The impact of health expenditure on environmental quality: the case of BRICS

Fortune Ganda

Faculty of Management Sciences, Department of Accounting, Walter Sisulu University, Butterworth, South Africa

ABSTRACT
There is a significant and deadly link between air-borne pandemics (for example, COVID-19) and air pollution, as airborne particulate matter enhances the spread of such diseases. Moreover, economically disadvantaged groups are more susceptible. This paper analyses the effects of health expenditure on carbon emissions in BRICS (that is, Brazil, Russia, India, China and South Africa) countries from 2000 to 2017. The Fully Modified Ordinary Least Square (FM-OLS), the Vector Error Correction Model (VECM) Granger causality and the Dumitrescu–Hurlin causality tests are employed. In terms of aggregate health expenditure, the level of current health expenditure is significantly and negatively connected with carbon emissions. With regard to disaggregated variables, private health expenditure is also negatively and significantly linked to emissions. However, domestic general government health expenditure and external health expenditure are positively and significantly associated with carbon emissions. Country-specific results are also provided. The causality tests confirm bi-directional causality between the level of current health expenditure, private health expenditure, and domestic general government health expenditure, and carbon emissions. External health expenditure in BRICS does not cause emissions, and vice-versa. VECM causal links are also discussed. The results point to the need to review health expenditure sub-policy programs to achieve zero-carbon targets.

1. Introduction

There are growing reports that the novel human coronavirus disease (COVID-19) is a crisis of the natural environment as well as health (Hamid, Mir, and Rohela 2020; Paital 2020). Liu, Kuo, and Shih (2020) highlight that COVID-19 is the fifth global pandemic since the 1918 influenza pandemic. The World Economic Forum (2020, 1) elaborates that ‘the spread of COVID-19 has been hastened and exacerbated by humanity’s long-term assault on the natural world.’ For example, information from the medical field indicates that different forms of emissions influence all forms of mortality (Apergis et al. 2018b; Owusu and Sarkodie 2020). In the modern age where thousands of people are dying daily from COVID-19 and other diseases, research on the link between health and the environment has become extremely important (World Health Organisation 2020; Worldometers 2020).

The spread of diseases can be attributed to air pollution, high temperature levels, and other meteorological factors (Sarkodie and Owusu 2020; Tosepu et al. 2020). Recent research also demonstrates that climate change is transforming the normal activities of both fauna and flora within their ecosystems, with both positive and negative effects, although in most cases the impacts are dangerous to health (World Health Organisation 2016; Zeng and He 2019). For example, the current COVID-19 public health disaster is regarded as having strong natural environmental origins (Hamid, Mir, and Rohela 2020; Paital 2020).

The existing literature notes that air pollution has numerous adverse health outcomes and welfare costs that impact long-term economic sustainability and human development (Ganda 2021; Owusu and Sarkodie 2020). Furthermore, global variations in health expenditure have also resulted in changes in maternal and infant morbidity and mortality (Owusu, Sarkodie, and Pedersen 2021). However, there is a paucity of research on the impact of both aggregate and disaggregate health expenditure on environmental pollution.

This paper examines the impact of health expenditure on carbon dioxide emissions in the BRICS countries – Brazil, the Russian Federation, India, China, and South Africa. These countries’ health care systems have different characteristics. Brazil’s 1988 Federal Constitution provides for free health services at federal, state, and municipal level (the same applies to health financing schemes) (Santos, Delduque, and Alves 2016). The health care
system in Russia comprises compulsory health insurance that provides for health care along with funds from the state, regional budgets, and different organizations. Commercial companies also offer voluntary health insurance (Popovitch et al. 2011). The Indian health care system is mixed since it is a diverse economy although it is significantly privatized by global standards. Social insurance is compulsory and is largely adopted in the formal sector. The Central Government Health Scheme (CGHS) and the Employees’ State Insurance Scheme (ESIS) are components of health insurance (Perianayagam and Goli 2013). The Chinese health care system is also undergoing privatization, although the government has sought to improve access to medical facilities for all. Challenges encountered by economically disadvantaged groups include overcrowded health centers, administrative problems and a lack of medical experts (Tam 2010). South Africa’s health care system is funded through the public sector and the ever-growing private sector; it is hence comprised of two sub-systems (World Health Organisation 2015). The country also offers a basic health care system that is inadequate for citizens. Challenges include the burden of HIV and/or AIDS, and Tuberculosis which puts a strain on the system and budgets, as well as a lack of qualified medical personnel (World Health Organisation 2015).

Few studies have considered health expenditure as an explanatory variable that predicts environmental quality. From an environmental perspective, health expenditure ensures that public health systems lower the risks of disease through a healthy natural environment, and also improve the economy’s green productivity. It may thus be a vital factor that influences environmental quality. It is therefore important to estimate the health costs of carbon emissions for both environmental and health policy development. From a natural environmental policy point of view, tough legislation may result in companies suffering lower profit margins, while less stringent laws can damage public health (decision makers thus face the dilemma of a trade-off between economic gain and health expenses). Failure to measure health expenses as a result of carbon emissions can undermine the quality and efficiency of zero-carbon policies. Having outlined the BRICS health systems, we now turn to the environmental quality contexts in these economies.

Carbon dioxide emissions were selected as one of the principal variables as these are one of the chief sources of environmental damage and the cause of declining health standards. Balsalobre-Lorente et al. (2019) note that, in 2013 the BRICS group was responsible for 40 percent of aggregate global carbon emissions. Chishti et al. (2021) present the following statistics to show that these countries are among the top 10 high carbon-emitting nations: World – 58%; China – 29%; India – 6%; Russia – 5%; Brazil – 1%; and South Africa – 1%. BP indicates that by 2017, emissions in these economies comprised 41.82% of global carbon emissions, and it was anticipated that this percentage would increase. The World Bank (2018) notes that while BRICS have experienced rapid economic growth in recent years they also generate high emissions, which rose from 4901 million tons in 1985 to 13,768 million tons in 2018, a threefold increase.

From a green accounting perspective, a major research and policy concern is to investigate how the various types of health expenditure in the BRICS countries influence environmental quality. Therefore, our research questions included: How does the aggregate level of current health expenditure (CHE) affect carbon dioxide emissions in the BRICS? Decomposing aggregate health expenditure into several forms, we also examine how domestic private health expenditure (DPH) influences carbon dioxide emissions. Third, the effect of domestic general government health expenditure (DGG) on carbon dioxide emissions is examined across the BRICS countries. Fourth, we assess the impact of external health expenditure (DHE) on carbon dioxide emissions.

