UNIVERSIDADE
BEIRA INTERIOR

The repercussions of corruption on green growth: Evidence from BRICS+

Versão final após defesa

Rui Filipe Marques de Matos

Dissertação para obtenção do Grau de Mestre em
Economia
(2º ciclo de estudos)

Orientador: Prof. Doutor António Manuel Cardoso Marques

julho de 2024

Declaração de Integridade

Eu, Rui Filipe Marques de Matos, que abaixo assino, estudante com o número de inscrição M12440 do 2º Ciclo em Economia da Faculdade de Ciências Sociais e Humanas, declaro ter desenvolvido o presente trabalho e elaborado o presente texto em total consonância com o **Código de Integridades da Universidade da Beira Interior**.

Mais concretamente afirmo não ter incorrido em qualquer das variedades de Fraude Académica, e que aqui declaro conhecer, que em particular atendi à exigida referenciação de frases, extratos, imagens e outras formas de trabalho intelectual, e assumindo assim na íntegra as responsabilidades da autoria.

Universidade da Beira Interior, Covilhã 22/07/2024

Agradecimentos

Em primeiro lugar, quero agradecer ao meu orientador, Professor Doutor António Manuel Cardoso Marques, por todo o conhecimento transmitido, pela sua disponibilidade sempre que necessitei e pela simpatia com que sempre me recebeu.

Em segundo lugar, quero agradecer aos meus amigos por facilitarem a realização deste trabalho, através de boa disposição, companheirismo e principalmente pelo exemplo que são.

Por último, quero agradecer à minha família, não só durante o tempo que dediquei à realização desta dissertação, mas sim por todo o meu percurso até agora. Aos meus avós por manterem tradições, por rezarem por mim e por todo o amor incondicional. Ao meu irmão pela união, pela amizade e pela ligação que temos. E por último, aos meus pais pela educação dada, pelos valores enraizados, pelos sacrifícios feitos, pelas condições de vida, pelas experiências vividas e pelo orgulho que sei que têm em mim, estarei sempre eternamente grato aos dois por tudo.

A todos, o meu sincero obrigado.

Resumo

A corrupção é uma praga cultural e social que afeta os principais setores de uma economia. Consequentemente, também é suscetível de ameaçar a sustentabilidade ambiental, onde as alterações climáticas já são reconhecidas como um tema crucial para a sobrevivência da humanidade. Com esta questão em mente, este estudo centra-se nos efeitos da corrupção no crescimento verde dos BRICS existentes, incluindo os cinco novos membros que aderiram no início de 2024. Para lidar com os objetivos deste estudo, são elaborados dados em painel, para 10 países entre 2001 e 2020. O método aplicado é o modelo autorregressivo de defasagem distribuída (ARDL), com o estimador de Driscoll-Kraay acompanhado de efeitos fixos, possibilitando assim averiguar os impactos dinâmicos de curto e longo prazo. Os resultados mostram repercussões de longo prazo negativas e significativas da corrupção no crescimento verde para os BRICS+, sugerindo que países com um elevado nível de corrupção apresentam menos possibilidades de melhorar as consequências ambientais do rápido crescimento económico. As conclusões sublinham a necessidade de prevenir a corrupção para alcançar um desenvolvimento económico sustentável e amigo do ambiente, especialmente à medida que a Agenda 2030 rapidamente se aproxima.

Palavras-chave

Corrupção;sustentabilidade;ambiente;crescimento verde;dados em painel;BRICS+

Resumo alargado

A nível mundial, os BRICS+ destacam-se como o maior exemplo de economias emergentes. No entanto, apesar da sua trajetória promissora, estes países deparam-se com obstáculos que os impedem de otimizar o seu desenvolvimento. Dentro destes obstáculos, este estudo frisa o papel da corrupção. Não obstante, embora a corrupção seja reconhecida como uma preocupação, é importante salientar que a sua extensão e impacto pode variar entre os diferentes países do grupo BRICS+, através de uma série de fatores como socioeconómicos, políticos e culturais. Dito isto, a corrupção pode influenciar todos os setores de uma economia, sendo ela simultaneamente capaz de afetar a eficácia das energias renováveis, especialmente na redução das emissões de CO_2. Além disso, a literatura existente fornece poucas evidências sobre a correlação entre corrupção e sustentabilidade ambiental, principalmente em países ainda em desenvolvimento.

Compreender e enfrentar este desafio é imperativo para desbloquear o potencial dos BRICS+ relativamente ao seu desenvolvimento sustentável. Ao combater a corrupção e aumentar a transparência, estes países podem criar um ambiente propício para alcançar os seus objetivos económicos e ambientais, consolidando assim o seu papel como "players" essenciais a nível mundial.

Posto isto, esta pesquisa tem como objetivo analisar o impacto da corrupção no crescimento verde dos BRICS+ entre 2001 e 2020. Assim sendo, os indicadores de crescimento verde (GG) e controlo de corrupção (CORR), são consideradas neste estudo como as principais variáveis. A seleção do grupo de países e do horizonte temporal é feita de acordo com a disponibilidade de dados, a fim de garantir um painel equilibrado. Para toda a componente econométrica, são utilizados os programas estatísticos Stata e Eviews.

As variáveis formação bruta de capital fixo, número total de população empregada, geração de eletricidade renovável, emissões de CO_2 e total das rendas de recursos naturais são incorporadas neste estudo como variáveis de controlo. De realçar que todas as variáveis deste estudo são convertidas em logaritmos e primeiras diferenças.

Após confirmar que não existem adversidades de colineariedade nas variáveis, são incluídos testes de raízes unitárias de primeira e de segunda geração. Testes estes que revelam a ordem de integração das variáveis. Uma vez que nenhuma variável demonstra ser I(2), o modelo autorregressivo de defasagem distribuída (ARDL) torna-se válido para o estudo. Este modelo examina o curto e longo prazo das variáveis, permitindo assim uma avaliação objetiva e dinâmica em dois momentos distintos. Além disso, admite o uso de variáveis com integração I(0) e I(1), e também permite o uso de dummies.

Posteriormente aos testes de Hausman que ditam os efeitos fixos como estimador mais apropriado, efetuam-se um conjunto de testes diagnósticos para verificar a existência de fenómenos comuns em análises econométricas. De acordo com estes testes, verifica-se a presença de dependência seccional, heteroscedasticidade e autocorrelação de primeira ordem. Posto isto, e de forma a atestar a robustez do modelo econométrico, elege-se o estimador Driscoll-Kraay.

De seguida, são estimados dois modelos: o modelo completo e o modelo parcimonioso. A consistência entre os dois modelos, revela robustez nos resultados encontrados. Consequentemente, desenvolve-se uma estimativa com as semi-elasticidades e elasticidades, com o intuito de analisar os impactos de curto e longo prazo de forma mais concreta e detalhada. Conforme esperado, os resultados para os dez países comprovam um impacto negativo e significativo da corrupção no crescimento verde a longo prazo. Já a variável formação bruta de capital fixo apresenta efeitos positivos a curto e longo prazo, com a variável geração de eletricidade renovável também os partilhando, somente a curto prazo. De resto, todas as outras variáveis exibem repercussões negativas no crescimento verde.

A principal ilação deste estudo é que, para conseguir progressos sustentáveis, é necessário efetuar uma prevenção da corrupção, o que exige esforços concentrados de todos os sectores da sociedade, incluindo o governo, as empresas, a comunidade internacional e a voz do povo em geral. Trabalhando em conjunto para atingir objetivos comuns e defendendo valores partilhados de integridade, transparência e responsabilidade, é possível construir um futuro mais limpo e próspero para todos os cidadãos.

Abstract

Corruption is a cultural and social plague that affects the main sectors of an economy. Consequently, it is also likely to threaten environmental sustainability, where climate change is already recognized as a crucial issue for the humankind survival. With this issue in mind, this study focuses on the effects of corruption on the green growth of the existing BRICS, including its five new members that joined at the beginning of 2024. To deal with the objectives of this study, panel data is drawn up for 10 countries between 2001 and 2020. The method applied is the autoregressive distributed lag (ARDL) model, with the Driscoll-Kraay estimator accompanied by fixed effects, thus making it possible to assess the short- and long-term dynamics. The results show significant negative long-term repercussions of corruption on green growth for BRICS+, implying that countries with large corruption are unlikely to improve the environmental ramifications of accelerated economic growth. The findings underline the need to prevent corruption in order to achieve sustainable and environmentally friendly economic development, especially as the 2030 Agenda quickly arrives.

Keywords

Corruption;sustainability;environment;green growth;panel data;BRICS+

Index

Figures List

Tables List

Acronyms List

ARDL	Autoregressive Distributed Lag
BRICS+	Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Iran, Saudi and UAE
CD	Cross-section Dependence
CIPS	Cross-sectionally Augmented Im, Pesaran and Shin Test
CO_2	Carbon Dioxide
CORR	Control of Corruption
CPI	Corruption Perceptions Index
DFE	Dynamic Fixed Effects
DK	Driscoll and Kraay
ECT	Error Correction Term
EKC	Environmental Kuznets Curve
EMP	Employment
FE	Fixed Effects
GDP	Gross Domestic Product
GFCF	Gross Fixed Capital Formation
GG	Green Growth
IEA	International Energy Agency
IPCC	International Panel on Climate Change
KWH	Kilowatt per Hour
MG	Mean Group
MW	Maddala and Wu
NRR	Natural Resource Rents
OECD	Organisation for Economic Co-operation and Development
PMG	Pooled Mean Group
RE	Random Effects
REG	Renewable Electricity Generation
SO_2	Sulphur Dioxide
UAE	United Arab Emirates
UECM	Unrestricted Error Correction Model
US	United States
USD	United States Dollar
VIF	Variance Inflation Factor
WGI	World Governance Indicators

1. Introduction

As stated by the IPCC (2014) reports, rising emissions and climate change will surely harm the power of emerging countries' economies, as they are responsible for a hefty share of overall global emissions and energy consumption. As such, these emerging economies are searching for energy-saving solutions that will allow them to continue economic growth, while conserving energy resources and lowering carbon emissions, which will ultimately have a long-term positive influence on the environment (Nie et al., 2019). In short, there is a definite energy-led economic growth tendency in emerging countries, and the relationship between emissions and energy in these economies must be highlighted.

Since regulators and policymakers are constantly urging towards an environmentally sustainable growth for current and upcoming generations, the term "green growth" has risen. This sort of growth makes the most out of natural resources, in order to aid humanity and the planet. Several factors have shown to either promote or hinder this type of growth (Tawiah et al., 2021; Zhang et al., 2021). Nevertheless, these factors are mostly technological or economic by nature, with hardly any consideration towards social issues like corruption.

