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RESEARCH ARTICLE

# Carbon neutrality along the way to participate in global value chains: the threshold effect of information globalization of BRICS countries

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## Abstract
Using panel data from BRICS countries over the period 2000 to 2018, a multi-variate threshold model was built to investigate how global value chain (GVC) participation and information globalization affects $CO_2$ emission. We further decompose the information globalization into two indicators, i.e., de facto measure and de jure measure. The main findings show that the estimated value of threshold is 4.02 and 1.81 for both de facto and de jur measures of information globalization. The findings suggest that information globalization rate above the threshold level negatively affects the carbon emissions. De facto and de jure measures show a strong single threshold effect when GVC participation is chosen as the major explanatory variable. Similarly, participation in GVCs has a large single threshold impact when information globalization is taken as the primary independent variable. Overall, the results show that the larger the information globalization for the countries under analysis, the modified impact of GVC participation on $CO_2$ emission reduction is larger. The robustness test validates the stability and coherence of the study's findings. The opportunities that the information globalization along the approach to participate in GVCs presents for the accomplishment of carbon neutrality should be properly utilized by policymakers. There should be expansion the participation in GVCs with digital infrastructure and to enhance the assessment system for the use of technology spillover effects to increase environmental-friendly GVC ladder.

**Keywords** $CO_2$ emissions · GVC participation · Information globalization · Threshold effect · Panel data · BRICS

## Introduction

Climate change is currently recognized as one of the largest problems human society is facing, and carbon dioxide emissions are thought to be its main cause. Global value chains (GVCs) "have an essential role in many of the most important environmental stressors and societal difficulties" (Thorlakson et al. 2018), a statement made in the most recent Sustainable Development Goals report that amplifies the effect of GVCs on the environment. Since the start of this century, environmental safety groups have been working to endorse international collaboration and look forward to implementing a continuous emission decline plan (Aydin et al. 2019). Meanwhile the start of the COVID-19, especially, the need to maintain environmental harmony and stop epidemic adversities from worsening the climate issue has acquired increased worldwide acceptance. There is no question that the carbon peaks and emission reduction targets of several countries have accelerated. Evenly distributed production networks from across the world are incorporated into the dispersion of the global manufacturing system as economic globalization increases. Developed nations currently

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occupy the upstream position in the GVCs due to technological advantages. While they transfer high-carbon industries and reduce their own emissions, this increases pressure on downstream developing nations to increase their carbon emissions. International low-carbon barriers in the domain of value-added imports and exports are continuously rising as countries steadily implement low-carbon import regulations. The BRICS countries' environmental issues, like the rapid rise in carbon dioxide and the environmental degradation, have become worse in recent years.

China leads the BRICS countries in both per capita car ownership and shale oil consumption followed by India, and their high ranking in the world for per capita carbon emissions is maintained based on multiple factors. Although Russia has a small population and has benefited from recent economic growth, the country's rapid expansion in the mining and shale industries has contributed to a continuous increase in per capita carbon emissions. All nations now agree that low-carbon and energy-efficient technology development is important. The firms participating in GVCs and the governments must assess the total greenhouse gas emissions that will be created over a given time period along the value-added production activities in order for the undertaking to be considered "carbon neutral." The pursuit of carbon neutrality is an inescapable decision to support the formation of a society with a shared future for humanity and a scientific evaluation of the comprehensive range of climate protection and adaptation options, in particular with respect to being a requisite technical requirement for the worldwide economy to achieve ecological and environment-friendly economic development (Rehman et al. 2021).

Globalization has had a huge impact on our lives and has greatly enhanced economic innovation, the flow of technology, and communication channels (Xia et al. 2022; Shahzad et al. 2022). The role of advanced technology in the growth of low-carbon value-added industries is becoming increasingly important. To achieve carbon neutrality, value-added sectors can use digital technologies to drive energy efficiency and emission reduction. Nations all over the world are actively speeding up the development of new generations of information technology in order to encourage the Internet, big data, fifth-generation mobile communication (5G), artificial intelligence (AI), and other developing technologies within their economies. These innovations will be closely incorporated with value-added green and low-carbon industries. GVC analysis focuses on how different tasks, activities, and operation types are distributed across various locations along the value chain ladder (Horner and Nadvi 2018).

New energy solutions must concentrate on lowering carbon emissions from the GVC side. In order to considerably lower carbon emissions from energy use, green spots and green data hubs must be created within the GVC ladder. In addition to producing the most spectacular reductions in energy consumption, the interaction of information globalization and GVCs also speeds up the digital transition of high energy consumption industries, such as transportation across the spreading of production activities and energy efficiency. This paper has a greater importance and differs from previous studies because it examines the impact of information globalization to modify the role of GVC participation on the shift to digital technology in value-added production process. Therefore, in the cutting-edge areas of economic and social development characterized by the digital economy, this study has vital role to encourage the organic incorporation and cooperation among the firms participating in global value chains (GVCs), carbon surge, and carbon neutrality in a comprehensive manner which was ignored in previous literature. Further, the importance of this study is to evaluate how the digital economy with GVCs plays an important role in achieving carbon neutrality is crucial.

The remaining study is structured as follows: "Theoretical model" section describes the data and variables after "Literature review" section analyzes the literature. Theoretical model is constructed in "Theoretical model" section. The model and the econometric technique are designated in "Methodology and variable selection" section. The empirical findings and discussion are presented "Results and discussion" section. The findings are summarized in "Conclusions and policy implications" section together with the worldwide policy implications.