The paper thus makes a number of contributions. Firstly, it employs both aggregate and disaggregate variables of health expenditure to examine its influence on environmental quality in BRICS (which represents a comprehensive examination of health expenditure in relation to carbon emissions). To the best knowledge of the author, this paper is the first to undertake such research in this setting. Previous studies have not evaluated the social, economic and environmental costs of health measures by including health expenditure irrespective of the related economic and social ramifications (for instance, pollution can trigger respiratory diseases that negatively impact labor productivity and economic development). Secondly, both country-specific and panel-based effects are examined, thereby providing a broader view of how health expenditure influences environmental quality. Third, this study applies both relationship and causal analysis to ascertain if the explanatory variables of health expenditure are related, cause, and/or are caused by emissions (using Fully Modified Ordinary Least Squares (FM-OLS), and Dumitrescu-Hurlin causality techniques). Fourth, the paper adds to the current literature by deploying the STIRPAT model to incorporate health expenditure as a governing factor of the affluence constituent. Fifth, to the best of our knowledge, this is the first study to analyse the impact of health expenditure on carbon emissions within the BRICS economies. It hence offers new knowledge to assist the development of green strategies and
health policies in harmony with the natural environment. The study is topical given the increasing incidence of global pandemics with a strong association with changes within the natural ecosystem.

In addition, this paper addresses the challenges associated with pollution in the context of heightening worldwide pandemics by evaluating the many aspects of health expenditure that may be linked to increased carbon emissions (which ultimately worsen health conditions). The existing literature does not outline the sophisticated parameters that are imperative to mitigate carbon emissions within the health sector. Given the growing literature on the strong relationship between pandemics such as COVID-19 and carbon emissions, this research is part of a wider project which examines the parameters linked to environmental quality that appear to influence the transmission mechanisms of pathogens. The paper thus provides information that will assist society in integrating and managing effective policy strategies in crisis situations. Furthermore, it is vital that emerging economies adopt effective health expenditure designs and structures to improve the health of both society (a lower risk of infection in the face of global pandemics) and the natural environment (reduced emissions to mitigate global warming). 

The remainder of this paper is organized as follows: Section 2 presents a literature review; Section 3 outlines the research methodology; Section 4 presents the results and discussion; and Section 5 discusses the study’s implications, with the conclusion presented in Section 6.

2. Literature review

There is a growing body of literature on the effect of health expenditure on environmental quality (Erdoğan, Yıldırım, and Gedikli 2019; Çakar, Gedikli, and Erdoğan 2021). A summary of selected literature on this theme is outlined in Table 1. The summary points to mixed findings. For example, Yazdi, Zahra, and Nikos (2014); Khoshnevis and Khanalizadeh (2017), and Narayan and Narayan (2008) found a positive relationship between emissions and health expenditure, while Lu et al. (2017) and Zaidi and Saidi (2018) demonstrate a negative link. A survey by Apergis, Jebli, and Youssef (2018a) established bi-directional causality involving emissions and health expenditure while Chaabouni, Zghidi, and Mbarek (2016) found unidirectional causality. This study is unique in that it deploys aggregate and disaggregated variables of health expenditure to ascertain both the relationship and causality between health expenditure and environmental quality.

The BRICS bloc was selected as a sample for a number of reasons. The BRICS economies are developing and have a significant influence on the global economy (Ganda 2019a). Shahbaz et al. (2018) also note that these countries have a large agricultural labor force, with a small services sector. The bloc is responsible for 16.8% of global trade (and 19% of total global exports). Zaman et al. (2016) also draw attention to the BRICS countries’ abundant low-cost labor, and rich mineral and agricultural resources as well as technological innovations. Shahbaz et al. (2016) observe that, in the past 30 years these countries contributed 21 percent of global Gross Domestic Product (GDP), used 40% of global energy sources and are home to more than 40% of the global population. However, they add that this region is also a major contributor to the increase in global emissions. The International Energy Agency (2007) notes that three BRICS nations (India, China and Russia) are among the top 5 emitting countries in the world. Dong, Sun, and Hochman (2017) state that BRICS were responsible for 40% of worldwide emissions in 2016, with China being the second biggest economy but the highest global emitter. Given this scenario, Zaman et al. (2016) submit that, while the BRICS economies occupy a unique place amongst growing economies since they sustain rapid economic development, they simultaneously confront health and environmental challenges, and those emanating from population growth, energy needs and global warming.

3. Methodology

This section covers the data used for the study, the econometric proposition, the test of cross-section dependence and slope-homogeneity, unit root tests, co-integration tests, the long-run estimation process – the Fully Modified Ordinary Least Squares (FM-OLS) technique, and the Dumitrescu-Hurlin causality method.

3.1. Data

The sample is BRICS – Brazil, the Russian Federation, India, China and the Republic of South Africa. The period is from 2000 to 2017. A detailed analysis of the data is presented in Table 2 below.

3.2. Econometric proposition

To elaborate on the natural environment as well as identify the variables affecting this environment, I suggest the IPAT model, which is I = PAT. The fundamental basis of the IPAT model is expressed in a way that environmental impacts (I) are a function of motivating
Table 1. Empirical research and results.

| Author(s) | Country(s) | Period       | Variables                                          | Methodology                          | Result(s)                                                                 |
|-----------|------------|--------------|----------------------------------------------------|--------------------------------------|---------------------------------------------------------------------------|
| Apergis, Jebi, and Youssel (2018) | 42 sub-Saharan African countries | 1995–2011 | Renewable Energy, Health Expenditure, Carbon emissions (CO₂), Economic Growth | Granger causality                    | Bidirectional causality involving health expenditure and CO₂ emissions is present in the long run. Unidirectional causality between economic growth and health expenditure is valid in the short run. |
| Jerrett et al. (2003) | 49 counties in Ontario, Canada | 1990–1992 | Health expenditure, Pollutant toxic emissions, mortality ratios, Environmental defensive expenditures, Income, a Location quotient of medical experts and employment ratios | A sequential two-stage regression model | Pollutant toxic emissions, mortality ratios along environmental defensive expenditure generate significant relationships with health expenditure. Counties with increased emissions had high health expenditure while those with high spending on environmental defensive practices had reduced expenditure on health. |
| Lu et al. (2017) | 30 Chinese provinces | 2002–2014 | Health Expenditure, Carbon emissions (CO₂), Economic Growth | Simultaneous equation model (SEM) | A negative influence of emissions on public health. GDP negatively affected perinatal mortality rates. Education and medical conditions heightened economic growth and public health. |
| Apergis et al. (2018b) | United States of America (USA) states Sub-Saharan African countries | 1966–2009 | Health Expenditure, Carbon emissions (CO₂), Economic Growth | Quantile regressions | The impact of emissions on health care was much higher for US states that had increased health expenditure. |
| Zaidi and Saidi (2018) | 51 countries | 1995–2013 | Health Expenditure, Carbon emissions (CO₂), Nitrous oxide emissions, Economic Growth | Dynamic Simultaneous equation model (SBM) | Except for low-income economies, there is unidirectional causality from carbon emissions to health expenditure. Health impacts on economic growth reduce environmental damage. |
| Chaibouni, Zghidi, and Mbarek (2016) | 14 Latin American and Caribbean economies | 1980–2013 | Health expenditure, Green energy, Permanent cropland, High technology exports, Carbon dioxide (CO₂) emissions. | Panel co-integration Regression analysis | Health expenditure contributes to more emissions. |
| Li, Lu, and Li (2020) | China | 2002–2017 | Health Expenditure, Carbon emissions (CO₂), Economic Growth | Static models, Co-integration and two-stage least square (2SLS) instrumental variables technique | An increase in pollution-intensive industrial agglomeration firms increases urban health expenditure but reduces rural health expenditure. |
| Narayan and Narayen (2008) | 8 OECD countries | 1980–1999 | Health Expenditure, Carbon monoxide emissions (CO), Nitrogen oxide emissions, Sulphur oxide emissions, Economic Growth | Panel co-integration | All the variables were co-integrated. In both the short and the long run, the results show that income and carbon monoxide emissions have a positive impact on health expenditure. In the long run, sulphur oxide emissions also demonstrate a positive effect on health expenditure. |
| Mohmmed et al. (2019) | Top 10 emitting countries | 1991–2014 | Population, Economic growth, energy intensity, carbon emissions intensity, Human Development Index, Health Life Expectancy. | The logarithmic mean Divisia index (LMDI) method | Health Life Expectancy had a strong link with sector carbon dioxide emissions. A policy that creates a safe environment is imperative. |
| Malik et al. (2018) | 15 Australian health sectors | 2014–2015 | Health Expenditure, Carbon emissions (CO₂). | Observational economic input-output lifecycle assessment Dynamic Ordinary Least Squares (OLS) regression, Error Correction Model techniques | The health care system adds about 7% of emissions to Australia’s total carbon footprint. Economic growth and emissions determine health expenditure. In both the short and the long run, health expenditure has a direct relationship with emissions, indicating that increased environmental damage will cause health problems. |
| Mehrara, Sharzei, and Mohaghegh (2012) | 114 developing countries | 1995–2007 | Health Expenditure, Carbon emissions (CO₂), Economic Growth. | Correlation coefficients and data reviews | Economic growth spurs an improved quality of life and a positive health outlook although the natural environment deteriorates. This situation stimulates the incidence of diseases and ultimately the health system incurs a high financial burden. The studied variables are co-integrated. Income and all the forms of emissions have a positive link with health expenditure. In the long run, all the studied variables are co-integrated in both short- and long-run economic growth, and all types of emissions have a statistically positive relationship with health expenditure. |
variables, namely, Population size (P), affluence (A), and technology level (T). In this case, PAT are identifiable socioeconomic factors that have an impact on the natural environment. The empirical literature identifies environmental impact (I) as carbon dioxide emissions (Koçak and Ulucak 2019; Zhang, Zhang, and Pan 2019); hence this variable is employed.