It is well known that corruption is not a new phenomenon, it has persisted for an extended period. Prior research on this topic can be traced back to the pioneering studies of rent seeking conducts, to measure the consequences and costs of corruption (Mauro et al., 1997). This field has piqued the interest of researchers, scholars and policymakers, due to its considerable effects on economies trough several transmission routes.

For instance, corruption can have an impact on the effective usage of essentially natural resources by diminishing the strictness of environmental preservation policy and legislation. According to literature, the absence of, or insufficient environmental legislation, leads to inadequate usage of natural resources, resulting in environmental deterioration (Yuan & Xiang, 2018; Sinha et al., 2019; Zhou & Li, 2021). Moreover, corrupt practices also have an indirect impact on a nation's ability to go green, by reducing income, causing poor administration, diverting government interest, and misusing funds intended for environmental initiatives, in addition to weakening environmental regulations as a whole (Cole, 2007; Leitão, 2010; Biswas et al., 2012).

Accordingly, the purpose of this research is to investigate the dynamic impacts of corruption on green growth in the BRICS+ group. To achieve precision in estimations, this study controls the effects coming from control variables on green growth. This panel data analysis has a time range of 20 years, from 2001 to 2020. To attain the objectives of this study, the autoregressive distributed lag (ARDL) model is used to analyse the short and long run dynamics.

Regarding the choice of BRICS+, one can assume that it makes for an exciting and nowadays case study, since these are the world's leading growing countries, as they individually have remarkably risen the economic ladder. However, due to their rising importance in the global economic system, substantial levels of corruption began to arise (Kurakin & Sukharenko, 2018). Most of these countries have been held back by corruption in varying ways, yet some of the BRICS+ countries have handled this issue better than others.

Given the objective of this study, two main research questions are established: "Does corruption hinder or facilitate the promotion of sustainable development/green growth in the BRICS+ nations?"; "To what extent do all related variables present in this study collectively shape the overall progress of green growth initiatives in the BRICS+ group?".

Even though this study includes new and modern aspects, it is still inserted in a relatively high studied field of research, such as the energy-growth nexus. Yet, this field remains dynamic and continuously evolves in order to address emerging environmental issues. As such, it is not intended to exhaust such a vast subject, but to contribute with a unique empirical work that can be useful for all those interested. Nonetheless, this paper differs from the current literature and adds to in the following ways.

First, in contrast to earlier research that focused on pollution and CO_2 emissions, this study provides insight on how corruption affects the path a nation takes in utilizing its natural resources. This is achieved by adopting the OECD's latest green growth measure, which considers a nation's efficient use of its natural assets to spur economic growth in addition to carbon emissions alone.

The goal of "green growth" is for nations to become greener without sacrificing their ability to prosper economically. The evaluation of environmental effectiveness with greenhouse gas emissions is biased, assuming that zero emissions is the best for environmental performance. Zero-emissions are basically impossible to achieve since no economy can be brought to a halt. As such, it is critical to adopt a performance indicator that focuses on the efficiency of producing fewer emissions while attaining economic growth.

Second, this study tests variables rarely used in literature, and with increasing potential of explanation of effects such as the total natural resource rents. Testing new variables into a study likely enables policymakers to formulate policies towards improvement, in this case, the goal is to achieve a greener economy. Lastly, this study analyses the 5 existing BRICS countries, as well as the new ones who joined in the beginning of 2024, therefore making this study differ from previous research on just the prior BRICS nations.

In terms of structure, this work is organized into six sections. The first section of this study simply corresponds to a summary and introduction on the theme of this paper. The second section presents a literature review about the concerned issue at hand. The third section exposes the data, with all variables and their respective hypothesis, as well as the method and tests used in the panel data. The fourth section shows the results. The fifth section is a discussion with a critical analysis of all the results obtained. And lastly, the sixth section highlights the main conclusions of this study, along with some limitations and suggestions for future research.

2. Literature Review

Before delving into the literature review, please note that this section is divided into two distinct parts. The first part covers the existing literature on corruption in general, as well as why and how it affects the environment. The second part encompasses an historical evolution of BRICS+, including where the group stand in terms of corruption and environmental developments.

2.1. Corruption and the environment

First and foremost, corruption doesn't have a universal definition. Even though associated with judicial matters, morality has always been linked to it. This phenomenon is included into the earliest debates and causes difficulty to achieve a robust definition (Rose, 2018). While it is difficult to agree on an accurate definition, it is consensual that corruption is associated with acts of misappropriation and personal benefits against the rules (Jain, 2001). Corruption can also be understood as the sale of government property by government officials all for their own gain. These gains can be acquired through bribes, extortion, embezzlement or even fraud (Shleifer & Vishny, 1993).

Environment-wise, harmful practices and policies may also arise at the hand of corruption, causing the postponement of stronger environmental regulations and their implementation. Just as most sectors in an economy, through methods mentioned above, like bribery and embezzlement, corruption can redirect funds meant for environmental causes towards personal use (Lisciandra & Migliardo, 2017).

Although dominated by pollution studies, a growing amount of research has demonstrated how corruption has an impact on the environment. Thus far, the literature has mostly been divided into two types. First, on a more specific note, this body of work shows how corruption impairs the development and subsequent application of environmental policies trough many channels.

For instance, research by Fredriksson & Svensson (2003) suggests that, when corruption is low, political instability has a negative impact on how strict environmental constraints are, meanwhile, when corruption is high, the impact is inverse. Essentially, the writers claim that corruption lessens the adverse impact that political instability has on the environment. Subsequently, according to Fredriksson et al. (2004), corruption weakens environmental rules by diverting the government's focus away from welfare onto bribery, to gather public support.

More recently, Chen et al. (2018) found that environmental policies are only functional when corruption and the shadow economy are under control. Later, Hao et al. (2020) disclosed that corrupt acts exacerbate the detrimental effects of misallocated resources on overall environmental effectiveness. The same authors, Hao et al. (2021), also discovered that environmental decentralization on air pollution is adversely affected by local corruption.

Essentially, this section of literature examines the influence of lobbying organizations and bureaucracy on the strictness of environmental laws, as well as the efficiency with which they are put into effective use. As for the second strand of literature, it describes on a more general note how corruption worsens the effects of other components on the natural environment. Meaning it analyses how corruption impacts environmental quality both indirectly and directly, i.e. through economic developments.

In more detail, Park (2012), via a variety of cross-sectional regressions, demonstrated that increased corruption leads to decreased economic development through the banking sector's poor loan channels. The link between corruption, pollution, and shadow economies were also examined by Biswas et al. (2012). Their findings displayed that the shadow economy adds to environmental decline. Nevertheless, this negative impact could potentially be mitigated if corruption is controlled.

In addition, D'Agostino et al. (2016) explored the relationships among government expenditures (particularly investment and military spending), economic development and corruption, for a sample of 106 different countries by employing an endogenous growth model. The outcome of the study corroborated the hypothesis that an increase of corruption negatively affects investment and military spending, which in turn has an adverse effect on economic development.

Furthermore, while Sekrafi & Sghaier (2018) showed that higher degrees of corruption decrease carbon emissions and economic growth, Wang et al. (2018) claimed that higher levels of corruption do not actually reduce said emissions. To achieve said results, the authors explored the moderating effects of corruption perception on 14 emissions-growth links for the BRICS economies between 1996 and 2015, using a partial least square regression approach.

Still regarding this strand's literature, a few empirical studies have investigated the consequences of corruption on the link between economic growth and pollution, by adopting the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis shows that economic growth causes pollution to worsen at lower income levels, however, it improves at higher income levels, hence, the link between pollution and economic growth has an inverted U-shaped design (Stern, 2004). In other words, the EKC theory implies the existence of environmental struggles in the beginning stages of economic growth, but as the economy grows, the same applies for the environment.

In line with this chunk of literature, corruption causes overall pollution levels to exceed the optimal social values for any level of income *per capita*, implying that corruption affects the EKC's turning point, arising at higher income *per capita* and emission levels, as opposed to the ideal optimal for society.

As for the research in specific, López (1994) established that the link among environment and economic growth depends on how flexible and simple it is to modify conventional indicators and pollutants in production, as well as the proportional degree of income utility curvature. Strictly speaking, high income, according to this empirical research, boosts pollution at lower elasticity of substitution and relative curvature coefficients (López, 1994; López and & Mitra, 2000).

One can assume that the direct influence of corruption on pollution is plainly "positive", as in pollution grows. Nonetheless, the indirect impact, while "negative", as in pollution lowers, is overshadowed by the direct impact (Welsch, 2004). Additionally, according to the author, corruption has an especially strong impact on increasing pollution, low-income wise.

Consequently, Leitão (2010) demonstrated that corruption has a significant negative influence on income *per capita*, yet, the level of corruption in a country has a positive effect on SO_2 emissions. Particularly, more corruption has an adverse repercussion on governmental concerns on the quality of the environment by causing tougher environmental legislation and delayed implementation. Furthermore, there is a positive correlation between corruption and the critical income barrier that causes a drop in SO_2 emissions.

Although the preceding literature contains ample and straightforward proof that corruption harms the climate by increasing pollution, the consequences of corruption on a “greener growth” can be more complex. The major indicators of environmental performance are clearly pollution metrics, mainly CO2 and SO2 emissions. As mentioned in the previous chapter, these metrics have issues, assuming that an ideal performance of the environment equals no emissions at all. Such an assumption is neither attainable nor realistic since emissions are unavoidable as long as people exist. Therefore, an indicator that reflects the effectiveness of resource usage may give an improved and deeper understanding on how corruption influences the environment, hence, the use of a green growth indicator.

2.2. The BRICS+ context

The origin of BRICS+ starts with Jim O'Neill, the chief economist at Goldman Sachs, who published a paper in 2001. He asserted that these nations (initially referred to as the BRIC countries, since South Africa joined the group only in 2010) were the up-and-coming powerhouses poised to lead the global economy in the 21st century. (Kurakin & Sukharenko, 2018). The formation of the previously known BRICS had the objective of fostering economic cooperation, enhancing trade and investment flows among members, and advocating for a multipolar international order that reflects these emerging economic realities, hence positioning themselves as key players in the global economy.

From the early 2000s to the mid-2010s, the BRICS experienced substantial economic growth. China, for instance, witnessed unparalleled industrial growth and urbanization, positioning itself as the world's second-largest economy. Similarly, India leveraged its demographic dividend and IT sector to boost economic growth. Brazil and Russia benefited significantly from commodity exports, while South Africa's inclusion in BRICS underscored its strategic importance on the African continent (Cooper, 2016).

On January 1, 2024, Egypt, Ethiopia, Iran, Saudi Arabia and the United Arab Emirates joined the bloc as full members, thus changing the name from "BRICS" to "BRICS+". Being a new addition, any common policy guidelines within BRICS+ might only apply to the countries that already belonged, as it is somewhat early for the new ones to completely share this common guidance.