## Literature review

Participation in the GVC has a variety of implications on $CO_2$ emissions and energy consumption. Chiou et al. (2011) claim that working closely with supply chain partners promotes the creation of environmentally friendly products, giving them an advantage over competitors by enabling them to produce goods of a greater quality. Danish and Khattak (2020) stated that GVCs serve as both the impetus for environmental upgrading and a channel for obtaining the information required for upgrading, particularly for companies operating in relational networks. According to Khattak and Stringer's (2017) analysis of the environmental impacts of GVCs, information is regularly produced and exchanged inside the GVCs, resulting in environmental gains. However, not all outcomes of GVC participation are advantageous for protecting the environment and conserving energy. Davis and Caldeira (2010) argue that a consumption-based accounting of $CO_2$ emissions indicates the potential for global carbon leakage, with the majority of international trade in $CO_2$ emissions coming from China and other developing markets and being exported to consumers in industrialized countries. Furthermore, Dünhaupt and Herr (2021) all considered the fact that the majority of developing countries, like China, join GVCs by exporting comparatively large amounts of finished goods in their early stages of development, which generates a significant amount of $CO_2$ emissions and forces the poorer nations to bear the costs of natural depletion.

It is said that globalization has harmed the environment in many ways because it was launched in the name of economic activities, such as trade and commercial operations, in order to generate income and foster international harmony. Sustainable economic activities under globalization are essential for our domestic and global economic institutions to enable inclusive environmental adaptation and global climate protection (Xu et al. 2022b). The consequences of industrial transfer zones and carbon transfer under globalization, according to Akbar et al. (2022), have increased $CO_2$ emissions, which have led to environmental tragedies. Globalization ideas have boosted environmental sustainability, which has been demonstrated in several empirical studies across many different countries. According to Jahanger (2022), economic integration within the context of globalization affects how key stakeholders in the process of environmental sustainability interact, change attitudes, and develop new tactics to maximize benefits and minimize risks of globalization. The reality is that only trade can replace damaging imports and reduce $CO_2$ emissions, notwithstanding the importance of examining how economic globalization affects climatic elements like air pollution and soil salinity. Trade under global integration, according to Marjit and Yu (2018), has an inversely proportional relationship in India since imports are mainly finished goods, the production of which may be polluting and is created outside of the nation.

Technology spillover has been shown to have a nonlinear threshold effect on $CO_2$ emissions in earlier research (Jiao et al. 2020). This has an impact on $CO_2$ emissions in a variety of ways, the biggest of which being social and economic variables (Xie et al. 2020). The impact of technological spillover on $CO_2$ emissions hence could not be linear. This suggests that the direction or intensity of the impact might abruptly shift when some variables reach a specific threshold. The sharing of knowledge through various routes, such as industrial and regional linkages, can be referred to as domestic technology spillover (Bai et al. 2020). The most common forms of technology spillover between various locations are horizontal and vertical spillovers, respectively (Lu et al. 2017; Ni et al. 2017). The combination between competitiveness and crowding-out effects determines how horizontal technological overflow affects $CO_2$ emissions.

The process of integrating national economies into the global economy through trade, investment, human mobility across borders, and the diffusion of technology is known as globalization. The promotion of technical spillover and an increase in environmental consciousness, both essential for environmental protection, may result in the technology effect. Cross-border input allocation is a key mechanism for value-added trade, environmental policy, and sustainable economic growth (Anwar et al. 2021a, 2021b; Ji et al. 2022). A growing body of research investigates how the analysis of trade and the sustainability of the environment are impacted by accounting for input reallocation across borders at the firm level. A growing body of literature investigates how the analysis of trade and the sustainability of the environment are impacted by accounting for input reallocation across borders at the firm level. The body of research described above as well as the empirical links between global productivity and pollution serve as the basis for this literature (Shapiro and Walker 2018; Najjar and Cherniwchan 2021; Barrows and Ollivier 2021; Chien et al. 2021; Liu et al. 2022). Cheng et al. (2022) came to the conclusion that when cross-border migration increases, so does ecological consciousness, making it the main argument for minimizing environmental damage in order to demonstrate the link between globalization and the environment. Although the expansion of the tourism sector is a key factor in promoting economic development, it may also have an effect on energy and environmental sustainability indicators (Cheng et al. 2022). Furthermore, Teng et al. (2021) found that increasing both domestic and foreign tourism in China results in an increase in $CO_2$ emissions. They did this by examining the geographic effects of $CO_2$ emissions from both types of tourism. The possibility that multi-national corporations (MNCs) support the dissemination of clean technologies and management techniques for a sustainable contribution of foreign direct investment to economic growth forms the basis for potential environmental spillovers given the close relationship between FDI and globalization and the fact that our data supports the idea that FDI influences the pollution in the host nation (Perkins and Neumayer 2008).

For the research in this study, the prior literature has established a strong foundation. By categorizing the existing studies, we discover that researchers mostly focus on the variables that influence carbon emissions. Researchers have expressed great worry about the impact of globalization on economic growth, yet there is a lack of rigorous studies on the impact of information globalization on carbon neutrality. To the best of our knowledge, research on how the information globalization and GVC participation affect carbon emissions is still in its early stages, there is a scarcity of relevant literature, and the majority of studies rely on qualitative analysis because quantitative research is lacking.

In conclusion, measuring the threshold effect of the information globalization on $CO_2$ emission is rarely done in the current literature. Most estimates of the digital economy use a single index approach, which makes it challenging to define the actual degree of information globalization. The main topic of a few studies was how information and communication technology (ICT) affected $CO_2$ emissions. The all-inclusive information globalization index, as opposed to ICT, may more accurately capture the impact of GVC participation on the value-added trade model, dispersion of production process, and transaction mode. Participation in global value chains (GVCs) has emerged as the key route for the global society to accomplish industrialization and green production along the approach.