In this vein, the IPAT model represents a simplified approach to analyse the natural environmental conditions produced by human practices. I present the IPAT model as follows:

\[ I = PAT \]  \hspace{1cm} (1)

Where I identify the environmental impacts, which are denoted by carbon dioxide emissions. P shows the population size of each country; A represents the country’s level of affluence, normally measured by GDP per capita; and T represents its level of technology.

Ideally, the IPAT model is developed into the STIRPAT model that represents a stochastic framework identified for the stochastic effects through a regression on population, affluence, and technology. Hence, it is identifiable as follows:

\[ I = \alpha P^\delta A^\mu T^\gamma e \]  \hspace{1cm} (2)

Where \( \alpha \) is a constant term; \( \delta, \mu \) and \( \gamma \) are coefficients of population, affluence, and technology levels, respectively; and \( e \) is the error term.

To analyse the IPAT model, equation [1] is changed into its linear form by adopting the logarithm transformation. Ideally, the use of logarithm form enhances the study to minimize the problems associated with heterogeneity.

\[ \log_{it} = \log_{it} + \delta \log_{Pit} + \mu \log_{Ait} + \gamma \log_{Tit} + \log_{it} \]  \hspace{1cm} (3)

Where \( i \) and \( t \) represent cross-sections and time, respectively.

The state of the natural environment is not only explained by the effects of population, affluence, and technology but can also be explained by other factors. To comprehensively understand the motivating factors of environmental impacts, this paper considers an additional set of explanatory factors. The extended or modified STIRPAT models adopted are as follows:

\[ \log_{EQit} = \alpha_i + \delta \log_{Pit} + \mu \log_{GDPit} + \gamma \log_{Tit} + \varphi \log_{CHEit} + \epsilon_{it} \] \hspace{1cm} (4)

\[ \log_{EQit} = \alpha_i + \alpha \log_{Pit} + \mu \log_{GDPit} + \gamma \log_{R&Dit} + \eta \log_{DPhilit} + \beta \log_{DGGit} + \theta \log_{DHEit} + \epsilon_{it} \] \hspace{1cm} (4.1)

Where in the main equation [4] LogCHE denotes the country’s current health expenditure. LogDPH, LogDGG and LogDHE in sub-equations [4.1] represent the disaggregated form of LogCHE represented by domestic private health expenditure (LogDPH); domestic general government health expenditure (LogDGG) and external health expenditure (LogDHE). LogR&D represents research and development expenditure. Affluence is denoted by LogGDP. Technology (T) in the STIRPAT model is regarded as relying on population, affluence and other motivators that would preferably be part of the error term rather than determining it separately (Wei 2011; Zhao et al. 2014).

Stata and e-views software were employed to perform econometric analysis. The procedures are detailed below.

### 3.3. Test of cross-sectional dependence and slope-homogeneity

Cross-sectional dependence is a problem that occurs when the \( n \) countries in the study sample cease to generate independently verifiable observations but influence another country’s results (Henningsen and Henningsen 2019). In this case, the shocks arising in a specific country affect another country if they have been put in a particular panel data set, which is evident in this paper. This study employs the Breusch and Pagan (1980) LM test, Pesaran (2004) scaled LM test and the Pesaran (2004) CD test to investigate
cross-sectional dependence in the BRICS panel data set. Rejection of the null hypothesis of ‘no cross-sectional dependence’ implies that the alternative hypothesis of ‘cross-sectional dependence’ is accepted.

Moreover, in a panel data set, unidentified heterogeneity is embedded in country-specific constants in cases where they can be observed to be either fixed and/or random. It follows that slope coefficients can be also country-specific. For example, different inclinations among countries may produce specific country elasticities. As such, not taking this type of heterogeneity into consideration will inevitably generate biased estimates and inferences. Therefore, I also deploy the Pesaran and Yamagata (2008) standardized approach of homogeneity test (delta tests) by Swamy (1970). With this technique, using a null hypothesis of homogeneity, Swamy (1970) is initially modified, then the standard dispersion estimates are computed. The biased standard dispersion estimates are also computed.

### 3.4. Unit root tests

To mitigate the problems associated with spurious regression, it is critical to analyse if the series is stationary and not stationary. I deploy Choi’s (2001) augmented Dickey-Fuller test (ADF) that undertakes unit root tests for the time series on an individual context and then aggregates the p-value estimates of the tests to generate an overall test. I also employ Levin, Lin, and Chu’s (2002) Levin-Lin-Chu test, which assumes homogenous autoregressive coefficients for all individuals and its process involves pooling the t-statistic of the estimator to analyse the hypotheses. Finally, I utilize the Harris-Tzavalis Test (Harris and Tzavalis 1999), which assumes that the time dimension is fixed; the εt (error term) is independent and homogeneously distributed, normally with constant variances across panels. Nonetheless, these first-generation tests are unable to allow cross-sectional dependence; Pesaran’s (2007) second generation tests, CIPS, are thus employed.