That said, the BRICS+ collectively are home to about 46% of the population, 30% of GDP, and 50% of total carbon dioxide emissions (Worldometer, 2024). Additionally, in 2022, five countries in the BRICS+ were present in the top ten countries with most primary energy consumption in the world (Statista, 2023). However, especially in the previous BRICS, the group faced diverse challenges such as economic slowdowns, declining commodity prices, and the need for structural reforms, prompting a shift towards more sustainable and diversified economic models.

Historically, the BRICS+ countries have grappled with varying levels of corruption, which has significantly impacted their institutional quality and governance efficacy (Kurakin & Sukharenko, 2018). Corruption Perceptions Index (CPI) has highlighted persistent challenges in curbing corruption across these nations. Yet some of the BRICS+ nations have handled this issue worse than others. For instance, Brazil and Russia have faced high-profile corruption scandals that have undermined public trust and governance, respectively Operation Car Wash (Lava Jato) and the poisoning of Alexei Navalny, a prominent opposition leader and anti-corruption activist.

India faces this issue as well, particularly in bureaucracy and public services. High-profile scandals, such as the 2G spectrum and coal allocation scams, have underscored the prevalence of graft (Sukhtankar & Vaishnav, 2015). China has launched an extensive anti-corruption campaign, targeting both "tigers and flies" (high- and low-ranking officials). While this has led to numerous prosecutions, critics argue it also serves to eliminate political rivals and consolidate power (Lang, 2018). Corruption in South Africa has been highlighted by the Gupta family scandal and state capture during former President Jacob Zuma's tenure. Despite significant anti-corruption measures and institutions, corruption continues to affect public procurement and state-owned enterprises, hampering economic progress (Mahlala et al., 2023).

Regarding the five new additions to the BRICS+ bloc, Egypt still has widespread corruption, particularly within the bureaucratic and judicial sectors. The lack of transparency and accountability in government operations, combined with weak enforcement of anti-corruption laws, has fostered an environment where bribery and nepotism are commonplace (Mohamed, 2022). According to Kirya (2018), Ethiopia's corruption challenges are tied to its rapid economic growth and state-led development model. Recent reforms under the current government aim to address these issues, but systemic corruption remains a significant hurdle.

In Iran, corruption is pervasive, with significant issues in the public sector. Sanctions and economic difficulties have exacerbated corrupt practices, with patronage networks and the influence of the Revolutionary Guard contributing to the entrenchment of corruption (Salihu & Jafari, 2020). Saudi Arabia's Vision 2030 includes anti-corruption as a key pillar, and like China, although it was framed as a move against corruption, some viewed it as a power consolidation tactic. Nonetheless, corruption remains a challenge, particularly in public procurement (Rahman et al., 2020). The UAE is an exception, since corruption levels are relatively low compared to its regional counterparts and BRICS+ members, attributed to strong institutions and zero-tolerance policies.

Moving on to environmental efforts, the BRICS+ countries act in a relatively modest way, often overshadowed by the imperative of economic growth. However, participation in international agreements such as the Kyoto Protocol marked the beginning of a gradual shift towards integrating environmental sustainability into national policies. According to OECD (2024), recent initiatives have seen some BRICS+ countries making strides in promoting green growth. While China and the UAE lead with substantial investments and strategic plans, countries like Russia and Iran face more significant obstacles. For instance, China is heavily investing in renewable energy and electric vehicles. Its ambitious goals include achieving carbon neutrality by 2060 (Zhao et al., 2022). On the other hand, Russia has shown limited progress compared to its BRICS+ counterparts, focusing more on energy efficiency and less on renewable energy adoption (Stepanov & Makarov, 2022).

3. Methodology

3.1. Data

To assess the impact of corruption on green growth, this study adopts a cohesive and balanced panel data analysis for 10 countries (all the oldest and newest members of BRICS+), namely Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Iran, Saudi Arabia, and the UAE, in 20 years, observed between 2001 and 2020. The selection of time corresponds to the most recent years with available data.

Table 1. Variables description and source

Variable	Description	Source
GG	Green growth headline indicator (2015 US$ per Kg)	OECD Statistics
CORR	Control of corruption: estimate	World Bank
GFCF	Gross fixed capital formation *per capita* (constant 2015 US$)	World Bank
EMP	Total employed population	World Bank
REG	Renewable electricity generation *per capita* (measured in kWh)	IEA
CO2	CO2 emissions *per capita* (measured in tons)	World Bank
NRR	Total natural resources rents (% of GDP)	World Bank

- **Green growth**

The dependent variable is an indicator of resource and environmental productivity that has recently been developed by the OECD. It is production-based on CO2 productivity, GDP per unit of energy-related CO2 emissions, measured in 2015 US dollars per Kilogram. Productivity is calculated as real GDP generated per unit of CO2 emitted (USD/kg). Included are CO2 emissions from combustion of coal, oil, natural gas and other fuels (OECD, 2023). As stated by the OECD (2017), green growth is the effective use of natural resources or capital for both consumption and production. Therefore, this sustainable development indicator includes additional data on the environment that is rarely used in econometric models.

Considering the complex character of environmental problems, green growth is bound to be shaped through numerous distinct factors and, although it is impossible to manage all the elements that trigger green growth, this model includes various variables that should parsimoniously influence many of its aspects.

- **Control of corruption**

The key independent variable is the control of corruption estimate from the WGI created by Kaufmann and Kraay in 1996. As per said authors, corruption control is the perception of whatever public authority is used for private benefit in small and large-scale corruption. The estimation runs from minus 2.5 to plus 2.5, with higher numbers suggesting lower corruption. For the sake of clarity and comprehension, an inverse format is adopted, ranging from 0 to 5, with higher values suggesting greater levels of corruption. This adjustment is obtained by subtracting 2.5 from the country's initial score.

While corruption itself is a social issue, its consequences to the environment cannot be ignored. Even though corruption could have a positive impact on green growth in the BRICS+ group, some empirical studies such as Tawiah et al. (2023), Wang et al. (2018) and reports from organizations like World Bank and Transparency International support the view that corruption is a significant barrier to achieving sustainable growth, as it usually causes less stringency in energy policies. Accordingly, the first hypothesis is raised (H1): Corruption has a negative impact on green growth.

- **Gross fixed capital formation**

This macroeconomic indicator is the gross fixed capital formation *per capita*. It represents investment, defined as the acquisition of produced assets, including the production of such assets by producers for their own use, minus disposals (Worldbank, 2024). Note that the GFCF certainly increases conventional growth, meaning that, by directing capital towards green and sustainable initiatives, GFCF should also play a crucial role in fostering economic growth that is environmentally sustainable and socially responsible. Therefore, the second hypothesis is suggested (H2): Gross fixed capital formation has a beneficial effect on green growth.

- **Employment**

The employment variable is achieved by multiplying unemployment by total labour force, then dividing this value by 100, and finally by withdrawing said value from total labour force, thus obtaining the total employment value. This variable is included since, in theory, employment should have an interconnected bidirectional relationship with sustainable growth, meaning that increased employment has the potential to support green growth and vice-versa. As such, the third hypothesis is proposed (H3): Employment has a favourable influence on green growth.

- **Renewable electricity generation**

This indicator from the International Energy Agency represents the *per capita* electricity generation from renewable sources, which corresponds to the sum of hydro, tide, wind, solar (photovoltaic and thermal), biofuel and geothermal energy sources, divided by total population to obtain *per capita* values. Given the environmental and resource productivity nature of green growth, this variable is included as it produces zero greenhouse gas emissions during its lifecycle, thus contributing to environmental sustainability by mitigating climate change. In agreement with many prior studies, renewable energy should contribute significantly towards environmental sustainability. Having said that, the fourth assumption (H4) is suggested: renewable electricity generation drives green growth.

- **Carbon emissions**

This indicator depicts CO2 emissions *per capita* measured in tons. The top 10 countries with most carbon emissions include 6 BRICS+ countries alone. Increasing carbon emissions can result in more frequent and severe weather events, disruptions to ecosystems, rising sea levels and other adverse impacts. According to most literature, these climate change effects pose challenges to environmental sustainability, which opposes the overall aim of green growth, as it generally seeks to achieve economic growth while ensuring environmental sustainability and social well-being. Thus, the fifth hypothesis (H5) is set, with carbon emissions having a detrimental impact on green growth.

- **Natural resource rents**

This rarely used environmental indicator represents the total natural resources rents as a share of GDP, achieved by the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents and forest rents. According to Worldbank (2024), rents from non-renewable resources - fossil fuels and minerals - as well as rents from overharvesting of forests, indicate the liquidation of a country's capital stock. When countries use such rents to support current consumption rather than to invest in new capital to replace what is being used up, they are in fact, borrowing against their future. All in all, it depends on how these resources are managed, the degree of environmental responsibility applied, and the efforts made to transition towards sustainable and low-impact economic activities. Notwithstanding, the sixth hypothesis is raised (H6): Natural resource rents have a negative effect on green growth.

3.2. Method and Preliminary analysis

Considering the main aim of this dissertation, it is helpful to analyse both short- and long-run dynamic effects separately by recurring to the ARDL model (Pesaran & Shin, 1999). This method deals with cointegration, allows distinct lag-lengths, is robust in spite of endogeneity, handles cointegration and also permits different integration orders of variables, for instance, I(0) and I(1), but not I(2). Furthermore, it enables the correction of potential outliers by using dummy variables, ensuring solid results even with small and moderate sample sizes. All variables have been converted into natural logarithms and first differences to make the non-linear relations as linear as possible and to render the series as stationary, since non-stationary series are not suitable to develop economic models due to their unpredictability in producing reliable outcomes.