Therefore, the contribution of this study can be seen in a number of significant places. We first concentrate on the BRICS nations (see Appendix Table 8), which over the past few decades have been the major sources of carbon emissions. The theoretical foundation for the impact of the information globalization and GVC participation on carbon neutrality is further strengthened by this paper. Additionally, we create two different types of indicators to systematically assess the aspects of the information globalization, including the de facto and de jur measures. Last but not least, this paper develops a panel threshold model based on quantitative research to reflect the phased effects of the information globalization on carbon emissions.

## Theoretical model

The general equilibrium model of GVCs and the environmental sustainability put forth by Xu et al. (2022a) predict that a country's carbon emissions will increase due to the scale effect of GVC participation while decreasing due to the globalization effect. The population expands geometrically while sustenance rises arithmetically, hence according to classical economists, as population density rises, the sustainable production cannot be maintained. Accordingly, if population expansion exceeds the region's carrying capacity, environmental deterioration happens given the fixed resources. Later, Ehrlich and Holdren (1971) presented an IPAT approach that emphasized the population, technology, and the affluent as possible determinants of environmental quality. A regression on population growth, affluence, and technology (STIRPAT), which is accepted by Dietz and Rosa (19,940), is how the current research, by upgrading the IPAT model, uses the stochastic effect. In view of this, the empirical model may be expressed as follows:

$$\mathrm{CO2_t} = a_0 + a_1 P_t + a_2 A_{it} + a_3 T_{it} + \varepsilon_{it} \tag{1}$$

where $CO_2$ is carbon emissions, $P$ is population proxied by urbanization, $A$ is affluence proxied per capita GDP, $T$ is technology proxied by information globalization, and $\varepsilon$ is the error term. The model in Eq. (1) is further modified by adding the scale effect, which considers GVC participation and information globalization as the determinants of $CO_2$ emission. Since this study intends to evaluate the asymmetric impact of GVC participation and information globalization on the environment, this study considers both GVC participation and information globalization use as the determinants of $CO_2$. Thus, the model of this study can be written as:

$$\mathrm{CO2_t} = a_0 + a_1 U_t + a_2 \mathrm{GDPPC}_{it} + a_3 \mathrm{ING}_{it} + a_4 \mathrm{GVC}_{it} + \varepsilon_{it} \tag{2}$$

where "ING" stands for "information globalization" and "GVC" stands for "global value chains participation." This study collects annual data for the BRICS economies covering the years 2000 to 2018 to evaluate the asymmetric impact of the GVCs' participation and information globalization on the environment. Urbanization statistics from WDI are utilized, together with per capita $CO_2$ emissions, to capture environmental variables. To measure affluence, data on per capita real GDP are used and were obtained from WDI, and to gauge the technological level, information globalization index is used and is obtained from KOF a Swiss economic institute. Data on GVC participation are obtained from TiVA-OECD database. The logarithmic form of each variable in Eq. (2) assists in addressing the issue of heteroscedasticity and provides accurate estimations.

## Methodology and variable selection

### Econometric approach

#### Cross-sectional dependency

When employing the panel data approach for econometric analysis, there will frequently be a significant correlation between sections and its evaluation criterion is the existence of cross-sectional correlation among error terms. Because the unidentified and broad economic impacts on the dependent variables are integrated into the error term rather than being introduced as independent variables, the model estimates will be skewed and inconsistent. So, before estimating the model, a cross-sectional dependency test is required.

#### Unit root test

Data from multiple countries' macroeconomic time series are gathered for this study. The mean value and variance of time series fluctuate over time in the majority of economic areas. Regression models based on non-stationary economic variables will produce erroneous results. In order to assess the stability of economic variables in this study, the problem must be addressed. In light of the possibility of autocorrelation in the disturbance term, Levin et al. (2002) proposed a high-order difference lag term:

$$\Delta y_{it} = \delta y_{it-1} + z'_{it\beta_i} + \sum_{j=1}^{p_i} \Phi_{ij}\Delta y_{i,t-1} + \varepsilon_{it} \tag{3}$$

where $\delta$ is the common root, or common autoregressive coefficient; $P_i$ is the distinct individual that can have different lag orders, $\{\varepsilon_{it}\}$ is the autoregressive moving average model; different individuals are independent of one another; and heteroscedasticity is allowed. We can guarantee that $\varepsilon_{it}$ is white noise by including a differential lag term of high enough order.

### Cointegration test

The long-term equilibrium association between non-stationary economic factors is known statistically as cointegration. Even if a single time series might not be stationary on its own, with linear combination, two or more time series will be stable. After linear combination, the stationary series exhibits a long-lasting, stable equilibrium relationship known as the cointegration relationship. Although short-term cointegration-related variables may deviate from this relationship, long-term changes will nonetheless cause them to re-enter this cointegration equilibrium relationship. We use the Johansen cointegration test because it performs better than the conventional Granger two-step test since the stationary linear data series produced in this study is the relationship between more than two variables.