### 3.5. Cointegration tests

This paper utilizes three forms of panel cointegration test techniques. The first was proposed by Kao (1999) and is a type of two-step residual-based test (Engle and Granger 1987). Kao (1999) suggests two tests (a Dickey-Fuller type test and an Augmented Dickey-Fuller type test) falling under a null hypothesis of no cointegration for panel data, and the alternative hypothesis of cointegration for panel data. These tests move towards a standard normal distribution through the sequential limit theory. The Kao tests assume the presence of one regressor in the cointegrating equation and/or relation.

The Johansen Fisher Cointegration test is also deployed. It uses two diverse methods to ascertain the presence of cointegrating vectors in a time series. In this context, the likelihood ratio trace test and the maximum eigenvalue statistics are proposed (Johansen 1988). Using the trace test, the null hypothesis is the at most r cointegrating equation, while its alternative hypothesis is ascertained as the full rank r = n cointegrating equation. The maximum eigenvalue statistics confirm that its null hypothesis is to investigate r cointegrating equations, while the alternative hypothesis is r + 1 cointegrating vectors. Trace tests are preferable in cases where its estimates and those of the maximum eigenvalue generate different results.

Finally, this research also utilizes the Pedroni cointegration test to determine the long-term equilibrium association amongst the considered parameters (Pedroni 1999, 2004). This procedure is founded upon the Engle-Granger two stages residual-based cointegration process, which considers two forms of test statistics (that is, panel test along with group tests). The panel tests are contingent on four statistics, namely, the panel rho-statistics, panel v-statistics, panel ADF statistics and the panel PP statistics inside dimension method. These approaches pool unit root evaluation data in accordance with the approximate residual over different elements. They consider particular time variables while allowing for heterogeneity. The group test involves three investigations; the group PP-statistics, group rho statistics and the group ADF-statistics which are reliant on dimensions. These tests sum up to seven and are spread asymptotically as the ordinary norm. They require diverse variables of interception along with trends over the countries under study. The connection of co-integration is specified by the equation below:

\[
Y_{it} = \delta_i + \sigma_{it} + \alpha_1 X_{i1,t} + \alpha_2 X_{i2,t} + \ldots + \alpha_{ik} X_{ik,t} + \epsilon_{it}
\]

In this context, y together with x are hypothetically positioned to be integrated into order one. The values of \(\delta_i\) are identified as the country-particular fixed effects. The coefficients of \(\sigma_{it}\), permit for deterministic tendencies. \(\alpha_{1i}, \alpha_{2i}, \ldots, \ldots, \alpha_{ki}\) are identified as the slope of the coefficients in the regression framework. \(\epsilon_{it}\) is the derived residual that is integrated with order one (the null hypothesis is that of no-cointegration, while the alternative hypothesis confirms cointegration of the complete panel data). \(\epsilon_{it}\) is the derived residual that shows deviation from the long-run association.
3.6. Long-run estimation process: Fully Modified Ordinary Least Squares (FM-OLS) technique

Due to the presence of co-integration, the use of OLS may produce spurious estimates (Pedroni 2000). In order to generate long-run estimates of the cointegrating equation this paper employs the Fully Modified Ordinary Least Squares (FM-OLS) approach proposed by Phillips and Hansen (1990). The FM-OLS method is applied to mitigate problems of cross-sectional heterogeneity, serial correction and endogeneity in the regression framework due to available co-integrating associations. The FM-OLS approach is also capable of producing consistent results in a small sample (Pedroni 2000, 2001). Furthermore, it considers problems associated with simultaneous bias (Narayan and Narayan 2010). The FM-OLS equation is presented as follows:

\[ Y_{it} = \delta_i + \beta_i X_{it} + \epsilon_{it} \]

(6)

In this case, \( Y_{it} \) is the dependent factor. \( X \) indicates the independent parameters. \( \delta_i \) is the individual intercept of the regression. \( \beta_i \) show the slope of parameters and \( \epsilon_{it} \) represents the error term.

3.7. Panel vector error correction model

The short- and long-run associations can be analyzed by deploying the panel vector error correction model (Pesaran, Shin, and Smith 1999). The panelized Granger causality framework with dynamic error correction is suggested as follows:

\[
\Delta \text{LogEQ}_{it} = \beta_{1i} + \sum_{k=1}^{K} \beta_{11k} \text{LogEQ}_{it-k} + \sum_{k=1}^{K} \beta_{12k} \text{LogP}_{it-k} \\
+ \sum_{k=1}^{K} \beta_{31k} \text{LogGDP}_{it-k} + \sum_{k=1}^{K} \beta_{41k} \text{LogT}_{it-k} \\
+ \sum_{k=1}^{K} \beta_{51k} \text{LogCHE}_{it-k} + \lambda_1 \text{ECT}_{i,t-1} + \epsilon_{it}
\]

(7)

\[
\Delta \text{LogEQ}_{it} = \beta_{1i} + \sum_{k=1}^{K} \beta_{11k} \text{LogEQ}_{it-k} + \sum_{k=1}^{K} \beta_{12k} \text{LogP}_{it-k} \\
+ \sum_{k=1}^{K} \beta_{31k} \text{LogGDP}_{it-k} + \sum_{k=1}^{K} \beta_{41k} \text{LogR} & \text{D}_{it-k} \\
+ \sum_{k=1}^{K} \beta_{51k} \text{LogDPH}_{it-k} + \sum_{k=1}^{K} \beta_{61k} \text{LogDGG}_{it-k} \\
+ \sum_{k=1}^{K} \beta_{71k} \text{LogDHE}_{it-k} + \lambda_1 \text{ECT}_{i,t-1} + \epsilon_{it}
\]

(7.1)

In this setting, \( \Delta \) is the first differences. \( \beta_{ij} \) denotes the country fixed effects. \( \lambda_1 \) refers to the adjustment coefficient. \( \epsilon_{it} \) indicates the disturbance parameter. Hence, besides showing the direction of causality of parameters, this VECM technique enables differentiation between short-run and long-run causality.

3.8. The Dumitrescu-Hurlin causality technique

This paper incorporates the Dumitrescu-Hurlin causality methodology (which is an advanced model of Granger causality tests) to determine the causal associations of the variables. The major prerequisite of this methodology is that the variables are stationary (that is, integrated of order \( I(1) \)) as well as panel data which is heterogeneous (Dumitrescu and Hurlin 2012). The equation for this causality approach is outlined below:

\[ y_{it} = \alpha_i + \sum_{k=1}^{K} y_{it-k}^{(k)} y_{it-k} + \sum_{k=1}^{K} \beta_i^{(k)} y_{it-k} + \epsilon_{it} \]

(8)

From equation [5], \( x \) and \( y \) are variables over \( N \) individuals in \( T \) periods, and the aim is to ascertain if \( x \) is the major cause of \( y \), and vice-versa. Moreover, \( y_{it-k}^{(k)} \), as well as \( \beta_i^{(k)} \), are coefficients of the regression framework. \( \alpha_i \) is a constant term, and \( \epsilon_{it} \) is the error term. \( K \) show information with regard to the optimal lag interval. The null hypothesis posits the presence of no homogenous Granger causality for the variables, while the alternative hypothesis states that there is at least one causal association for the variables. This approach is the best causality method in situations where there is cross-sectional dependency between countries (Dumitrescu and Hurlin 2012).