The following equation reproduces the ARDL version of the general unrestricted error correction model (UECM) that accounts for the short- and long-term dynamics and their effects separately. The prefixes "Δ" and "L" represent the first differences and the natural logarithms, respectively. The letters i, t, and j indicate the country, the time and the lags, respectively. Lastly, α_i corresponds to the intercept, β_{ij} and γ_i the estimated parameters, and ε_{it} the error term. The model is specified as follows:

$$\begin{aligned}\Delta LGG_{it} = \alpha_i &+ \sum_{j=0}^{k} \beta_{1ij} \Delta LCORR_{it-j} + \sum_{j=0}^{k} \beta_{2ij} \Delta LGFCF_{it-j} + \sum_{j=0}^{k} \beta_{3ij} \Delta LEMP_{it-j} \\ &+ \sum_{j=0}^{k} \beta_{4ij} \Delta LREG_{it-j} + \sum_{j=0}^{k} \beta_{5ij} \Delta LCO2_{it-j} + \sum_{j=0}^{k} \beta_{6ij} \Delta LNRR_{it-j} + \gamma_{1i} LGG_{it-1} \\ &+ \gamma_{2i} LCORR_{it-1} + \gamma_{3i} LGFCF_{it-1} + \gamma_{4i} LEMP_{it-1} + \gamma_{5i} LREG_{it-1} \\ &+ \gamma_{6i} LCO2_{it-1} + \gamma_{7i} LNRR_{it-1} + \varepsilon_{it}\end{aligned} \quad (1)$$

An initial examination of the data in this study is essential for comprehensively understand the characteristics of the panel data, enabling the determination of the most suitable estimator. This analysis starts with the descriptive statistics present in table 2. When calculated considering the natural logarithm and first differences, most variables are not disparate, presenting rather low standard deviations, proving to be of greater interest in this study. In logarithmic form, one of the largest discrepancies comes from the renewable electricity generation (*REG*) variable as, despite of similar nature and exponentially developing, some countries are greatly ahead when it comes to generating sustainable energy. For example, in 2020, the *per capita* renewable electricity generation in Brazil was around 2400 kWh, which was around 12 times more than the average in Iran for that same year. Additionally, the employment variable (EMP) also has a notable discrepancy. This is expected, since two countries highly inflate the results, China and India, the two most populated countries in the world.

Table 2. Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
LGG	200	1.2396	0.6815	0.2776	2.8679
LCORR	200	0.9944	0.2397	0.2041	1.2923
LGFCF	200	7.0786	1.2303	4.0204	9.4790
LEMP	200	17.6046	1.5286	14.4950	20.4288
LREG	200	4.7785	2.2246	0.0000	7.8054
LCO2	200	1.3241	1.5228	-2.7525	3.3371
LNRR	200	2.2107	0.9819	-0.1464	4.0078
ΔLGG	190	0.0108	0.0465	-0.1335	0.1947
ΔLCORR	190	-0.0011	0.0614	-0.5459	0.1871
ΔLGFCF	190	0.0371	0.1048	-0.3042	0.3537
ΔLEMP	190	0.0200	0.0337	-0.0876	0.1971
ΔLREG	190	0.0899	0.2363	-1.2528	1.2462
ΔLCO2	190	0.0152	0.0510	-0.1395	0.1764
ΔLNRR	190	-0.0273	0.2784	-0.9013	0.8508

Note: the prefixes “L” and “Δ” denote the natural logarithm and the first differences, respectively.

Table 3 presents the CD-test, which Pesaran (2004) introduced. This approach is suited for panel data models with significant cross-sectional dependency in errors. According to the CD-test results, there is cross-section dependence in most variables.

Table 3. Individual cross section dependence

Variables	CD-test	Variables	CD-test
LGG	3.27***	*ΔLGG*	-0.35
LCORR	-0.87	*ΔLCORR*	-1.11
LGFCF	9.90***	*ΔLGFCF*	6.77***
LEMP	24.78***	*ΔLEMP*	10.17***
LREG	18.07***	*ΔLREG*	2.27*
LCO2	10.78***	*ΔLCO2*	5.98***
LNRR	20.12***	*ΔLNRR*	16.36***

Notes: *** represents significance levels of 1%. CD-test has N (0,1) distribution, under H0: cross-section independence.

To verify the degree of correlation between variables, the following correlation matrices examine the linear relationship between a pair of continuous variables, with values ranging from (-1) to 1. When the value is 0, there is no link between variables. Furthermore, whether they are opposite or identical, the variables behave perfectly whether the value is (-1) or 1. All variables with positive values show a direct proportional relationship, meaning that, if a single variable decreases or increases, the other follows suit. Inversely, if the value is negative, there is a direct inverse relationship. Overall, table 4 shows contrasting levels of correlation.

Table 4. Correlation matrices

	LGG	*LCORR*	*LGFCF*	*LEMP*	*LREG*	*LCO2*	*LNRR*
LGG	1.0000						
LCORR	0.0550	1.0000					
LGFCF	-0.4313***	-0.5950***	1.0000				
LEMP	-0.1021	0.5087***	-0.3833***	1.0000			
LREG	-0.0456	0.4776***	-0.2704***	0.6205***	1.0000		
LCO2	-0.7530***	-0.4258***	0.8807***	-0.3259***	0.2010***	1.0000	
LNRR	0.0396	-0.1223*	0.2592***	-0.6976***	-0.6132***	0.2205***	1.0000
	ΔLGG	*ΔLCORR*	*ΔLGFCF*	*ΔLEMP*	*ΔLREG*	*ΔLCO2*	*ΔLNRR*
ΔLGG	1.0000						
ΔLCORR	0.0984	1.0000					
ΔLGFCF	0.1591**	0.0252	1.0000				
ΔLEMP	-0.1861***	-0.0332	0.0492	1.0000			
ΔLREG	0.0345	0.0011	-0.0909	0.0874	1.0000		
ΔLCO2	-0.5073***	-0.0266	0.4312***	-0.0517	-0.0796	1.0000	
ΔLNRR	-0.1714**	0.0027	0.1529**	0.0477	-0.0327	0.2306***	1.0000

Note: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.

Moreover, to check the multi-collinearity among variables, the Variance Inflation Factor (VIF) is executed and added in the following table. When a VIF value is more than 10, it indicates that several regressors are highly linked with one another, distorting confidence intervals, standard errors and delivering untrustworthy probability estimates. The lack of multicollinearity is maintained by the low values of 3.86 and 1.11 on the mean VIF, meaning that multicollinearity is not an issue in this study.

Table 5. VIF statistics

Variables	VIF	Variables	VIF
LGFCF	6.55	*ΔLCO2*	1.29
LCO2	4.91	*ΔLGFCF*	1.25
LNRR	3.21	*ΔLNRR*	1.06
LEMP	3.11	*ΔLEMP*	1.02
LCORR	3.05	*ΔLREG*	1.02
LREG	2.30	*ΔCORR*	1.00
Mean VIF	3.86	Mean VIF	1.11

To ensure that all variables are stationary, the first- and second-generation panel unit root tests are performed, with the inclusion of two lags. The Maddala & Wu (1999) first-generation unit root panel test assumes cross-sectional independence, hence, it might not be useful as most variables show evidence of cross-sectional dependency. Therefore, the more robust second-generation panel unit root enhanced cross-sectional IPS test (CIPS) by Pesaran (2007) is conducted, as it deals with the presence of sectional dependency in panel data. In the appendix, table A2 exhibits that the variables are either I(0) or I(1), with no evidence of I(2), implying that the ARDL model is a suitable method, as it enables the first two integration levels at once.

To cope with the unique features of panel data, the presence of individual effects is examined. Accordingly, the Hausman test is applied for fixed effects (FE) against random effects (RE), where the null hypothesis assumes the difference in coefficients not being systematic. In other words, the null hypothesis considers random effects as more appropriate. The sigmamore and sigmaless options are also included to enhance robustness (Fuinhas et al., 2015). The results confirm the rejection of the null hypothesis in all three tests with a significance level of 5%, approving the use of the fixed effect model.

Table 6. Hausman tests

	Statistics
Hausman	13.40**
Hausman, sigmamore	12.83**
Hausman, sigmaless	13.31**

Notes: ** represents significance levels of 5%. H0: difference in coefficients is not systematic.

The Pooled Mean Group (PMG) and Mean Group (MG) estimators are also tested, considering the sample of countries chosen, this analysis answers any doubts regarding the existence of heterogeneity. While the PMG estimator supports homogeneous long-run coefficients and heterogeneous short-run coefficients, the MG estimator is effective whenever the long-run coefficients are heterogeneous. Compared to the PMG estimator, the MG estimator has greater flexibility (Pesaran et al., 1999).

Once again, the Hausman test is performed to verify which estimator is more appropriate. The outcomes of the PMG and MG estimators are also compared to the Dynamic Fixed Effects (DFE) estimator. This estimator is used in panel data analysis to account for both entity-specific effects and dynamic relationships between variables. Unlike standard fixed effects models, the DFE estimator includes lagged dependent variables to capture the influence of past values on current outcomes. This approach allows for better control of unobserved heterogeneity and provides more accurate estimates. By observing the results of all three estimations and their respective Hausman tests in table 7, it is possible to confirm that the fixed effects estimator is indeed adequate.

Table 7. Heterogeneous estimators and Hausman test

Models	PMG	MG	DFE
ECT	-0.0199	-0.6094***	-0.1508***
ΔLCORR	0.5425**	1.2057	-0.3992
ΔLGFCF	0.6105***	-0.2169	0.1366*
ΔLEMP	-0.1635	-1.7804	-0.3055**
ΔLREG	-0.0597	0.3804	0.0226
ΔLCO2	-0.4856***	0.3979	-0.0414
ΔLNRR	-0.1228***	-0.0936	-0.0879*
Constant	0.0321	-2.1920	0.9516***
LCORR	0.0620	0.0869	0.0204
LGFCF	0.1970***	0.1143	0.1868***
LEMP	0.2344	0.5181***	-0.3064***
LREG	0.0283*	0.0041	0.0163
LCO2	-0.8660***	-0.7280***	-0.7054***
LNRR	0.0016	0.0153	-0.0107
Hausman tests	PMG vs MG	MG vs DFE	PMG vs DFE
	chi2(6) = -212.73	chi2(6) = 0.00	chi2(6) = 0.00

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. ECT denotes error correction term. H0: difference in coefficients is not systematic.

Given the series integration order, existence of dynamic effects, cross-sectional dependency, and heterogeneous data, the cointegration test established by Westerlund (2007) is applied. This is a second-generation test with a bootstrapping option to generate robust critical values. Table 8 shows the outcome of the Westerlund cointegration test for all variables. The results reveal the rejection of the null hypothesis, suggesting no co-integration.

Table 8. Cointegration test

Statistics	Value	Z-value	P-value	Robust P-value
Gt	-1.880	3.145	0.999	0.525
Ga	-2.832	5.061	1.000	0.660
Pt	-4.567	3.326	1.000	0.625
Pa	-1.741	4.067	1.000	0.844

Notes: bootstrapping regression made with 800 reps. Gt and Ga test cointegration for every country individually. Pt and Pa test cointegration for the panel as whole. H0: no co-integration.

To select a robust estimator in the presence of fixed effects, an additional set of specifications tests needs to be performed. First, the Pesaran (2004) test, which assesses cross-sectional dependence by examining the correlation of residuals across cross-sections. Second, the Frees (1995) test, that utilizes a test statistic based on the sum of squared rank correlations of residuals to detect cross-sectional dependence. Third, the non-parametric Friedman (1937) test, used to detect the presence of cross-sectional dependence by comparing the rank sums of residuals across different cross-sections. Fourth, the Modified Wald test, developed by Baum (2000), which is used to test for group-wise heteroscedasticity in the error terms of a fixed effects model. And lastly, the Wooldridge (2002) test, that assesses the presence of serial correlation in panel data models. It is specifically designed to detect whether the residuals from a regression model are serially correlated.