For $k$ time series $y_t = (y_{1t}, y_{2t}, y_{3t}, \ldots, y_{kt})$, $(t = 1, 2, \ldots, n)$, the elements of a vector with $k$ dimensions, $y_t$ is known as $(b, d)$ order cointegration, in which it is noted as $y_t \sim CI(b,d)$. If each element in $y_t$ is $y_t \sim I(b, d)$, cointegration vector α, commonly known as a nonzero vector, exists, so that:

$$\alpha' y_t \sim I(b-d), 0 < d \le b.$$

If matrix $A$ is the matrix made up of the cointegration vector of $y_t$ and matrix A's rank is $t$, then $0 < t < k$. For the subsequent mode, $y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \mathrm{B}\, x_t + U_t$, $y_t$

When there is a non-stationary series in the formula, $A_1, A_2, \ldots, A_p$ is a matrix of order $k \times k$, where $U_t$ is a $k$-dimensional random error vector and $x_t$ is a steady $d$-dimensional exogenous vector expressing deterministic terms like constant term and trend term. The formula below is the result of differential transformation:

$$\Delta lny_t = \prod lny_{t-1} + \sum_{i-1}^{p-1} \tau_i \Delta lny_{t-1} + \mathrm{B}\ \ln x_t + U_t \tag{4}$$

If:

$\Pi = \sum_{i=1}^{p} A_i - \mathrm{I}$, $\tau_i = -\sum_{j=i+1}^{p} A_j (i = 1, 2, \ldots, p-1)$, $\Pi$ indicates a dense matrix. Let the characteristic root of the matrix $\Pi$ be $\Psi_1 > \Psi_2 > \cdots > \Psi_k$ determined using the trace statistics and eigenvalue of the Johansen cointegration test. For null hypothesis $H_{t0}$: $\Psi_t > 0$, $\Psi_{t+1} = 0$, is that at most $t$ cointegration vectors exist, and the alternative premise $H_{t1}$: $\Psi_{t+1} > 0$, is that $r$ cointegration vectors are present $(t = 1, 2, \ldots, k-1)$ and the associated test statistics are as follows:

$$\omega_t = -n \sum_{i=t+1}^{k} \left(1 - \Psi_i\right) \ldots (t = 0, 1, 2, \ldots, k-1) \tag{5}$$

The importance of the statistics is examined once at a time using the eigenvalue and trace statistic abbreviated as $\omega_t$. Accepting the null hypothesis, $H_{t0}$, which suggests that there are $\omega_r$ cointegration vectors, is appropriate when $t$ is smaller than the crucial number. When $\omega_t$ exceeds the critical value, then null hypothesis $H_{t0}$ is rejected, indicating the existence of at least $t + 1$ cointegration routes.

### Threshold test

The model is typically established using a grouping test, an interaction-term test, or the inclusion of dummy variables in previous research when it is necessary to examine the complex nonlinear mutation of one independent variable's explanatory power on another independent variable's explanatory power with the change of another independent variable. The interaction term test is constrained by the cross-item form's ambiguity, but the grouping test defines the separation point through subjectivity. The significance of the threshold effect cannot be determined by them. The threshold regression analysis provided by Hansen (2000) can be used to get over the constraints of the aforementioned two strategies. It can successfully perform the significance test in addition to providing an appropriate threshold value estimate. Panel threshold approach does not require the threshold to be chosen based on theoretic value or experience, in contrast to the conventional subjective grouping. Threshold regression can group the sample data in an endogenous way, removing subjectivity, and assess the importance after setting the threshold level of the sample data. Using a single threshold model as a base, this method can also be utilized to generate multi-threshold models. The benefits of cross-sectional people and continuous time series in context of two-dimensional data may also be combined to compute the threshold value in panels. This study employs the following methodology to develop a threshold model of the effect of GVC participation on carbon emission using information globalization as the threshold variable.

$$\mathrm{CO2_{it}} = \eta_{it} + \beta_1 lnX_{it} + \beta_2 \mathrm{GVC}_{it} \times I\left(\mathrm{DT}_{it} \le \alpha_1\right) + \beta_3 \mathrm{GVC}_{it} + \left(\mathrm{DT}_{it} > \alpha_1\right) + \varepsilon_{it} \tag{6}$$

where $t$ and $i$ are year and country, respectively; $\eta_{it}$ is value of a constant term, and $X$ is a matrix of control variables. Furthermore, $I(\bullet)$ is an indicator function showing that if the parenthesized statement is true, then its value is 1; otherwise, the value is 0; $\alpha$ is an estimate of the threshold. We additionally configured the multi-threshold model to address the possibility of numerous thresholds as follows:

$$\begin{aligned} \mathrm{CO2}_{\mathrm{it}} = \eta_{it} + a_1 lnX_{it} + a_2 GVC_{it} \times \mathrm{ING}\left(\mathrm{DT}_{it} \le \alpha_{21}\right) \\ + a_3 \mathrm{GVC}_{it} \times \mathrm{ING}\left(\alpha_{21} < \mathrm{DT}_{it} > \alpha_{22}\right) \\ + a_{n+1} \mathrm{GVC}_{it} \times \mathrm{ING}\left(\mathrm{DT}_{it} > \alpha_{2n}\right) + \varepsilon_{it} \end{aligned} \tag{7}$$

### Threshold effect test

Two problems need to be solved in order to determine thresholds. The essential parameter DT and regression threshold must first be determined. Examining the expected threshold value, which is created by reducing the residual estimate values of the OLS estimate under the expected threshold value, is the second step. This method is then used to determine threshold and the primary research variable, DT. After finding the accurate parameter estimates, it is needed to confirm the application of the threshold impact and the confidence level of the predicted threshold value. The null hypothesis for the threshold effect significance test is $H_0$: $\gamma_1 = \gamma_2$, which states that there is no threshold effect and the alternative hypothesis is $H_1$: $\gamma_1 \neq \gamma_2$, which states that there is a threshold effect in our data. The test results show:

$$F_1 = \frac{S_0 - S_1\left(\hat{\alpha}\right)}{\hat{\sigma}^2} = \frac{S_0 - S_1\left(\hat{\alpha}\right)}{S_2\left(\hat{\alpha}\right)/n(T-1)} \tag{8}$$

where $\hat{\sigma}^2$ is the residual variance under threshold estimate and $S_0$ and $S_1\left(\hat{\alpha}\right)$ are the residuals' sum of square under the null hypothesis and threshold estimate, respectively. Although the asymptotic distributions of the likelihood ratio (LR) test can be reproduced by "self-bootstrapping," the $p$ value that results this from also performs asymptotically well. The $F_1$ statistic does have a non-standard distribution since the threshold for the hypothesis cannot be specified. If the $p$ value is less than the crucial value we set, we can claim that the threshold is significant and reject the null hypothesis; otherwise, we can infer that threshold effect is absent from the model.