4. Results and discussion

This section presents a summarized analysis of variables, the cross-dependence test and the slope homogeneity results. It also presents the panel unit root tests results, CIPS test results of unit roots, co-integration test results, FM-OLS results, VECM Granger findings and the Dumitrescu-Hurlin causality outcomes.

Table 3 presents a summarized analysis of statistical information regarding the variables in this paper. It shows that Brazil’s average GDP per capita of 3.944638 makes it the highest income generating economy amongst the BRICS, followed by Russia (3.812317), while India (2.917291) is the lowest-income economy. In terms of carbon dioxide emissions, Russia (1.055116) has the highest average emission estimates and the lowest values are found in India (0.1084869). China (9.122566) has the largest population and South Africa (7.702296) the smallest. The table also shows that Brazil (0.9208901) has the bloc’s highest current health expenditure (LogCHE) and India (0.5648736) has the lowest. Turning to domestic private health expenditure (LogDPH), India (1.444535) has the lowest and Brazil (2.510941) the highest expenditure. Brazil (2.390633)
also has the highest domestic general government health expenditure (LogDGG) while India (0.9221881) has the lowest. In the BRICS region, South Africa (0.8613251) has the highest external health expenditure (LogDHE), and India (−0.362349) has the lowest. Finally, China (0.1778463) has the highest expenditure on research and development, and South Africa (−0.103437) has the lowest. The uneven nature of skewness and kurtosis values in the table generally show non-normality of data (which ultimately implies fat-tailed conduct that confirms asymmetrical time series). The following section presents the findings of the cross-sectional dependence tests.

Table 4 presents the outcome of the four cross-sectional dependence tests undertaken in this study. The findings reject the null hypothesis of cross-sectional independence at a 1% significance level in all four tests. Moreover, the results reject the null hypothesis of slope-homogeneity (meaning that all the slope coefficients are the same across the cross-sectional units) at a 1% significance level. Hence, we can highlight that the data is cross-sectionally correlated, and the slopes of the data are heterogeneous. The following section discusses the findings of the unit root tests.

Table 5 outlines the findings obtained by the three panel unit root tests utilized in this paper. Variables such as carbon dioxide, population, economic growth, domestic private health expenditure, domestic general government health expenditure, external health expenditure and research and development are stationary in one or two tests while the rest have a unit root. It should be noted that all three tests – ADF, LLC and the Harris-Tzavalis – show that all the variables become stationary when the associated first difference estimates are considered, except for population under the Harris-Tzavalis Test. However, evidence from the other two tests – ADF and LLC – supports that population is stationary at first difference, hence decisively rejecting the null hypothesis of a unit root as regards population. The data used in this paper was ascertained to be cross-sectionally dependent (results from Table 4); hence I run a second-generation unit root test (CIPS test) that permits for cross-sectional dependence along with serial correlation.

Table 6 below shows that, the hypothesis tests of stationarity using the CIPS test estimates are supported by comparisons of such values with critical table values (estimates made by Pesaran [2007]) employing
Monte Carlo simulations). The null hypothesis (presence of a unit root in the series) is rejected in a case where the values estimated by CIPS are found to be larger than the estimated values of the critical table and the alternative hypothesis is confirmed and/or accepted (Pesaran 2007).

In Table 5 the estimates of the CIPS test are found to be greater than those in the critical table for most variables, in the level setting. Nonetheless, at the first difference, the series indicates that it is stationary at a 1% level of significance. On that note, I proceed to investigate the co-integration association between the variables before ascertaining the long-run coefficients of the regression model.

Table 7 reviews the findings of the Kao cointegration test and the Johansen Fisher panel cointegration tests for the regression model [equation 4.1] characterized by disaggregated health expenditure variables. With regard to the Kao cointegration, the ADF test statistic (at the 5% level of significance test) leads to rejection of the null hypothesis of no cointegration, and hence acceptance of the alternative hypothesis of cointegration. Therefore, the Kao test confirms that the variables (carbon emissions, population, economic growth, domestic private health expenditure, domestic general government health expenditure, external health expenditure, research and development expenditure) in the regression model [equation 4.1] have a cointegrating relationship, implying the existence of a long-run relationship. In agreement with these results, the Johansen Fisher panel cointegration tests are based on both the trace test statistic and the maximum eigenvalue test statistic. Thus, all these tests (in most cointegrating equations) indicate the existence of a cointegrated association between the variables at either 1% and/or 5% level of significance (hence, confirming the rejection of the null hypothesis of no cointegration). The concurring results of cointegration using the Kao cointegration test and the Johansen Fisher panel cointegration tests are in line with Yazdi, Zahra, and Nikos (2014) on Iran and Khoshnevis and Khanalizadeh (2017) on MENA countries who also confirm that environmental quality and health expenditure variables move together in the long-term.

Table 8 outlines the results of the Kao cointegration test and the Johansen Fisher panel cointegration tests for the regression model [equation 4] using aggregated

### Table 4. CD test results and slope homogeneity outcomes.

| Variables | LM Breusch Pagan | LM Pesaran-scaled | LM Bias-corrected scaled | CD Pesaran |
|-----------|-----------------|------------------|--------------------------|------------|
| LogCO₂    | 58.4992***      | 10.8447***       | 10.6976***               | 6.218457***|
| LogP      | 123.8859***     | 25.46567***      | 25.31861***              | 5.446199***|
| LogGDP    | 157.9547***     | 33.08367***      | 32.93661***              | 12.55892i***|
| LogCHE    | 43.58083***     | 7.508901***      | 7.361843***              | 5.029282***|
| LogDPH    | 142.0321***     | 29.52327***      | 29.37621***              | 11.86262***|
| LogDGG    | 157.3848***     | 32.95624***      | 32.80918***              | 12.53851***|
| LogDHE    | 24.33809***     | 3.206095***      | 3.059037***              | 1.703746*  |
| LogR&D    | 22.24914***     | 2.738991***      | 2.591933***              | 0.880584   |

Notes: ***, ** and * indicate that the coefficients are significant at the 1%, 5% and 10% level of significance, respectively.

