-side policies are required to promote green development. The idea of reducing GDP is unrealistic because it would lead to India reaching the turning point in Figure 1 late and cause higher aggregate CO2 emissions. An example of a demand side policy would be to lower interest rates for green projects so firms are able to invest in projects that can bring them closer to net-zero emissions or purchase lower-emission capital to reduce their production emissions. This would encourage investment and therefore increase GDP, whilst reducing the impact on CO2 emissions and have a large impact in a short space of time in India since it is a developing economy and its GDP is rising rapidly, investment must also be rapidly increasing. Another example could be using government spending on projects to reduce CO2 emissions such as building low-emissions railways, which provide an alternative to driving petrol or diesel cars, therefore reducing CO2 emissions. This also creates jobs and could provide a cheaper method on transport, both effects lead to an increase in consumption and therefore GDP.

In summary, the effect of each economic indicator on CO2 emissions is heterogeneous by country, but it can be concluded from this research through reviewing literature and the use of econometric techniques that economic development is significant in affecting CO2 emission in developing economies. Developing economies are all dependent on energy for economic growth, and therefore the overriding policy needed for sustainable economic growth is to invest in infrastructure to increase energy efficiency and the use of renewables. If this is achieved, it will minimise CO2 emissions without a trade-off in economic performance or competitiveness.

Appendices:

Table 1: Augmented Dicker-Fuller test for non-stationarity

Augmented Dickey Fuller Test	China All Variables	China No Gini	China No Urb
CO2	0.04997	0.04997	0.04997
GDP	0.03977	0.03977	0.03977
FDI	0.0426	0.0426	0.0426
URB	0.479	0.479	
GINI	0.009997		0.009997

Augmented Dickey Fuller Test	India All Variables	India No Gini	India No Urb
CO2	0.01	0.01	0.01
GDP	0.01894	0.01894	0.01894
FDI	0.01	0.01	0.01
URB	0.2711	0.2711	
GINI	0.01		0.01

Augmented Dickey Fuller Test	South Africa All Variables	South Africa No Gini	South Africa No Urb
CO2	0.04997	0.04997	0.04997
GDP	0.03977	0.03977	0.03977
FDI	0.0426	0.0426	0.0426
URB	0.479	0.479	
GINI	0.01768		0.01768

Table 2: Heteroskedasticity Results

Test	China All Variables	China No Gini	China No Urb
BP test	0.002735	0.001739	0.002076
Whites Test	7.70E-06	5.06E-05	4.24E-06

Test	India All Variables	India No Gini	India No Urb
BP test	0.001958	0.00064	0.04993
Whites Test	0.05257	0.004519	0.007952

Test	South Africa All Variables	South Africa No Gini	South Africa No Urb
BP test	0.003984	0.001739	0.01091
Whites Test	8.67E-05	5.06E-05	0.0002707

Table 3: Autocorrelation Results

Test	China All Variables	China No Gini	China No Urb
Durbin Watson	0.12	0.8	0
Breusch Godfrey LM	0.248	0.9674	0.002172
Durbins H	1.783967	1	-1.020311

Test	India All Variables	India No Gini	India No Urb
Durbin Watson	0.864	0.902	0.928
Breusch Godfrey LM	0.5246	0.07162	0.146
Durbins H	1	1	0

Test	South Africa All Variables	South Africa No Gini	South Africa No Urb
Durbin Watson	0.858	0.788	0.804
Breusch Godfrey LM	0.9908	0.9674	0.9862
Durbins H	1	1	1

Table 4: Multicollinearity Results

VIF	China All Variables	China No Gini	China No Urb
GDP	1.430066	1.151277	1.352761
FDI	1.365779	1.152598	1.333153
URB	1.46526	1.010916	
GINI	1.032245		1.019182

VIF	India All Variables	India No Gini	India No Urb
GDP	1.940036	1.877334	1.213828
FDI	1.519066	1.425602	1.248814
URB	1.643152	1.639445	
GINI	1.080724		1.078286

VIF	South Africa All Variables	South Africa No Gini	South Africa No Urb
GDP	1.189968	1.151277	1.181616
FDI	1.153738	1.152598	1.144747
URB	1.011185	1.010916	
GINI	1.044527		1.044249