### Consistency test between real value and threshold value

The null hypothesis for the consistency test of threshold value is $H_0$ : $\hat{\alpha} = \alpha_0$ and $H_1$: $\hat{\alpha} \neq \alpha_0$. Although $\hat{\alpha}$ is a reliable estimator of $\alpha_0$ according to the threshold effect, its asymptotic distribution is not uniform. Nevertheless, LR statistics can be used to determine the non-rejection zone of. The LR test statistics are created as follows:

$$LR_1(\alpha) = \frac{S_1(\alpha) - S_1\left(\hat{\alpha}\right)}{\hat{\sigma}^2} \tag{9}$$

where $LR_1(\alpha)$ is a nonstandard distribution and $S_1(\alpha)$ is residuals' sum of square under unrestricted conditions. When $LR_1$ $(\alpha) > c\ (\beta)$, the null hypothesis is disproved and it is assumed that the assessed value of the threshold was not equal to its actual value, if $c(\beta) = -2\ln(1-\sqrt{1-\beta})$, where $\beta$ is the significance level. To more easily see the rejection region and confidence interval of the threshold value, an LR test chart might be created concurrently. Examining the confidence interval and significance of the subsequent threshold in context for the single threshold model is important to ascertain whether the model has multiple thresholds. The single threshold assumption can be accepted if the test is unsuccessful. Otherwise, to move on to other threshold tests and similar measures.

### Threshold regression with fixed effect model

The objects of the study for panel threshold model are based on $T$ period and $n$ entities. For panel data, the formula is $\{y_{i,t}, x_{i,t}, p_{i,t}: 1 \le i \le n, 1 \le t \le T\}$, where $n$ is the entities and $T$ is time period. Hansen (2000) examines the threshold regression model with fixed effects and uses a within dimension to remove fixed effects:

$$y_{i,t} = \eta_{i,t} + \gamma'{}_1 x_{i,t} + \varepsilon_{i,t} + ifp_{i,t} \le \alpha \tag{10}$$

$$y_{i,t} = \eta_{i,t} + \gamma'{}_1 x_{i,t} + \varepsilon_{i,t} + ifp_{i,t}\alpha > \tag{11}$$

In the formulas above, $\varepsilon_{i,t}$ is subject to an independent identical distribution, $p_{i,t}$ is the threshold variable (which may or may not be an explanatory variable), and $\alpha$ is the threshold value to be calculated. The equations can be written as follows using the indicative function I(•):

$$y_{i,t} = \eta_{i,t} + \gamma'{}_1 x_{i,t} \bullet \mathrm{I}\left(p_{i,t} \le \alpha\right) + \gamma''_1 x_{i,t} \bullet \mathrm{I}\left(p_{i,t} > \alpha\right) + \varepsilon_{i,t} \tag{12}$$

Our study is based on the following variables to fulfill its objectives as mentioned above.

## Carbon emission ($CO_2$)

The consumption of energy in the course of current economic development results in the inevitable by-product of carbon emissions. Carbon emissions are a double-edged sword since they both greatly represent the scope of economic activity and contribute to the climate effect. Reduced carbon emissions are essential for promoting carbon neutrality (Khan et al. 2020). The solution to this issue lies in promoting profound de-carbonization while simultaneously fostering high-quality GVC-based trade constructed on the idea of green innovation. The major contributor to global carbon emissions has been trade. Some poor nations are increasingly serving as a haven for the transfer of industries under the GVC ladder with large carbon emissions on a global scale. As trade liberalization has progressed in wealthy and emerging nations, different countries' environmental concerns have emerged under different pollution tax rates (Chen et al. 2021). This study collects information on per-person carbon emissions to illustrate how the environment is faring in various nations (unit: metric tons).

## GVC participation

The overall forward and backward participation (GVC-related components) divided by the nation's gross exports indicates the degree of a country's participation in GVCs. Data for indices are collected from the OECD-TiVA database in December 2016 (for 1995–2011) and December 2018 (for 2012–2018). Thus, 1995 to 2018 constitutes the sample period for our investigation. We use the OECD-TiVA database to retrieve countries' gross exports, domestic value-added exports for other countries' re-export, and foreign value-added embodied in exports. Following Koopman et al. (2010), we then calculate the nation GVC participation index as follows:

(i) Forward GVC participation index $=\left(\frac{\mathrm{DVA}_{\mathrm{gvc}}}{x}\right)\times 100$

(ii) Backward GVC participation index $=\left(\frac{\mathrm{FA}_{x}}{x}\right)\times 100$

(iii) Total GVC participation index $=\left(\frac{\mathrm{DVA}_{\mathrm{gvc}}}{x}\right)\times 100+\left(\frac{\mathrm{FA}_{x}}{x}\right)\times 100$,

where $\mathrm{DVA}_{\mathrm{gvc}}$ is a country's domestic value-added exported for another country's re-export, $\mathrm{FVA}_x$ is foreign value-added in exports, and $x$ gross exports. All values are in US dollars.