The results from the Pesaran test shows that the null hypothesis is rejected at 1% for variables on level and lags, with the hypothesis being rejected at 10% in first differences. The same goes for the Frees test, rejecting the null hypothesis at 1% in level and lags, however, in first differences, the null hypothesis is not rejected. The Friedman test also indicates the rejection of the null hypothesis at 1% for variables in level and lags, yet the null hypothesis for first differences is only rejected at 5%. Albeit having different significance levels, overall, the results indicate that the residues are correlated and cross-section dependent.

Furthermore, the rejection of the null hypothesis at 1% in level, first differences and lags on both the Modified Wald and Wooldridge tests supports the existence of heteroscedasticity and first-order serial correlation, respectively.

Table 9. Specification tests

	Level	1st Differences	Lags
Pesaran test	3.475***	1.815*	2.878***
Frees test	0.610***	0.123	0.637***
Friedman test	34.611***	20.804**	28.421***
Modified Wald test	170.00***	123.41***	204.97***
Wooldridge test	140.074***	11.618***	105.876***

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Pesaran/Friedman/Frees tests H0: residues are not correlated. Modified Wald test H0: sigma(i)^2 = sigma^2 for all i (homoscedasticity). Wooldridge test H0: no first order autocorrelation.

Upon witnessing the presence of cross-section dependence, heteroscedasticity and first-order autocorrelation in the diagnostic tests, the Driscoll & Kraay (1998) estimator is an appropriate choice to validate the framework and its properties. The Driscoll Kraay (DK) standard errors estimator is nonparametric, proven to be suitable, as it can be used whenever these types of phenomena are present (Hoechle, 2007; Fuinhas et al., 2015). Additionally, it enables the fixed effects of a regression to be implemented, as well as keeping its robust nature with the addition of dummy variables (Vogelsang, 2012). Nevertheless, it is still preferable to utilize dummy variables sporadically.

4. Results

Before anything else, the presence of disturbances should be emphasized, since not considering socio-economic events could produce misleading results. Accordingly, a visual assessment of the series needs to be fulfilled, accompanied by unit root tests with structural breaks, particularly the Zivot & Andrews (2002) unit root test to help identify breakdowns and anomalies within the chosen time period. Individual unit root tests with structural breaks are conducted in each country where graphic inspection suggests the presence of possible outliers. It is important to keep in mind that the unit root tests with structural breaks do not alter the first- and second-generation unit root tests made previously (Leal & Marques, 2021). The Zivot and Andrews unit root tests with structural breaks can be consulted on table A1, in the appendix.

In more detail, Brazil experienced a severe economic crisis between 2014 and 2016, due to policies that reduced the growth capacity of the economy, therefore generating high fiscal costs (Barbosa Filho, 2017). According to the Zivot and Andrews test, the shocks happened in 2014, where Brazil's fixed capital formation dropped sharply and the unemployment rate highly increased, causing every major sector to deteriorate. Adding to this crisis, a series of corruption scandals uncovered by Operation Car Wash (Lava Jato), engulfed many influential politicians. The combination of an economic crisis alongside corruption scandals culminated in the impeachment of then president, Dilma Rousseff.

In 2008-2009, the fixed capital, employment and co2 emissions highly decreased in Russia. The explanation is rooted in the Russo-Georgian War. This war took place in August 2008, following a diplomatic crisis between Georgia and Russia, both previous constituent republics of the Soviet Union. Alongside the war, the global financial crisis of 2008 caused a great recession in Russia, where the price of Urals heavy crude oil lost more than 70% of its value. Overall, in late 2008 to early 2009, during the onset of the crisis, Russian markets plummeted, and more than 1 trillion dollars were wiped off the value of Russia's shares.

China had a massive shock due to the Covid-19 pandemic. However, since China was the first country to experience its effects, the widespread lockdowns and strict containment measures imposed in early 2020 helped curb the spread of the virus. Thus, the structural break happened in 2019. After the outbreak of Covid-19 in late 2019, the normal economic growth of 6% suddenly dropped to 2.2%. This pandemic hindered consumer demand, production, investment and international trade. Furthermore, during the Covid-19 period, many private companies closed, causing unemployment to grow in unprecedented speeds.

From 2017 to 2019, Egypt highly increased its renewable energy sources, therefore diminishing carbon emissions. In this time space, many large-scale renewable energy projects in Egypt reached operational status. This includes the Benban Solar Park, which began commercial operation. This solar park was also a feature of Egypt's Nubian Suns Feed-in Tariff program, which served as a major push to the private sector funding and expertise, in order to accomplish the objective of generating 20% of the country's power from renewable sources by 2022.

Just like Egypt, from 2017 onwards, Saudi Arabia made huge investments in renewable energy projects, with efforts to reduce reliance on fossil fuels for electricity generation. With the launch of Vision 2030 in 2016, Saudi Arabia began to primarily focus on solar energy sources, due to the country's abundant sunlight. During this period, the kingdom also launched several large-scale solar projects, including the Sakaka Solar Power Plant, which is one of the largest solar installations in the Middle East.

Lastly, the collapse in global oil prices starting in mid-2014 and continuing into 2015 had profound implications for the UAE, a major oil producer, impacting its revenue, budget, and investment capabilities. In response, the UAE accelerated its economic diversification efforts, aligned with COP21 and UAE Centennial 2071, emphasizing sustainability and reducing oil dependency. This period also saw increased investments in renewable energy, highlighted by projects such as the Mohammed bin Rashid Al Maktoum Solar Park and commitments under the Dubai Clean Energy Strategy 2050, which shifted patterns in renewable electricity generation.

The factors mentioned above indicate the presence of outliers in Brazil (2014), Russia (2009), China (2019), Egypt (2017), Saudi Arabia (2017) and the United Arab Emirates (2015). To control said phenomena, six impulse dummies are added to control the structural breaks and outliers. The impulse dummies derive from an individual visual inspection of all shocks, followed by the Zivot and Andrews unit root test with structural breaks.

Table 10 shows the results of the ARDL model, such as described in Equation (1), both in full and parsimonious options, with the inclusion of all impulse dummy variables. In the full model, all variables stay in the estimation. For the parsimonious model, solely the significant variables remain. The variables excluded on short-run due to lack of statistical significance are corruption control and natural resource rents. Note that the renewable generation variable becomes significant at 10% in the parsimonious model. On long run, the employment variable also becomes significant at 10% in the parsimonious model, with the excluded variables being renewable generation and CO2 emissions.

Overall, the results are somewhat consistent as there are no signal changes between both models. Additionally, one can assume a robust relationship between variables, since all models display reasonable R^2 values (Fuinhas et al., 2019).

Table 10. Estimated results

ΔLGG	FE-DK (Full Model)	FE-DK (Parsimonious Model)
ΔLCORR	0.0046	
ΔLGFCF	0.1855***	0.1835***
ΔLEMP	-0.3396**	-0.3472*
ΔLREG	0.0173	0.0173*
ΔLCO2	-0.7228***	-0.7355***
ΔLNRR	-0.0067	
LGG (-1)	-0.1518***	-0.1458***
LCORR (-1)	-0.0686**	-0.0739***
LGFCF (-1)	0.0194	0.0188***
LEMP (-1)	-0.0397	-0.0360*
LREG (-1)	0.0009	
LCO2 (-1)	-0.0020	
LNRR (-1)	-0.0140**	-0.0115*
Brasil2014	-0.0226**	-0.0213***
Russia2009	-0.0445***	-0.0453***
China2019	0.0241**	0.0244**
Egypt2017	-0.0512***	-0.0537***
Saudi2017	-0.0548***	-0.0570***
UAE2015	0.0344**	0.0388**
Constant	0.8680	0.8005**
N	190	190
R^2	0.6388	0.6376
F	F (19, 18) = 5354.40	F (15, 18) = 2884.76

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. "FE-DK" denotes the use of Driscoll and Kraay estimator with fixed effects.

In terms of the extent of the impacts, semi-elasticities and elasticities are implemented. Regarding the semi-elasticities, they are disclosed as the variable's coefficients estimated in first differences. As for the elasticities, the values are achieved by dividing the estimated long-run coefficients by the Error Correction Term (ECT) and then multiplying the obtained values by (-1). The semi-elasticities, elasticities and speed of adjustment are exhibited in the subsequent table.

Table 11. Semi-elasticities, elasticities and speed of adjustment

ΔLGG	FE-DK (Parsimonious model)
Semi-elasticities	
ΔLGFCF	0.1835***
ΔLEMP	-0.3472*
ΔLREG	0.0173*
ΔLCO2	-0.7355***
Constant	0.8005**
Elasticities	
LCORR (-1)	-0.5069***
LGFCF (-1)	0.1289***
LEMP (-1)	-0.2469*
LNRR (-1)	-0.0789*
Speed of adjustment	
ECT	-0.1458***

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. "FE-DK" denotes the use of Driscoll and Kraay estimator with fixed effects. ECT denotes error correction term.

According to table 11, in short-term, an increase on gross fixed capital formation in 1 percentual point (pp) has a positive impact on green growth of 0.1835 pp. However, if the total employment population increases by 1 pp, then, green growth decreases by 0.3472 pp. Regarding the generation of electricity by renewable sources, assuming it grows by 1 pp, green growth will increase by 0.0173 pp. Additionally, green growth is negatively affected by CO_2 emissions, as an increase of 1 pp in carbon emissions causes a decline of 0.7355 pp on green growth.

On long-run, corruption control is the variable with the highest impact on green growth, as an increase of corruption by 1% causes green growth to worsen by 0.5069%. Gross fixed capital formation continues to benefit green growth, as an increase of 1% causes the dependent variable to grow by 0.1289%. On the other hand, employment maintains the negative impact, since an increase of 1% causes a decline of 0.2469% on green growth. Moreover, a growth of 1% in total natural resource rents is detrimental to green growth by 0.0789%. The results from the employment variable in short- and long-term are the only that do not validate its respective hypothesis (H3), which justifies further discussion in the next chapter.

At last, by analyzing the low, negative and statistically significant ECT value, one can deduce the notion about having long memory data, with the ECT value for green growth indicating that 14.58% of the balance is rectified in one year. This can be attributed to the inherent complexities and slower dynamics often associated with green growth indicators, as observed in similar empirical studies.