Table 5: Misspecification Results

Test	China All Variables	China No Gini	China No Urb			Test	India All Variables	India No Gini	India No Urb
RAMSAY RESET	0.1989	0.3245	0.00177			RAMSAY RESET	0.6675	0.2831	5.71E-05
Test	South Africa All Variables	South Africa No Gini	South Africa No Urb						
RAMSAY RESET	0.1652	0.3245	0.01931						

Table 6: OLS Granger Causality Test Results

Granger test	China All Variables	China No Gini	China No Urb			Granger test	India All Variables	India No Gini	India No Urb
GDP	0.1985	0.1985	0.1985			GDP	0.05785*	0.05785*	0.05785*
FDI	0.0009478****	0.0009478****	0.0009478****			FDI	0.01477**	0.01477**	0.01477**
Urb	0.2238	0.2238				Urb	0.005084***	0.005084***	
Gini	0.2626		0.2626			Gini	0.01027**		0.01027**
Granger test	South Africa All Variables	South Africa No Gini	South Africa No Urb						
GDP	0.3091	0.3091	0.3091						
FDI	0.7459	0.7459	0.7459						
Urb	0.1775	0.1775							
Gini	0.008038***		0.008038***						

Note, significant levels: *=10%, **=5%, ***=1%, ****=0.1%

Table 7: China VAR Granger Causality Results

Pairwise Granger Causality Tests
Date: 03/23/23 Time: 13:55
Sample: 1961 2021
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause CO2	59	1.66614	0.1985
CO2 does not Granger Cause GDP		0.18848	0.8288
GINI does not Granger Cause CO2	59	1.37074	0.2626
CO2 does not Granger Cause GINI		2.14475	0.1270
URB does not Granger Cause CO2	59	1.53925	0.2238
CO2 does not Granger Cause URB		0.17578	0.8393
FDI does not Granger Cause CO2	59	7.94111	0.0009****
CO2 does not Granger Cause FDI		9.65052	0.0003****
GINI does not Granger Cause GDP	59	0.25945	0.7724
GDP does not Granger Cause GINI		1.77046	0.1800
URB does not Granger Cause GDP	59	3.14872	0.0509*
GDP does not Granger Cause URB		0.28454	0.7535
FDI does not Granger Cause GDP	59	7.32621	0.0015**
GDP does not Granger Cause FDI		2.27589	0.1125
URB does not Granger Cause GINI	59	0.36180	0.6981
GINI does not Granger Cause URB		0.54388	0.5836
FDI does not Granger Cause GINI	59	0.53266	0.5901
GINI does not Granger Cause FDI		0.53697	0.5876
FDI does not Granger Cause URB	59	0.39387	0.6764
URB does not Granger Cause FDI		1.52571	0.2267

Table 8: India VAR Granger Causality Results

Pairwise Granger Causality Tests
Date: 03/23/23 Time: 14:08
Sample: 1961 2021
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause CO2	59	3.00580	0.0578*
CO2 does not Granger Cause GDP		3.50371	0.0371**
GINI does not Granger Cause CO2	59	2.37487	0.1027
CO2 does not Granger Cause GINI		1.41373	0.2521
URB does not Granger Cause CO2	59	5.83367	0.0051
CO2 does not Granger Cause URB		0.96125	0.3889
FDI does not Granger Cause CO2	59	4.56192	0.0148**
CO2 does not Granger Cause FDI		6.51110	0.0029***
GINI does not Granger Cause GDP	59	1.67816	0.1963
GDP does not Granger Cause GINI		0.62030	0.5416
URB does not Granger Cause GDP	59	8.42381	0.0007****
GDP does not Granger Cause URB		0.53114	0.5910
FDI does not Granger Cause GDP	59	5.91404	0.0048**
GDP does not Granger Cause FDI		10.1976	0.0002****
URB does not Granger Cause GINI	59	1.82974	0.1703
GINI does not Granger Cause URB		0.07423	0.9286
FDI does not Granger Cause GINI	59	1.59263	0.2128
GINI does not Granger Cause FDI		1.56615	0.2182
FDI does not Granger Cause URB	59	0.18629	0.8306
URB does not Granger Cause FDI		1.99019	0.1466