## Threshold variable

According to the KOF globalization index, information globalization is defined by two measures, de facto and de jure. The actual flow of information, including the transmission of digital information, the flow of scientific knowledge, and the flow of technological information, is depicted by the de facto measure that contains three components: internet bandwidth, high technology exports, and international patents. De jure measures the capability of sharing information across national borders or the conditions or policies that obstruct or promote the actual flow. De jure measures also include more than three factors, such as the number of people with internet access, the number of televisions per person, and press freedom, which are seen to have an impact on the real flow of information. Environmental quality is anticipated to be significantly impacted by information globalization. For example, informational globalization accelerates trade modernization in various ways, such as by technology spillover through internet usage and encouraging investment and economic activity, which is a key factor in environmental sustainability (Latif et al. 2018). Similarly, information globalization improves the movement of intermediate goods and services between nations via various contemporary communication methods, which may have a direct impact on the environmental quality (Zafar et al. 2020; Qin et al. 2021).

## Control variables

Even though it is simple to estimate the direct relationship between GVC participation and the intensity of carbon dioxide emissions, doing so runs the risk of underestimating the significance of other major explanatory variables for carbon emissions, which could cause uncertainty and bias outcomes in the estimation results. To further reduce the aforementioned problems, additional control factors affecting carbon emissions are included to the model for analysis in accordance with past studies (Fuchs 2008; Naranpanawa 2011; Long et al. 2018; Wang and Han 2021). This study uses the per capita GDP measured in constant 2010 US dollars as well as the urbanization rate (URB), which is estimated as the percentage of the population that lives in cities.

Given that the BRICS countries are well known for being recently industrialized countries that contribute significantly to the world's carbon emissions, when the BRICS countries are examined, it becomes clear that these nations are known for their rapid economic development, which is mostly fueled by fossil fuel-based technologies (Azam 2020). Because of the prevalence of this economic development pattern, $CO_2$ emissions have been rising steadily in many nations, which has prompted politicians to start changing how people use energy (Zafar et al. 2019). Now that these changes call for an increase in innovation in these countries, it is necessary to increase their reliance on the manufacturing-based value-added sector while promoting the expansion of information globalization. Since the turn of the century, certain countries have introduced carbon neutrality targets one after another. This analysis uses panel data from 5 BRICS economies from 2000 to 2018 due to the reliability and accessibility of the data. The data are taken from the World Bank's WDI database, TiVA-OECD database, and KOF Swiss Economic Institute.

All of the data have been converted into their natural log form in order to remove any potential heteroscedasticity. Table 1 displays the statistical breakdown of the sample data.

## Results and discussion

### Cross-sectional dependence and unit root test

The variables in our model, particularly for the threshold, have to be stationary for the regression model to work. As a result, each panel data series' unit root must be taken into account before the empirical regression. The panel unit root test can be broken into two portions depending on the time of occurrence. Results for this test may not be reliable if there is section correlation since different sections are necessary for the first-generation panel unit root test. In addition to assuming the spatial effect of section correlation, the second-generation panel unit root test defines a variety of parameters for the type of sectional correlation, which may also take into consideration both correlation and heterogeneity within the same section. The results of the test for cross-sectional dependence indicate that there is no cross-sectional dependency. We decide to use the first-generation unit root test as a result.

To confirm the stationarity of all variables in light of the reliability of the test results, this paper applies the Fisher test for heterogeneous panel unit root hypothesis and the LLC (Levin et al. 2002) test for homogeneous panel unit root hypothesis. Tests show that the original series is unstable and has unit roots. The individual test results are presented in Table 2 after the first-order difference. As can be seen, each variable's series exhibits stationarity at the 1% level of significance and exhibits a consistent trend at the first lag order.

### Cointegration test

There is no rejection of the null hypothesis that there is only one cointegration relationship, as shown by Table 3's trace statistics and Max-Eigen statistics, which are both bigger than their respective 5% critical values. Therefore, there is at most one cointegration relationship between carbon emissions, GVC participation, information globalization, urbanization, and per capita GDP.

**Table 1** Descriptive statistics of the selected variables

| Variable types | Names | Symbol | Mean | Standard deviation | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Dependent variable | $CO_2$ emission | $CO_2$ | 1.8155 | 0.5040 | 0.8872 | 2.4717 | 0.6508 | 2.9362 |
| Core explanatory variable | GVC participation index | GVC | 4.1029 | 0.6147 | 0.9752 | 3.7983 | −0.8591 | 3.3976 |
| Threshold variables | Information globalization | ING | 5.4172 | 0.2805 | 0.6137 | 5.9802 | −1.1097 | 3.1877 |
| | De facto measure | DF | 2.6367 | 0.2310 | 0.5273 | 6.6772 | −0.4569 | 1.9524 |
| | De jure measure | DJ | 1.1788 | 0.0742 | 0.1713 | 4.9745 | −1.5295 | 4.9734 |
| Control variables | GDP per capita | GDPPC | 4.3692 | 0.6275 | 2.3038 | 5.7656 | −0.5770 | 3.7390 |
| | Urbanization | URB | 1.7375 | 17.6439 | 0.3751 | 2.4609 | −0.9105 | 3.2735 |

All variables are in log form

**Table 2** Unit root test results

| Variable name | Form | LLC test | | Fisher test | |
|---|---|---|---|---|---|
| | (ct,tt,l) | Test statistic | Probability | Statistic | Probability |
| $CO_2$ emission | (ct,0,1) | −2.8627 | 0.0000 | 221.9514 | 0.0000 |
| GVC | (ct,0,1) | −3.3718 | 0.0000 | 63.5580 | 0.0000 |
| ING | (0,tt,1) | −2.1900 | 0.0047 | 211.2066 | 0.0000 |
| De facto measure | (0,tt,1) | −1.8638 | 0.0691 | 165.9603 | 0.0000 |
| de jure measure | (0,tt,1) | −2.2928 | 0.0171 | 287.1325 | 0.0000 |
| GDP per capita | (ct,0,1) | −1.7615 | 0.0703 | 99.8945 | 0.0000 |
| Urbanization | (ct,0,1) | −4.2490 | 0.0000 | 213.2073 | 0.0000 |

ct, tt, and l indicate test with constant term (ct), time trend (tt), and chosen lag order (l), respectively