### Table 5. Panel Unit test results.

| Variable | Fisher ADF statistic | Harris-Tzavalis statistic | Levin-Lin-Chu statistic | Fisher ADF statistic | Harris-Tzavalis statistic | Levin-Lin-Chu statistic |
|----------|----------------------|----------------------------|-------------------------|----------------------|----------------------------|-------------------------|
| LogCO₂   | −2.3408              | 0.8928                     | −2.8353                 | 7.4948               | 0.1969                     | −2.1682                 |
| LogP     | 35.6185              | 0.9848                     | 2.7411                  | 18.4438              | 0.9410                     | −3.8994                 |
| LogGDP   | 1.9990               | 0.9677                     | −2.4669                 | 2.5381               | 0.4081                     | −2.2583                 |
| LogCHE   | −1.0064              | 0.8609                     | −0.1615                 | 7.9782               | 0.0893                     | −3.8882                 |
| LogDPH   | −0.5902              | 0.9271                     | −1.3587                 | 8.4232               | 0.2815                     | −3.7280                 |
| LogDGG   | −0.7583              | 0.9384                     | −2.9140                 | 2.6581               | 0.4069                     | −2.4307                 |
| LogDHE   | 2.5903               | 0.7676                     | 0.3402                  | 19.9506              | −0.0911                    | −2.1826                 |
| LogR&D   | 0.1550               | 0.8946                     | −2.8458                 | 8.0315               | 0.0875                     | −3.4729                 |

Notes: ***, ** and * indicate that the coefficients are significant at the 1%, 5% and 10% level of significance, respectively.
health expenditure as the only main independent variable of interest. Firstly, the Kao cointegration test (at 1% level of significance) supports panel co-integration. Secondly, the Johansen Fisher test findings also report the presence of a long-term cointegrating link between the variables (carbon emissions, population, economic growth, current health expenditure, research and development expenditure) at 1% and/or 5% level of significance.

This section also presents the co-integration findings utilizing the Pedroni co-integration process.

Tables 9 and 10 present the panel co-integration findings deploying the Pedroni co-integration tests. The findings in the two tables support the outcomes generated by the Kao panel co-integration tests and the Johansen Fisher panel co-integration test by confirming that the variables in this study have a long-run relationship. Tables 9 and 10 illustrate that four of the eight statistics are significant. According to Pedroni (1999, 2004) the panel ADF-statistic together with the group ADF-statistic tests are more reliable than other statistics, which is apparent in this study. Given this, the research proceeds by presenting the long-run relationships of equation 4 in Table 11.

Table 11 below reviews the results of the FM-OLS approach with regard to equation 4 with aggregated health expenditure as the main variable of interest. It shows that current health expenditure (LogCHE) is negatively and significantly related to carbon emissions for the BRICS economies. In this case, a 1% increase in aggregate current health expenditure can significantly lower emissions by 0.773943%. These findings contradict Zaman and Abd-el Moemen’s (2017) study on 14 Latin American and Caribbean economies that concluded that health expenditure increases carbon emissions although the case of Brazil was insignificantly negative (with Russia indicating a positive and insignificant link). The results also show that population is positively and significantly linked with carbon emissions for the BRICS. Thus, an increase of 1% in the BRICS population significantly adds 0.043356% to carbon emissions. This finding concurs with de Souza Mendonça et al. (2020) who found that a percentage increase in population increases emissions by 1.67% for the 50 largest global economies. However, this paper’s panel results for the BRICS contradicts country-specific outcomes as, in all the BRICS countries, population is negatively and significantly associated with emissions.

Moreover, the findings demonstrate that a 1% increase in economic growth significantly contributes to a 0.5127% increase in emissions. This outcome is
supported by Mikayilov, Galeotti, and Hasanov (2018) who concluded that economic growth increases emissions in the long run for Azerbaijan. In terms of country results, the results for Brazil and South Africa concur with the findings from the panel although, in the Chinese context, the findings are not significant. For India, there is a negative and significant link between economic development and carbon emissions but in the case of the Russian Federation, the link is negative and not significant. The panel outcomes also illustrate that a 1% rise in research and development within the BRICS region significantly increases emissions by 0.4626%. These findings disagree with Ganda (2019b) who illustrates that spending on research and development lowers carbon emissions for a sample of Organisation for Economic Co-operation and Development (OECD) economies. The country-specific results for India and China support the panel findings, while the results for South Africa and Russia show that research and development expenditure has a negative and significant effect on carbon emissions (the outcome for Brazil is insignificantly negative).

Table 12 below disaggregates current health expenditure into several measurable spendings. It presents the findings on the relationship between health spending (which has been disintegrated) and carbon emissions. Firstly, a 1% increase in private health expenditure (LogDPH) significantly decreases carbon emissions by 0.2714%, which contradicts Zaman and Abd-el Moemen’s (2017) findings. The country-specific results support the panel results for India, but the output remains insignificant, while South Africa, China and Brazil’s private health expenditure significantly increases carbon emissions by 0.675%, 1.0066% and 0.6783%, respectively (the case of Russia is not significant). Secondly, a 1% increase in domestic general government health expenditure (LogDGG) significantly increases carbon emissions by 0.3789% for the BRICS economies. Turning to the country-specific outcomes, the findings for India concurs with the panel results (but Russia’s output is insignificantly positive). On the other hand, the results for Brazil, China and South Africa demonstrate that a 1% increase in domestic general government health expenditure (LogDGG) significantly mitigates emissions by 0.9423%, 0.4396% and 0.6438%, respectively. Third, a 1% increase in external health expenditure (LogDHE) results in a significant 0.2653% surge in carbon emissions. These panel results are in line with Malik et al.’s (2018) survey of 15 Australian health sectors. Furthermore, some of the country-specific findings agree with the panel results. For instance, the outcomes for South Africa are positive

**Table 9. Panel co-integration tests: aggregated health expenditure.**

| Pedroni panel co-integration tests | Between-dimension (panel statistics) |
|-----------------------------------|-------------------------------------|
| **Table 9. Panel co-integration tests:** aggregation health expenditure. | **Table 9. Panel co-integration tests:** aggregation health expenditure. |
| Test | Statistic | Probability | Test | Statistic | Probability |
| Pedroni (1999) | | | | | |
| Panel v-statistic | 0.231784 | 0.4084 | Panel rho-statistic | 2.316207 | 0.9897 |
| Panel rho-statistic | 1.316461 | 0.9060 | Panel PP-statistic | −3.324530 | 0.0004*** |
| Panel PP-statistic | −1.875675 | 0.0303** | Panel ADF-statistic | −2.370323 | 0.0089*** |
| Panel ADF-statistic | −2.700476 | 0.0035*** | | | |
| Pedroni (2004) Weighted Statistic | | | | | |
| Panel v-statistic | −0.159601 | 0.5634 | | | |
| Panel rho-statistic | 1.424246 | 0.9225 | | | |
| Panel PP-statistic | −0.810315 | 0.2089 | | | |
| Panel ADF-statistic | −1.721807 | 0.0426** | | | |

Notes: ***, ** and * indicate that the coefficients are significant at the 1%, 5% and 10% level of significance, respectively.

**Table 10. Panel co-integration tests: disaggregated health expenditure.**

| Pedroni panel co-integration tests | Between-dimension (panel statistics) |
|-----------------------------------|-------------------------------------|
| **Table 10. Panel co-integration tests:** disaggregated health expenditure. | **Table 10. Panel co-integration tests:** disaggregated health expenditure. |
| Test | Statistic | Probability | Test | Statistic | Probability |
| Pedroni (1999) | | | | | |
| Panel v-statistic | −0.244506 | 0.5966 | Panel rho-statistic | 4.575851 | 1.0000 |
| Panel rho-statistic | 3.666591 | 0.9999 | Panel PP-statistic | −11.96364 | 0.0000*** |
| Panel PP-statistic | −7.942672 | 0.0000*** | Panel ADF-statistic | −0.805364 | 0.4660 |
| Panel ADF-statistic | −0.555390 | 0.2893 | | | |
| Pedroni (2004) Weighted Statistic | | | | | |
| Panel v-statistic | −2.721380 | 0.9967 | | | |
| Panel rho-statistic | 3.619556 | 0.9999 | | | |
| Panel PP-statistic | −11.12851 | 0.0000*** | | | |
| Panel ADF-statistic | −2.202118 | 0.0138** | | | |

Notes: ***, ** and * indicate that the coefficients are significant at the 1%, 5% and 10% level of significance, respectively.
and significant, although those for Brazil and China are insignificantly positive (Russia and China’s results are insignificantly negative).