Table 9: South Africa VAR Granger Causality Results

Pairwise Granger Causality Tests
Date: 03/23/23 Time: 14:28
Sample: 1961 2021
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause CO2	59	1.19999	0.3091
CO2 does not Granger Cause GDP		0.26287	0.7698**
GINI does not Granger Cause CO2	59	5.28132	0.0080***
CO2 does not Granger Cause GINI		3.55569	0.0354**
URB does not Granger Cause CO2	59	1.78561	0.1775
CO2 does not Granger Cause URB		4.45258	0.0162
FDI does not Granger Cause CO2	59	0.29470	0.7459
CO2 does not Granger Cause FDI		0.06185	0.9401**
GINI does not Granger Cause GDP	59	0.74724	0.4785
GDP does not Granger Cause GINI		4.59658	0.0143*
URB does not Granger Cause GDP	59	1.46032	0.2412
GDP does not Granger Cause URB		2.60642	0.0831
FDI does not Granger Cause GDP	59	2.44654	0.0961
GDP does not Granger Cause FDI		3.33615	0.0430
URB does not Granger Cause GINI	59	0.00474	0.9953
GINI does not Granger Cause URB		0.02221	0.9780
FDI does not Granger Cause GINI	59	0.44362	0.6440
GINI does not Granger Cause FDI		1.11832	0.3343
FDI does not Granger Cause URB	59	3.86856	0.0269**
URB does not Granger Cause FDI		0.47526	0.6243

Table 10: China VAR Engle-Granger Test for Cointegration

Null Hypothesis: RES_000 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.246197	0.0220
Test critical values:	1% level	-3.542097	
	5% level	-2.910019	
	10% level	-2.592645	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RES_000)
Method: Least Squares
Date: 05/04/23 Time: 14:05
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_000(-1)	-0.459160	0.141446	-3.246197	0.0019
C	-17472.91	44591.77	-0.391842	0.6966

R-squared	0.151541	Mean dependent var	-30122.09
Adjusted R-squared	0.137160	S.D. dependent var	373499.5
S.E. of regression	346940.6	Akaike info criterion	28.38393
Sum squared resid	7.10E+12	Schwarz criterion	28.45314
Log likelihood	-863.7099	Hannan-Quinn criter.	28.41106
F-statistic	10.53779	Durbin-Watson stat	1.803260
Prob(F-statistic)	0.001930		

Table 11: India VAR Engle-Granger Test for Cointegration

Null Hypothesis: RES_000 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.114532	0.0001
Test critical values:	1% level	-3.542097	
	5% level	-2.910019	
	10% level	-2.592645	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RES_000)
Method: Least Squares
Date: 05/04/23 Time: 15:00
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_000(-1)	-0.698890	0.136648	-5.114532	0.0000
C	6.80E+09	3.32E+10	0.204593	0.8386

R-squared	0.307174	Mean dependent var	1.64E+10
Adjusted R-squared	0.295431	S.D. dependent var	3.09E+11
S.E. of regression	2.59E+11	Akaike info criterion	55.43034
Sum squared resid	3.96E+24	Schwarz criterion	55.49954
Log likelihood	-1688.625	Hannan-Quinn criter.	55.45746
F-statistic	26.15843	Durbin-Watson stat	1.757374
Prob(F-statistic)	0.000004		

Table 12: South Africa VAR Engle-Granger Test for Cointegration

Null Hypothesis: RES_000 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.764535	0.0054
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RES_000)
Method: Least Squares
Date: 05/04/23 Time: 15:03
Sample (adjusted): 1962 2021
Included observations: 60 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES_000(-1)	-0.839171	0.222915	-3.764535	0.0004
C	-8.43E+08	8.59E+09	-0.098129	0.9222

R-squared	0.196361	Mean dependent var	-6.48E+09
Adjusted R-squared	0.182505	S.D. dependent var	7.25E+10
S.E. of regression	6.56E+10	Akaike info criterion	52.68287
Sum squared resid	2.49E+23	Schwarz criterion	52.75268
Log likelihood	-1578.486	Hannan-Quinn criter.	52.71018
F-statistic	14.17173	Durbin-Watson stat	1.335739
Prob(F-statistic)	0.000392		

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