**Table 3** Johansen cointegration test result

| Null hypothesis | Eigenvalue | Trace statistic | 5% Critical value | Max-Eigen statistic | 5% Critical value |
|---|---|---|---|---|---|
| None | 0.0822 | 51.9687 | 29.7972 | 42.3470 | 21.1317 |
| At most 1 | 0.0167 | 9.6215 | 15.4946 | 8.2965 | 14.2645 |
| At most 2 | 0.0027 | 1.3252 | 3.8414 | 1.3252 | 3.8416 |

## Regression results of threshold variable

There is just single threshold for ING at the level of significance of 5%, as shown in Table 4, and that threshold's value is 1.9252. The link between GVC participation and $CO_2$ emissions is regressed at different intervals to examine the effect of ING on GVC-related carbon emission at different scales, using 1.7252, 3.3505, and 1.8804 as the appropriate tipping points, in accordance with the processing strategy of the panel data threshold regression model proposed by Hansen (2000). There is only one de facto threshold at the 1% significance level as well.

The value of 22.151 for cross-sectional dependence does not disprove the null hypothesis. Therefore, across sections, the variables are independent of one another. The standard regression examination in this study employs the feasible generalized least square estimate (FGLS) method, which can efficiently deal with autocorrelation within-group and heteroscedasticity between-groups, and the outcomes are displayed in Table 6 column (1). At the 5% test level, carbon emissions are significantly influenced by GVC participation in both positive and negative directions. Regression with simply GVCs or with other control variables included yields the same results for panel threshold estimation.

By combining all the variables, we explain the regression results. The coefficient of GVCs is 0.552 when de factor measure of information globalization (ING) is less than or equal to 3.3505, which means that for every 1% increase in GVC participation, carbon emissions will rise by 0.55%. The coefficient of GVCs is 0.2357 when de facto is higher than 3.3505, which is likewise very significant. This shows that the modifying effect of GVCs on carbon emission eventually declines as the extent of information globalization grows. The level of Internet development can have an impact on a variety of digital low-carbon technology services, including the transmission efficiency, R&D process, degree of absorption, and effectiveness of technology spillover, which can then have an impact on raising a nation's low-carbon technological standard (Liddle 2018; Wang et al. 2020).

By utilizing a manufacturing digital platform for resource allocation and utilization under value added trade, it is possible to schedule and organize dispersed and abundant production resources, as well as increase the efficiency of value-added factor use and production resource matching (Balsalobre-Lorente and Leitão 2020; Yan et al. 2020). The estimated coefficient of GVCs when de jur measure of information globalization (ING) is chosen as the threshold variable is 0.2711 when de jur is not greater than 2.6004. However, when the threshold exceeds 2.6004, the coefficient decreases to 0.0273. It suggests that the BRICS nations will be able to increase the usage effectiveness of energy resources while participating in global value chains and help in the reduction of carbon emissions after they have reached a specific level of information globalization exploitation. The results are consistent with the static threshold, but the impact intensity is larger when looking at the estimated coefficients' absolute values (Table 5).

The impact of the digital economy on reducing carbon emissions is primarily seen in a number of areas. The digital value-added industry has its own environmentally favorable traits and little environmental impact (Wei et al. 2020; Alola 2019). The information sector, which includes internet businesses and the information services sector, dominates the digital production, and its level of sustainability is typically higher than that of traditional industrial output. Additionally, due to their substantial economic power, digital companies usually give environmental advantages more attention (Fu and Zhang 2015; Kaya et al. 2017). The digital value-added sector can motivate other sectors to reduce their carbon footprints. The digital value-added industry can transform traditional industries through the adoption and diffusion of digital technology, promote the development of smart and environmentally friendly industries, boost industrial value-added, and lower energy consumption and carbon emissions (Boamah et al. 2017; Wang and Zhang 2021). The development of a carbon trading benefits from the expansion of the modern GVC-based industry in order to considerably cut carbon emissions and attain carbon neutrality. When GVCs are taken into account as an endogenous explanatory

**Table 4** Significance test of threshold variables, their estimated value, and confidence interval

| Core explanatory variable | Threshold variable | Number of threshold | *F*-statistic | At 10% critical value | At 5% critical value | At 1% critical value | Threshold value |
|---|---|---|---|---|---|---|---|
| GVC | ING | Single | 43.91** | 48.8533 | 58.7291 | 85.0224 | 1.9252 |
| | | Double | 23.87 | 33.0938 | 42.8854 | 58.8961 | 1.7468 |
| | DF | Single | 94.01*** | 54.1670 | 64.6345 | 77.8549 | 3.3505 |
| | | Double | 21.12 | 133.8674 | 163.8153 | 252.5555 | 2.1918 |
| | DJ | Single | 39.96** | 54.0777 | 82.8461 | 85.7757 | 1.8804 |
| | | Double | 25.55 | 51.6575 | 79.4157 | 71.5792 | 76.0001 |