For instance, empirical analyses by Kalemli-Ozcan (2002), Pao & Tsai (2010), and studies focusing on the African context by Kumar & Managi (2016) have demonstrated that environmental and economic variables frequently exhibit gradual adjustments due to policy inertia and structural constraints. Despite the slower adjustment indicated by a low ECT, it remains statistically significant, underscoring the robustness of the long-term relationship within the given econometric framework. Therefore, this ECT value still provides valuable insights into the dynamics of green growth, emphasizing the importance of sustained policy efforts and long-term planning.

5. Discussion

Having explored the panel data for the BRICS+ group, which collectively shed light on the intricate interplay between corruption, green growth and related variables, this section interprets the findings obtained and discusses their implications for theory and policy making. First and foremost, to provide a deeper knowledge of the results achieved, a summary figure is made with all the statistically significant short and long run dynamics among variables.

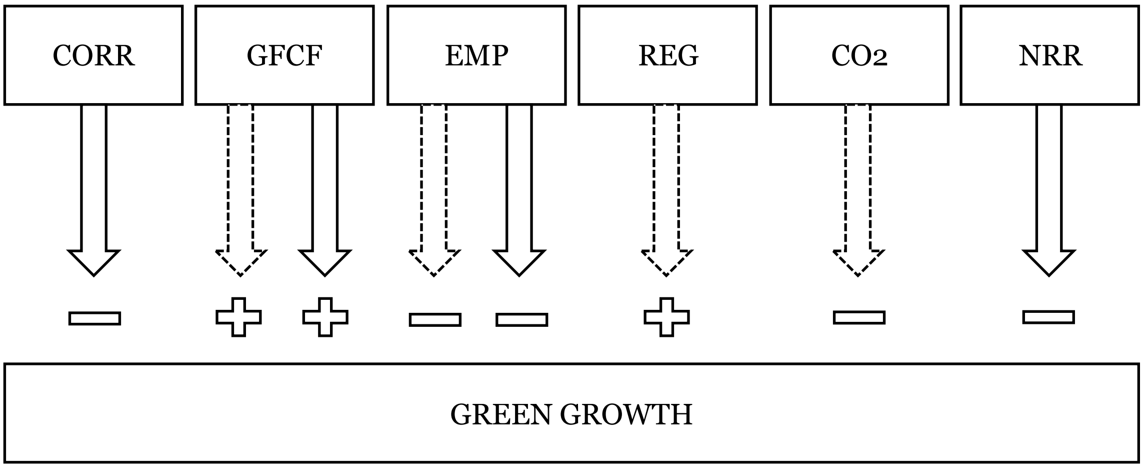

Figure 1. Main results with short- and long-run impacts

Source: author. Notes: Short-run impacts Long-run impacts

The significant negative long-term impact of corruption on green growth unveils a concerning trend, since corruption hampers environmental sustainability efforts over time. This result is expected since, as already mentioned in the literature review, corruption can undermine public confidence in institutions and impede effective governance mechanisms necessary for implementing and enforcing environmental regulations.

All things considered, the results suggest that corruption is disrupting international efforts to combat climate change and achieve sustainable development. Thus, reducing corruption is crucial not just to lessen the detrimental effects on an economy, but also for promoting sustainable development and creating a safer environment for present and future generations.

In the current BRICS+ scenario, these nations ought to reinforce the public's desire for anti-corruption measures and provide them more authority to hold the governments responsible. The creation of local surveillance initiatives can help achieve this goal. Second, it is imperative to put an end to impunity. This can be done by ensuring that corrupt individuals are held accountable and that the cycle of impunity is broken through efficient law enforcement. Third, the finance management and public administration need to be reformed. One way to do this is by disclosing budget information, which would stop waste and resource misuse, reducing corruption. Fourth, ensuring an independent and efficient judiciary force that can fairly adjudicate corruption cases. This includes providing adequate training for judges, prosecutors and law enforcement personnel specialized in handling corruption-related offenses.

Finally, the debate has very much been focused on combating corruption after a corrupt act has already taken place. What most developed countries do is, rather than battling it, they prevent corruption before the corrupt act even happens. The key is to avoid corruption by anticipation. This can be achieved by improving monitoring of major projects, by executing funds and major financings, and by supervising through independent bodies and citizens in general. All in all, the countries who most suffer from corruption should ratify various treaties and get an organized strategy for executing true democracy with corruption prevention initiatives.

Regarding the control variables, the findings of this study reveal compelling evidence regarding the positive impact of gross fixed capital formation on green growth, both in short and long terms. By harnessing the transformative potential of investment in physical capital, the BRICS+ bloc can accelerate the transition towards sustainability, fostering inclusive growth, and addressing pressing environmental challenges. Moving forward, concerted efforts from policymakers are essential to maximize the positive impact of gross fixed capital formation on green growth.

According to the results, higher employment levels translate to less sustainable growth in BRICS+ countries, which is an unexpected finding. Nonetheless, there are a few plausible explanations for this outcome. First, employment gains may stem from industries with high resource intensity and environmental footprint, such as manufacturing, construction and extractive sectors. Consequently, increased employment in these sectors could inadvertently exacerbate environmental pressures, as heightened production demands often lead to greater energy consumption, pollution emissions and natural resource depletion. Overall, one can presume that, in BRICS+ nations, most employment fields still do not go hand in hand with sustainable practices. Second, this variable includes the total number of people employed, regardless of the sector. Therefore, its negative impact on green growth can make sense, due to the BRICS+ members still highly depending on environmentally unfriendly industries.

Although only statistically significant in short-term, the results also reveal that renewable electricity generation is positive to sustainable growth. This finding underscores the immediate benefits of transitioning to renewable energy sources, which not only reduces carbon emissions but also stimulates economic activities associated with the development and deployment of renewables. This aligns with existing literature that highlights the role of renewable energy in promoting sustainable development and mitigating the adverse effects of climate change. Policymakers should, therefore, prioritize and accelerate renewable energy projects, leveraging their short-term benefits to drive long-term sustainable growth.

The short-term negative impact of CO_2 emissions on green growth suggests that higher emissions levels are associated with adverse effects on environmental sustainability within BRICS+ countries. Since research has proven that CO_2 emissions contribute to environmental degradation, such as air and water pollution, habitat destruction and climate change, one can assume it aggravates the ecosystem entirely. As such, by joining proactive policy interventions that prioritize emissions reduction, climate mitigation and sustainable development, policymakers can alleviate the short-term challenges associated with CO_2 emissions, while laying the foundation for long-term green growth.

The statistically significant negative impact of total natural resource rents on green growth in the long term raises important considerations for sustainable development strategies. This observation is consistent with the resource curse theory, which posits that resource-rich countries, such as BRICS+, may experience slower economic growth, weaker institutions and environmental degradation due to over-reliance on resource extraction. That said, it is essential to diversify the economy and reduce dependence on natural resource extraction as the primary driver of economic growth. Anti-corruption mechanisms are also an important factor to mitigate this impact, as such, enhancing the transparency and accountability in the management of natural resource rents is crucial.

6. Conclusion

To highlight how corruption impacts environmental sustainability, this study employed the use of a more contemporary environmental performance indicator. While a significant body of research is available on the matter at hand, most of it focuses on the impact of corruption on emission-related problems, which is only one aspect of environmental performance. Therefore, this research uses a production-based indicator that envelops both emissions and economic growth, known as "green growth". Yet, when talking about sustainable development or green growth, there is little consideration for societal issues like corruption. Addressing corruption and promoting transparency are essential for creating an environment conducive to sustainable practices.

Following these arguments, to investigate the repercussions of corruption on green growth, a panel data analysis for all BRICS+ countries over the time span of 20 years was made. The repercussions of gross fixed capital formation, employment, renewable electricity generation, CO_2 emissions and total natural resource rents were also studied. An individual examination of the short- and long-term impact of all variables was possible due to the use of the ARDL methodology. Once the required specification tests were carried out, the Driscoll-Kraay estimator with fixed effects was applied, since the model included cross-sectional dependency, heteroscedasticity, and first-order autocorrelation.

According to the results, hypotheses 1, 2, 4, 5 and 6 are supported. However, the same does not apply for hypothesis 3, as increases in employment do not necessarily raise sustainable growth in the BRICS+ members. Matching expectations, the crucial result implies that corruption is significantly harmful to green growth. Therefore, it is imperative that the BRICS+ group start to enforce anti-corruption measures, such as the ones discussed in the chapter above.

Nevertheless, implementing such mechanisms is easier said than done. Going to both extremes regarding the BRICS+ collectively, there is the Russian case where said policies are virtually impossible to enforce, due to the concentration of power and dominance of state-controlled institutions. However, there is also the UAE case, where many of the policy recommendations are already implemented. This country's legal system, based on Islamic law (Sharia), incorporates modern legal principles and procedures, offering a degree of transparency and predictability in the administration of justice.

The goal is not to say one country is better than the other. In truth, a big takeaway from this comparison is that some countries just need to look at proper examples of what corruption control is. There is no magic formula to control corruption, as there is proof on how to do it in this world. The key is about achieving sustained progress in preventing corruption, which requires concerted efforts from all sectors of society, including government, business, international community, and the people's voice in general.

Since this research is of challenging nature, there are some issues that need to be emphasized. First, the control of corruption estimate is mainly based on people's perceptions and not actual corruption itself. Second, being that this research studies BRICS+, obtaining valuable data is an arduous process, especially in the presence of countries like Ethiopia or Iran. To further expand on this study for an eventual follow-up, one can explore additional institutional variables such as political stability, regulatory quality and rule of law. Additionally, future investigations on this issue could undertake each country's political regime in consideration, allowing studies on this matter to be executed on multiple levels.

References

Barbosa Filho, F. de H. (2017). A crise econômica de 2014/2017. *Estudos Avançados*, *31*(89), 51–60. https://doi.org/10.1590/s0103-40142017.31890006

Baum, C. F. (2000). XTTEST3: Stata module to compute Modified Wald statistic for groupwise heteroskedasticity. *Statistical Software Components S414801*. Boston College Department of Economics.

Biswas, A. K., Farzanegan, M. R., & Thum, M. (2012). Pollution, shadow economy and corruption: Theory and evidence. *Ecological Economics*, *75*, 114–125. https://doi.org/10.1016/j.ecolecon.2012.01.007

Chen, H., Hao, Y., Li, J., & Song, X. (2018). The impact of environmental regulation, shadow economy, and corruption on environmental quality: Theory and empirical evidence from China. *Journal of Cleaner Production*, *195*, 200–214. https://doi.org/10.1016/j.jclepro.2018.05.206

Cole, M. A. (2007). Corruption, income and the environment: An empirical analysis. *Ecological Economics*, *62*(3–4), 637–647. https://doi.org/10.1016/j.ecolecon.2006.08.003

Cooper, A. F. (2016). *The BRICS: a very short introduction*. (Vol. 471). Oxford University Press.