Moreover, the panel section shows that a 1% increase in population significantly increases carbon emissions by 1.2254%, thereby agreeing with the findings in Table 8. Dong et al.’s (2018) investigation of 128 countries from 1990 to 2014 also found that population positively contributes to high carbon emissions. With regard to the country analysis, the findings for Russia and China concur with the panel results since a percentage increase in the population results in an increase of 11.468% and 38.178%, respectively, in carbon emissions. Conversely, a 1% hike in population reduces emissions by 2.0523%, 0.2579% and 1.2045% in Brazil, India and South Africa, respectively. Furthermore, the panel output shows that a 1% increase in economic growth generates a 0.7778% significant addition to emissions. This disagrees with Zhu et al.’s (2016) study on Association of South-East Asian Nations (ASEAN-5) countries that found that economic development is negatively associated with emissions for the high-emission countries. However, the country-specific outcomes of this study conflict with those of Zhu et al. (2016), since a rise in economic growth increases emissions by 2.965%, 0.8707%, 1.905%, and 2.6% for Brazil, India, China and South Africa, respectively. Finally, the panel results show that a 1% surge in research and development expenditure significantly increases carbon emissions by 0.2386%, contradicting Ganda’s (2019b) survey of OECD economies. The findings for Brazil, India and China indicate that spending on research and development significantly lowers carbon emissions, while contradictory results are found for Russia and South Africa.

Table 13 presents the panelized Granger causality results by applying the vector error correction model in the case of aggregated health expenditure. The results are based on a short- and long-run setting. Firstly, in the long run, only population and the level of current health expenditure regressions have a negative and significant error correction coefficient (that describes how quickly parameters converge to equilibrium) and, hence are good fits, while the remaining equations violate the downward correction principle. Thus, it is apparent that there is a bi-directional causal relationship between population and the level of current health expenditure, confirming feedback effects. There are uni-directional causal long-run links from carbon emissions to the level of current health expenditure. This finding is supported by Li, Lu, and Li’s (2020) study on China spanning the period 2002–2017 that used regression analysis to show that an increase in industrial pollution causes increased health expenditure. Moreover, a one-way causal long-run association is found from carbon emissions to population. The other long-run findings show uni-directional causal connections between population and economic growth, population and research and development, level of current health expenditure and research and development, and level of current health expenditure and economic growth.

The VECM short-run causal relationships employing aggregated health expenditure illustrate uni-directional causality running from research and development to carbon emissions. Howbeit, Wang and Wang’s (2019) survey of the US also shows that research and development intensity and efficiency result in carbon emissions decoupling. Moreover, for this research, other uni-directional causal links are evident between population and research and development, population and the level of current health expenditure, and research and development and economic growth, as well as research and development and the level of current health expenditure. In addition, population and economic growth have a bi-directional causal short-run relationship.

Table 14 presents the findings arising from the use of disaggregated health expenditure parameters. From the long-run perspective, it reveals a uni-directional causal long-run connection running from carbon emissions to
population. Other long-run causal relationships include those between population and the remaining parameters. On the other hand, short-run uni-directional causal associations are present between population and economic growth, along with domestic general government health expenditure and economic growth.

It should be noted that Baloch, Mahmood, and Zhang (2019) observe that the VECM Granger causality approach fails to consider heterogeneity and cross-sectional dependence in panel data, while the Dumitrescu and Hurlin causality tests do so. This paper thus extends this analysis by presenting the Granger causality test outcomes using the Dumitrescu and Hurlin causality technique. Table 15 reviews the findings on the causality of variables resulting from Dumitrescu–Hurlin panel causality analysis. In brief, the null hypothesis posits that there is no homogenous Granger causality, and the alternative supports the existence of at least one causal association in the studied data set. Most variables indicate strong evidence of a bi-directional causality relationship. For example, there is a two-way association between population and carbon emissions. However, Rahman, Saidi, and Mbarek’s (2020) survey of five South Asian countries only found uni-directional causality from population to carbon emissions. The results illustrate bi-directional causality between economic growth and carbon emissions, thereby also disagreeing with Rahman, Saidi, and Mbarek’s (2020) conclusion that causality was one-way. In addition, there is a bi-directional link between current health expenditure (LogCHE) and emissions, domestic general government health expenditure (LogDGG) and emissions, and private health expenditure (LogDHE) and emissions. These findings are in line with Apergis, Jebli, and Youssef’s (2018) study on 42 sub-Saharan African nations over the period 1995–2011. The research concludes that a two-way link involving health expenditure and carbon emissions is valid. The remaining health variable, external health expenditure (LogDHE) null hypothesis that this factor does not homogeneously cause carbon emissions is rejected, and also vice-versa. The implication is that external health expenditure in the BRICS does not cause emissions, and emissions in the BRICS do not cause external health expenditure. Finally, uni-directional causality from carbon emissions to research and development expenditure is found in the BRICS. However, Wang et al. (2012) found bi-directional

### Table 12. FM-OLS output for disaggregated health expenditure on emissions.

| Variables | Panel | Brazil | Russia | India | China | South Africa |
|-----------|-------|--------|--------|-------|-------|-------------|
| LogP      | 1.225387*** | −2.052480*** | 11.46767*** | −0.257948 ** | 38.17821** | −1.204452*** |
| (0.059122) | (0.448003) | (3.036539) | (0.099958) | (14.62687) | (0.299213) | 
| LogGDP    | 0.777843*** | 2.965308*** | −0.498312 | 0.870725** | 1.905233** | 2.600649*** |
| (0.090199) | (0.328031) | (0.392749) | (0.390423) | (0.596084) | (0.601635) | 
| LogDHE    | −0.271429** | 0.678231** | 0.211649 | −0.253906 | 1.006574*** | 0.675261*** |
| (0.119926) | (0.262711) | (0.180095) | (0.191391) | (0.289460) | (0.135811) | 
| LogDGG    | 0.378912*** | −0.942347*** | 0.041412 | 0.179712 * | −0.439555** | −0.643846*** |
| (0.128891) | (0.265109) | (0.140788) | (0.083551) | (0.167064) | (0.108495) | 
| LogR&D    | 0.265308** | 0.018430 | −0.040889 | −0.026927 | 0.032276 | 0.142034* |
| (0.120969) | (0.012413) | (0.030853) | (0.023531) | (0.019953) | (0.070142) | 
| LogCHE    | 0.238758** | 0.379674 | −0.249513** | 0.448667*** | 1.140874*** | −0.036145 |
| (0.126360) | (0.143429) | (0.081040) | (0.342377) | (0.182993) | (0.182993) | 
| S.E. of regression | 0.962652 | 0.920985 | 0.920985 | 0.956720 | 0.994125 | 0.502006 |
| R²         | 0.079527 | 0.017876 | 0.017876 | 0.020413 | 0.014460 | 0.035555 |

Notes: [1] *** and ** indicate that the coefficients are significant at the 1%, 5% and 10% level of significance, respectively. Numbers in brackets are standard error estimates. [2] For robustness check, confidence ellipses (Appendix B) are presented that demonstrate that the model has a good confidence level that is significant.