D'Agostino, G., Dunne, J. P., & Pieroni, L. (2016). Corruption and growth in Africa. *European Journal of Political Economy*, *43*, 71–88. https://doi.org/10.1016/j.ejpoleco.2016.03.002

Driscoll, J. C., & Kraay, A. C. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics*, *80*(4), 549–560. https://doi.org/10.1162/003465398557825

Fredriksson, P. G., & Svensson, J. (2003). Political instability, corruption and policy formation: the case of environmental policy. *Journal of Public Economics*, *87*(7–8), 1383–1405. https://doi.org/10.1016/S0047-2727(02)00036-1

Fredriksson, P. G., Vollebergh, H. R. J., & Dijkgraaf, E. (2004). Corruption and energy efficiency in OECD countries: theory and evidence. *Journal of Environmental Economics and Management*, *47*(2), 207–231. https://doi.org/10.1016/j.jeem.2003.08.001

Frees, E. W. (1995). Assessing cross-sectional correlation in panel data. *Journal of Econometrics* 69: 393–414.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association* 32: 675–701

Fuinhas, J. A., Marques, A. C., & Couto, A. P. (2015). Oil rents and economic growth in oil producing countries: evidence from a macro panel. *Economic Change and Restructuring*, *48*(3–4), 257–279. https://doi.org/10.1007/s10644-015-9170-x

Fuinhas, J. A., Belucio, M., Santiago, R., & Afonso, T. L. (2019). Exercícios Introdutórios de Análise Económica de Dados. Covilhã, Portugal, UBI–*Universidade da Beira Interior*.

Hao, Y., Gai, Z., & Wu, H. (2020). How do resource misallocation and government corruption affect green total factor energy efficiency? Evidence from China. *Energy Policy*, *143*, 111562. https://doi.org/10.1016/j.enpol.2020.111562

Hao, Y., Gai, Z., Yan, G., Wu, H., & Irfan, M. (2021). The spatial spillover effect and nonlinear relationship analysis between environmental decentralization, government corruption and air pollution: Evidence from China. *Science of The Total Environment*, *763*, 144183. https://doi.org/10.1016/j.scitotenv.2020.144183

Hoechle, D. (2007). Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *The Stata Journal: Promoting Communications on Statistics and Stata*, *7*(3), 281–312. https://doi.org/10.1177/1536867X0700700301

Intergovernmental Panel on Climate Change. (2014). Climate Change 2014 Synthesis Report Summary for Policymakers. Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/02/AR5_SYR_FINAL_SPM.pdf.

Jain, A. K. (2001). Corruption: A review. *Journal of Economic Surveys*, *15*(1), 71–121. https://doi.org/10.1111/1467-6419.00133

Kalemli-Ozcan, S. (2002). Does the Mortality Decline Promote Economic Growth?*. In *Journal of Economic Growth* (Vol. 7).

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The Worldwide Governance Indicators: Methodology and Analytical Issues. Hague Journal on the Rule of Law, 3(02), 220–246. https://doi.org/10.1017/S1876404511200046

Kirya, M. (2018). Overview of corruption and anti-corruption in Ethiopia. *U4 Anti-Corruption resource center* Retrieved from https://www.u4.no/publications/overview-of-corruption-and-anti-corruption-in-ethiopia

Kumar, S., & Managi, S. (2016). Carbon-sensitive productivity, climate and institutions. *Environment and Development Economics*, *21*(1), 109–133. https://doi.org/10.1017/S1355770X15000054

Kurakin, A., & Sukharenko, A. (2018). Anti-corruption in the BRICS countries. *BRICS Law Journal*, *5*(1), 56–77. https://doi.org/10.21684/2412-2343-2017-5-1-56-77

Lang, B. (2018). China's anti-graft campaign and international anti-corruption norms: Towards a "new international anti-corruption order"? *Crime, Law and Social Change*, *70*(3), 331–347. https://doi.org/10.1007/s10611-017-9742-y

Leal, P. H., & Marques, A. C. (2021). The environmental impacts of globalisation and corruption: Evidence from a set of African countries. *Environmental Science & Policy*, *115*, 116–124. https://doi.org/10.1016/j.envsci.2020.10.013

Leitão, A. (2010). Corruption and the environmental Kuznets Curve: Empirical evidence for sulfur. *Ecological Economics*, *69*(11), 2191–2201. https://doi.org/10.1016/j.ecolecon.2010.06.004

Lisciandra, M., & Migliardo, C. (2017). An Empirical Study of the Impact of Corruption on Environmental Performance: Evidence from Panel Data. *Environmental and Resource Economics*, *68*(2), 297–318. https://doi.org/10.1007/s10640-016-0019-1

López and, R., & Mitra, S. (2000). Corruption, Pollution, and the Kuznets Environment Curve. *Journal of Environmental Economics and Management*, *40*(2), 137–150. https://doi.org/10.1006/jeem.1999.1107

López, R. (1994). The Environment as a Factor of Production: The Effects of Economic Growth and Trade Liberalization. *Journal of Environmental Economics and Management*, *27*(2), 163–184. https://doi.org/10.1006/jeem.1994.1032

Maddala, G. S., & Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics and Statistics*, *61*(s1), 631–652. https://doi.org/10.1111/1468-0084.61.s1.13

Mahlala, S., Lusanda Juta, Lewis Chigova, & Zweni, A. (2023). Conduits of Political Corruption and Patronage in South African Government. *International Journal of Social Science Research and Review*. https://doi.org/10.47814/ijssrr.v6i11.1586

Mauro, P., Driscoll, D. D. (1997). Why worry about corruption? (Vol. 6, pp. 1-19). Washington, DC: International Monetary Fund.

Mohamed, A. (2022). The Role of the Egyptian Leadership in Fighting Corruption: Insights from Egypt. *International Journal of Green Management and Business Studies*, *2*(2). https://doi.org/10.56830/ASYX5266

Nie, P., Chen, Z., Wang, C., & Chen, X. (2019). Innovation analysis under trading energy efficiency. *Energy*, *186*, 115866. https://doi.org/10.1016/j.energy.2019.115866

Organisation for Economic Co-operation and Development. (2017). Green Growth Indicators 2017. OECD. https://doi.org/10.1787/9789264268586-en

Organisation for Economic Co-operation and Development. (2023). OECD Data Explorer – Green Growth Indicators. Retrieved from https://data-explorer.oecd.org/vis?df[ds]=DisseminateFinalDMZ&df[id]=DSD_GG@DF_GREEN_GROWTH&df[ag]=OECD.ENV.EPI

Pao, H.-T., & Tsai, C.-M. (2010). CO2 emissions, energy consumption and economic growth in BRIC countries. *Energy Policy*, *38*(12), 7850–7860. https://doi.org/10.1016/j.enpol.2010.08.045

Park, J. (2012). Corruption, soundness of the banking sector, and economic growth: A cross-country study. *Journal of International Money and Finance*, *31*(5), 907–929. https://doi.org/10.1016/j.jimonfin.2011.07.007

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.572504

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H., & Shin, Y. (1999). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. In S. Strom (Ed.), *Econometrics and Economic Theory in the 20th Century* (pp. 371–413). Cambridge University Press. https://doi.org/10.1017/CCOL521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association*, *94*(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Rahman, K., Fatafta, M., & Jenkins, M. (2020). An overview of corruption and anti-corruption in Saudi Arabia. *Transparency International Anti-Corruption Helpdesk Answer*. Retrieved from https://knowledgehub.transparency.org/assets/uploads/helpdesk/Country-profile-Saudi-arabia-2020__PR.pdf

Rose, J. (2018). The Meaning of Corruption: Testing the Coherence and Adequacy of Corruption Definitions. *Public Integrity*, *20*(3), 220–233. https://doi.org/10.1080/10999922.2017.1397999

Salihu, H. A., & Jafari, A. (2020). Corruption and anti-corruption strategies in Iran: An overview of the preventive, detective and punitive measures. In *Journal of Money Laundering Control* (Vol. 23, Issue 1, pp. 77–89). Emerald Group Holdings Ltd. https://doi.org/10.1108/JMLC-01-2019-0001

Sekrafi, H., & Sghaier, A. (2018). Examining the Relationship Between Corruption, Economic Growth, Environmental Degradation, and Energy Consumption: a Panel Analysis in MENA Region. *Journal of the Knowledge Economy*, *9*(3), 963–979. https://doi.org/10.1007/s13132-016-0384-6

Shleifer, A., & Vishny, R. W. (1993). Corruption. *The Quarterly Journal of Economics*, *108*(3), 599–617. https://doi.org/10.2307/2118402

Sinha, A., Gupta, M., Shahbaz, M., & Sengupta, T. (2019). Impact of corruption in public sector on environmental quality: Implications for sustainability in BRICS and next 11 countries. *Journal of Cleaner Production*, *232*, 1379–1393. https://doi.org/10.1016/j.jclepro.2019.06.066

Statista. (2022). Primary energy consumption worldwide in 2022, by country (in exajoules). Retrieved from https://www.statista.com/statistics/263455/primaryenergy-consumption-of-selected-countries/

Stepanov, I. A., & Makarov, I. A. (2022). Greenhouse gas emissions regulation in fossil fuels exporting countries: opportunities and challenges for Russia. *Post-Communist Economies*, *34*(7), 916–943. https://doi.org/10.1080/14631377.2021.1943918

Stern, D. I. (2004). The Rise and Fall of the Environmental Kuznets Curve. *World Development*, *32*(8), 1419–1439. https://doi.org/10.1016/j.worlddev.2004.03.004

Sukhtankar, S., & Vaishnav, M. (2015). Corruption in India: Bridging research evidence and policy options. *In India Policy Forum* (Vol. 11, pp. 193-261).

Tawiah, V., Zakari, A., & Adedoyin, F. F. (2021). Determinants of green growth in developed and developing countries. *Environmental Science and Pollution Research*, *28*(29), 39227–39242. https://doi.org/10.1007/s11356-021-13429-0

Tawiah, V., Zakari, A., & Alvarado, R. (2023). Effect of corruption on green growth. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03152-w

Vogelsang, T. J. (2012). Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects. *Journal of Econometrics*, *166*(2), 303–319. https://doi.org/10.1016/j.jeconom.2011.10.001

Wang, Z., Danish, Zhang, B., & Wang, B. (2018). The moderating role of corruption between economic growth and CO2 emissions: Evidence from BRICS economies. *Energy*, *148*, 506–513. https://doi.org/10.1016/j.energy.2018.01.167

Welsch, H. (2004). Corruption, growth, and the environment: a cross-country analysis. *Environment and Development Economics*, *9*(5), 663–693. https://doi.org/10.1017/S1355770X04001500

Westerlund, J. (2007). Testing for Error Correction in Panel Data*. *Oxford Bulletin of Economics and Statistics*, *69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *The MIT Press. Cambridge, ma*, 108(2), 245-254.