### Table 13. VECM Granger causality tests results: aggregated health expenditure.

| Dependent variable | ΔLogCO₂ | ΔLogP | ΔLogGDP | ΔLogCHE | ΔLogR&D | Long-run relationship [ECT] |
|--------------------|---------|-------|---------|---------|---------|-----------------------------|
| ΔLogCO₂            | –       | −1.233841 | 0.299536 | −0.265832 | 0.196844* | 0.006623 |
|                    | [−0.72132] | [1.052413] | [−1.474337] | [1.689095] | [1.634130] | 
| ΔLogP              | 0.00000395 | – | 0.005612*** | 0.003210*** | −0.00184*** | −0.000138*** |
|                    | [0.025998] | [3.722641] | [3.361460] | [2.981258] | [0.340631] | 
| ΔLogGDP            | −0.001730 | −2.129*** | – | −0.037390 | 0.074888 | 0.006496*** |
|                    | [−0.030347] | [−2.91004] | [−0.484843] | [1.502467] | [3.746768] | 
| ΔLogCHE            | 0.089508 | 1.101959 | 0.222579 | – | −0.143621* | −0.005042* |
|                    | [0.918302] | [0.880801] | [1.106915] | [−1.684977] | [−1.825292] | 
| ΔLogR&D            | −0.040704 | 1.174504 | 0.643894*** | 0.259917 | – | −0.001839 |
|                    | [−0.302296] | [0.820206] | [2.239089] | [1.426739] | [−0.449125] | 

Notes: [1] *, **, *** represent significance at the 10%, 5% and 1% level of significance, respectively. [2] t-statistics are reported in parentheses.
null hypothesis are reported in parentheses. [2] r-statistics are reported in parentheses.

Table 14. VECM Granger causality tests results: disaggregated health expenditure.

| Dependent variable | Short-run relationship | Long-run relationship |
|--------------------|------------------------|-----------------------|
| ΔLogCO₂            | ΔLogP                  | ΔLogDHE               |
| −                  | 1.4510                 | 0.004969              |
|                    | [1.2013]               | [0.91222]             |
| ΔLogP              | −0.000000785           | 0.0000693             |
|                    | [−0.000281]           | [−0.001140]           |
| ΔLogDGP            | −0.06136               | 0.072764*             |
|                    | [−0.056419]          | [−0.001793]           |
| ΔLogDPH            | −0.21329               | 0.023877              |
|                    | [−0.107459]           | [−0.009908]           |
| ΔLogDGG            | −0.548745             | 0.72764*             |
|                    | [−0.510311]           | [−0.009908]           |
| ΔLogDHE            | 0.12310                | 0.9020               |
|                    | [0.10536]             | [−0.009908]           |
| ΔLogR&D            | 0.1796                 | 0.5216               |
|                    | [0.1957]              | [−0.009908]           |

Notes: [1] *, **, *** represent significance at the 10%, 5% and 1% level of significance, respectively. [2] t-statistics are reported in parentheses.

5. Implications of the study

Health care systems and structures play a critical role in mitigating the impacts of climate change. This paper found that the level of current health expenditure is lowering carbon emissions in the BRICS region, and most country-specific findings are also significantly in line with the panel data results. However, when disaggregated health expenditure is tested, variables such as external health expenditure and domestic general government health expenditure, except for private health expenditure, contribute significantly to carbon emissions at the regional level. There is thus a need to examine the different forms of spending on health and ensure that they are all in line with the country's green economy policy. A health strategy that does not consider concerns about environmental quality serves to escalate global warming and climate change. This is important given that the results indicate that the level of current health expenditure, domestic general government health expenditure and private health expenditure causes carbon emissions, and vice-versa. Since green health care facilities are important for human survival, increased spending is central towards improving standards of living, the quality of life and welfare (reducing mortality rates, ensuring a longer span and mitigating morbidity) as well as improving medical labor productivity, particularly in government medical and health institutions. Moreover, in the long run, investment geared towards achieving a low-carbon and/or zero-carbon environment ultimately reduces spending on health as a result of the prevailing natural environment and social advantages.

Total population was also found to increase carbon emissions in the BRICS, although some country-specific findings (especially Brazil, South Africa and India) indicate that the variable reduces environmental quality. The total population also show bi-directional causality links with carbon emissions. As such, family planning measures are vital to manage the growth of the population.
population in the BRICS. Green education is equally crucial to improve citizens and economic stakeholders’ environmental consciousness. This is important because the results also illustrate that economic growth in the region adds to carbon emissions, and that economic growth has a two-way causal connection with environmental quality. Thus, adopting strategies to reduce income inequality could enhance a country’s efforts to minimize environmental degradation. In addition, BRICS governments should introduce policies that create a green economy which is healthier and more productive, and hence capable of maintaining green development and sustainable production. The introduction of green policies that address poverty in the BRICS would reduce damage to the natural environment.

Finally, it was found that spending on research and development heightens carbon emissions in the BRICS. These countries should thus prioritize research and development initiatives that strategically decrease carbon emissions. This can be achieved by offering incentives as well the adoption of mandatory regulations in critical areas to enhance accountability and disclosure. Improved efficiency and intensity of research and development activities should be promoted to avoid unnecessary spending on areas that are not environmentally sound. Furthermore, research and development practices which employ emissions as raw material reduce net emissions as well as improve their productivity and economic efficiency. This is particularly important in light of this study’s finding of unidirectional causality running from carbon emissions to research and development expenditure.

6. Conclusion

This paper investigated the relationship between health expenditure and environmental quality in the BRICS bloc over the period 2000–2017. It used the FM-OLS technique to compute two regression models, namely, aggregated health expenditure and disaggregated health expenditure. In terms of the equation with an aggregated health factor, the level of current health expenditure was found to be significantly negatively associated with carbon emissions in the region. With regard to the equation with disaggregated health variables, private health expenditure is negative and significantly related to environmental quality. Conversely, domestic general government health expenditure and external health expenditure are both positively and significantly linked to carbon emissions. Country-specific results were also provided in both the aggregated and disaggregated contexts. The Dumitrescu–Hurlin panel Granger causality analysis demonstrated the existence of bi-directional causality between the level of current health expenditure, private health expenditure, and domestic general government health expenditure, and carbon emissions. External health expenditure in the BRICS was not found to cause emissions, and vice-versa. The results highlight the need to review health expenditure sub-policy programs in order to effectively manage carbon emissions mitigation, and to promote a healthy environment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Fortune Ganda @ http://orcid.org/0000-0003-2174-7384

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Appendices

Appendix A. Confidence ellipse for aggregated health expenditures
Appendix B. Confidence ellipse for disaggregated health expenditures