Worldometer. (2024). Countries in the world by population (2024). Retrieved from https://www.worldometers.info/world-population/population-by-country/

Worldometer. (2024). GDP by country (2024). Retrieved from https://www.worldometers.info/gdp/gdp-by-country/

Worldometer. (2024). CO2 Emissions by Country (2024). Retrieved from https://www.worldometers.info/co2-emissions/co2-emissions-by-country/

Worldbank. (2024). DataBank, Metadata Glossary - Gross fixed capital formation (constant 2015 US$). Retrieved from https://databank.worldbank.org/metadataglossary/world-developmentindicators/series/NE.GDI.FTOT.KD

Worldbank. (2024). DataBank, Metadata Glossary – Total Natural Resource rents (% of GDP). Retrieved from https://databank.worldbank.org/metadataglossary/worlddevelopment-indicators/series/NY.GDP.TOTL.RT.ZS

Yuan, B., & Xiang, Q. (2018). Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *Journal of Cleaner Production*, *176*, 895–908. https://doi.org/10.1016/j.jclepro.2017.12.034

Zhang, S., Wang, Y., Hao, Y., & Liu, Z. (2021). Shooting two hawks with one arrow: Could China's emission trading scheme promote green development efficiency and regional carbon equality? *Energy Economics*, *101*, 105412. https://doi.org/10.1016/j.eneco.2021.105412

Zhao, X., Ma, X., Chen, B., Shang, Y., & Song, M. (2022). Challenges toward carbon neutrality in China: Strategies and countermeasures. *Resources, Conservation and Recycling*, *176*, 105959. https://doi.org/10.1016/j.resconrec.2021.105959

Zhou, A., & Li, J. (2021). Impact of anti-corruption and environmental regulation on the green development of China's manufacturing industry. *Sustainable Production and Consumption*, *27*, 1944–1960. https://doi.org/10.1016/j.spc.2021.04.031

Zivot, E., & Andrews, D. W. K. (2002). Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of Business & Economic Statistics*, *20*(1), 25–44. https://doi.org/10.1198/073500102753410372

Appendix

Table A1. Zivot and Andrews unit root test

	Intercept	Break	Trend	Break	Both	Break
Brazil						
LGG	-3.8834*	2012	-3.0280	2010	-3.2756	2017
ΔLGG	-5.8166***	2010	-	-	-	-
LCORR	-3.8988*	2014	-4.4111	2012	-4.2727*	2010
ΔLCORR	-6.5155***	2012	-	-	-	-
LGFCF	-3.6764***	2014	-4.0494***	2013	-4.7656**	2010
ΔLGFCF	-3.8007*	2014	-	-	-	-
LEMP	-0.0606	2016	-1.5325***	2016	-1.5520	2016
ΔLEMP	-6.5219*	2014	-	-	-	-
LREG	-4.9952***	2013	-2.2202	2008	-3.8367***	2014
ΔLREG	-5.5069**	2016	-	-	-	-
LCO2	-2.1934**	2016	-3.4980***	2015	-3.4043**	2012
ΔLCO2	-7.2073***	2015	-	-	-	-
LNRR	-4.0513*	2014	-3.5918	2007	-3.9535*	2015
ΔLNRR	-	-	-	-	-	-
Russia						
LGG	-3.1802***	2007	-5.2222***	2008	-5.9186***	2007
ΔLGG	-4.4811**	2009	-	-	-	-
LCORR	-5.5189*	2012	-	-	-	-
ΔLCORR	-		-	-	-	-
LGFCF	-2.4079**	2006	-4.3535**	2009	-3.9713	2008
ΔLGFCF	-5.3799***	2009	-	-	-	-
LEMP	-1.4210**	2012	-	-	-	-
ΔLEMP	-		-	-	-	-
LREG	-2.7769*	2010	-3.2375***	2016	-3.1629	2015
ΔLREG	-6.2974**	2008	-	-	-	-
LCO2	-4.59091*	2015	-4.2677	2007	-4.4107*	2015
ΔLCO2	-4.2679	2009	-	-	-	-
LNRR	-5.7704**	2015	-4.8112	2009	-5.9214**	2015
ΔLNRR	-	-	-	-	-	-
China						
LGG	-4.7830***	2015	-4.5307**	2012	-4.2841*	2010

ΔLGG	-3.3104	2006	-	-		-
LCORR	-	-	-6.2933	2008	-6.1892	2012
ΔLCORR	-9.1506	2015	-	-	-	-
LGFCF	-2.3881**	2007	-4.0277***	2013	-3.8759**	2011
ΔLGFCF	-3.6876**	2014	-	-	-	-
LEMP	0.5212	2019	-0.9588***	2019	-0.8058**	2019
ΔLEMP	-0.8940	2011	-	-	-	-
LREG	-3.9123	2017	-8.3183***	2016	-7.7699**	2014
ΔLREG	-	-	-	-	-	-
LCO2	-5.0990***	2009	-4.9731	2012	-4.9012*	2011
ΔLCO2	-	-	-	-	-	-
LNRR	-	-	-3.7417	2008	-3.5180	2008
ΔLNRR	-5.4184**	2016	-	-	-	-
Egypt						
LGG	-	-	-2.1297***	2017	-2.4309**	2017
ΔLGG	-3.8997**	2011	-	-	-	-
LCORR	-	-	-	-	-	-
ΔLCORR	-5.7949**	2009	-	-	-	-
LGFCF	-4.2860	2012	-	-	-	-
ΔLGFCF	-3.2416**	2015	-	-	-	-
LEMP	-4.4546	2017	-	-	-	-
ΔLEMP	-	-	-	-	-	-
LREG	-1.6691**	2011	-3.3687***	2017	-4.0217	2017
ΔLREG	-4.2533*	2009	-	-	-	-
LCO2	-0.7731	2005	-1.1871***	2017	-1.2052	2017
ΔLCO2	-	-	-	-	-	-
LNRR	-3.8196**	2015	-	-	-	-
ΔLNRR	-	-	-	-	-	-
Saudi Arabia						
LGG	-3.0669*	2009	-2.8573**	2015	-3.3804*	2009
ΔLGG	-6.2956	2006	-	-	-	-
LCORR	-	-	-	-	-4.5367	2006
ΔLCORR	-7.9534*	2005	-	-	-	-
LGFCF	-	-	-2.5792	2008	-1.9199	2007
ΔLGFCF	-	-	-	-	-	-
LEMP	-4.7491	2017	-	-	-	-
ΔLEMP	-	-	-	-	-	-

LREG	-0.5637	2017	-	-	-	-
ΔLREG	-	-	-	-	-	-
LCO2	-1.7230***	2017	-6.6904***	2016	-5.9454***	2015
ΔLCO2	-6.8765***	2016	-	-	-	-
LNRR	-4.4857***	2015	-4.2241**	2012	-5.0052**	2015
ΔLNRR	-	-	-	-	-	-
United Arab Emirates						
LGG	-4.2248**	2008	-3.8923***	2013	-3.9532*	2008
ΔLGG	-	-	-	-	-	-
LCORR	-3.4198**	2012	-2.7210**	2015	-3.9153**	2012
ΔLCORR	-3.9930**	2011	-	-	-	-
LGFCF	-3.5013*	2010	-	-	-3.3844	2009
ΔLGFCF	-6.4619**	2008				
LEMP	-	-	-5.6303**	2010	-5.0529***	2012
ΔLEMP	-	-	-	-	-	-
LREG	-	-	-3.0830	2009	-2.7608	2008
ΔLREG	-5.6292*	2015	-	-	-	-
LCO2	-2.8479**	2006	-2.9219**	2010	-	2012
ΔLCO2	-4.4239**	2011	-	-	-	-
LNRR	-5.3430***	2015	-4.3243**	2012	-5.5438***	2015
ΔLNRR	-	-	-	-	-	-

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. Tests were performed with a maximum lag length of 4. (-) corresponds to a near singular matrix error. H0: respective series has a unit root with a structural break in intercept, trend or both.

Table A2. First and second-generation panel unit root tests

	First-Generation (MW)						Second-Generation (CIPS)					
	Without trend			With trend			Without trend			With trend		
Lags	0	1	2	0	1	2	0	1	2	0	1	2
LGG	24.131	18.034	26.787	15.883	38.007***	48.484***	0.245	-0.795	0.365	1.355	-0.218	0.965
LCORR	57.047***	13.445	22.746	71.463***	19.017	30.682*	-1.136	0.822	-0.021	-2.929***	-1.226	-1.595*
LGFCF	30.932*	37.415***	37.470***	4.337	6.497	10.096	-0.289	-1.215	-1.235	0.353	-1.276	-1.868*
LEMP	39.518***	32.907**	40.017***	3.839	5.863	12.381	0.101	1.358	0.836	-2.120**	-0.168	0.942
LREG	13.897	12.907	13.484	13.794	13.952	12.222	1.492	1.364	1.707	0.949	0.761	1.163
LCO2	58.362***	51.063***	34.091**	4.164	13.847	6.613	0.925	-0.515	0.344	2.569	1.259	2.140
LNRR	19.061	15.593	8.663	21.245	34.142**	16.558	0.002	-1.000	0.281	-0.378	-2.774***	1.483
ΔLGG	105.582***	67.035***	84.358***	75.131***	51.915***	67.600***	-4.810***	-2.814***	-1.560*	-3.508***	-1.887**	-0.785
ΔLCORR	313.688***	70.872***	53.006***	256.746***	46.930***	29.246*	-8.608***	-3.545***	-2.235**	-6.577***	-1.661**	-0.175
ΔLGFCF	73.956***	29.750*	15.444	74.608***	44.155***	23.467	-4.893***	-2.121**	-2.615***	-3.094***	0.023	-0.160
ΔLEMP	83.616***	24.849	11.636	92.821***	52.217***	39.272***	-5.407***	-3.018***	-1.352*	-4.690***	-1.777**	-0.271
ΔLREG	141.774***	78.294***	36.833**	118.446***	73.506***	34.785**	-6.321***	-2.749***	-1.109	-5.097***	-1.501*	0.237
ΔLCO2	55.453***	31.874**	21.239	62.825***	37.194**	37.444***	-2.618***	-0.589	0.198	-2.600***	-0.636	-0.245
ΔLNRR	144.698***	126.060***	51.573***	115.450***	100.300***	38.343***	-6.966***	-5.438***	-1.620*	-5.807***	-5.104***	-0.668

Notes: ***, ** and * represent significance levels of 1%, 5% and 10%, respectively. “MW” test assumes cross-sectional independence. “CIPS” test assumes cross-section dependence is in form of a single unobserved common factor. Tests performed with 2 lags included. For both tests H0: series are I(1) or are not stationary.