*$p<0.1$, **$p<0.05$, ***$p<0.01$

**Table 5** Threshold with GVC as endogenous variable

| Explanatory variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| GVC | 0.5378*** | | | | | | | 0.7507*** |
| | (0.0191) | | | | | | | (0.0390) |
| ING | −0.0066*** | | | | | | | |
| | (0.0002) | | | | | | | |
| GVC_0 | | 0.6146*** | 0.5522*** | 0.5510*** | 0.2711*** | 0.3194*** | 0.5364*** | 0.5390*** |
| | | (0.0181) | (0.0345) | (0.0200) | (0.0315) | (0.2352) | (0.3501) | (0.0211) |
| GVC_1 | | 0.5367*** | 0.8357*** | 0.4847*** | 0.0273*** | 0.1745*** | 0.4613*** | 0.3917*** |
| | | (0.0271) | (0.0101) | (0.0422) | (0.0391) | (0.0233) | (0.0488) | (0.0361) |
| Tipping point | | DF ≤ 1.6111 | DF ≤ 3 .3505 | DJ ≤ *3.3352* | DJ ≤ 2.6004 | DF ≤ *1.4431* | DJ ≤ *4.0238* | DF ≤ *1.8153* |
| | | DF > 1.6111 | DF > 3.3505 | DJ > *3.3352* | DJ > *2.6004* | DF > *1.4435* | DJ > *4.0238* | DF > *1.8153* |
| GDPPC | 0.0067 | | − 0.0168 | | − 0.0375 | − 0.1438 | 1.6044* | 0.22.34*** |
| | (0.0685) | | (0.0828) | | (0.0815) | (0.2126) | (0.8756) | (0.0815) |
| URB | 0.0080 | | −0.0282*** | | 0.0423*** | 0.0182 | 0.2501* | 0.0464*** |
| | (0.0053) | | (0.0095) | | (0.0095) | (0.0188) | (0.1626) | (0.0093) |
| _cons | −0.6502*** | −0.4038*** | −0.6333*** | −0.2640*** | −0.3385*** | 0.5265 | −0.8387*** | −0.8763*** |
| | (0.0977) | (0.0481) | (0.1039) | (0.0516) | (0.0967) | (0.5280) | (0.7788) | (0.1030) |
| *R* squared | | 0.7715 | 0.9074 | 0.8378 | 0.8081 | | | 0.8196 |
| *F* statistic | 3080.57 | 1316.39 | 399.78 | 1023.11 | 484.91 | | | 143.69 |
| Model | | | | | | Dynamic | Dynamic | FE |

The values in parenthesis are standard errors

*$p<0.1$, **$p<0.05$, ***$p<0.01$

**Table 6** Threshold with information globalization (ING) as endogenous variable

| Explanatory variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| ING_0 | − 8.1655 | −0.0482*** | −0.0248*** | −0.0187*** | 0.0038 (0.0047) | 0.0092 (0.0033) | 0.0346 (0.0227) |
| | (1.6993) | (0.0003) | (0.0003) | (0.0004) | | | |
| ING_1 | − 0.0157 | −0.0102*** | −0.0049*** | −0.008*** | −0.0155*** | −0.0125*** | −0.0660*** |
| | (0.0004) | (0.0003) | (0.0013) | (0.0003) | (0.0026) | (0.0053) | (0.0225) |
| Tipping point | DF ≤ 0.0763 | DF ≤ 3.6008 | DJ ≤ 4.4567 | DJ ≤ 3.6696 | DF ≤ 8.2699 | DJ ≤ 3.5585 | DF ≤ 9.2317 |
| | DF > 0.0713 | DF > 3.6008 | DJ > 4.4567 | DJ > 3.6696 | DF > 8.2699 | DJ > 3.5585 | DF > 9.2317 |
| GDPPC | | 0.2718*** | | 0.6256*** | 0.0154*** | −1.5187*** | 0.5087*** |
| | | (0.0915) | | (0.1014) | (0.1776) | (0.9565) | (0.0005) |
| URB | | 0.0661*** | | 0.0524*** | −0.0602*** | − 0.0777 | 0.0683*** |
| | | (0.0105) | | (0.0105) | (0.0135) | (0.1193) | (0.0095) |
| _cons | 1.0185*** | −0.0773*** | 1.0055*** | −0.5605*** | 0.2306 (0.4316) | 0.3250 (1.1294) | −1.8636*** |
| | (0.0065) | (0.1235) | (0.0065) | (0.1386) | | | (0.1817) |
| *R* squared | 0.6580 | 0.6103 | 0.5573 | 0.6812 | | | 0.7406 |
| *F*-statistic | 523.37 | 234.21 | 571.37 | 422.81 | | | 210.91 |
| Model | | | | | Dynamic | Dynamic | FE |

The values in the parenthesis are standard errors

*$p<0.1$, **$p<0.05$, ***$p<0.01$

variable, information globalization measures are significant in Table 6 at the 1% and 5% levels. The corresponding levels are, respectively, 3.6008 and 3.6696. The entire sample is divided into two threshold bands: countries with lower digital GVC-based trade and countries with strong digital value-added trade competitiveness. Depending on the absolute value, participation in global value chains has an impact on carbon neutrality in many threshold ranges. When the digital GVC-based trade level falls below the first threshold value of 3.6008, the variable of GVC participation affecting carbon emissions is assessed to be significant − 0.0482 and satisfies the significance test at the 1% level. When the de facto measure of information globalization (ING) hits 3.6008, the coefficient, which is − 0.0102, becomes significant at the 1% level. We can draw the conclusion that when digitized GVC-based trade efficiency is high, the effect of GVC participation on emissions reduction is more significant.

Therefore, when replacing fossil fuels with sustainable energy sources, countries should fully understand the role of developing online techniques and take benefit of the digital revolution to advance the technological frontier and help organize the relationship between modifying energy consumption and green productivity growth along the way to participate in global value chains (GVCs).

In terms of industrial structure, technological ability, the degree of carbon emission reduction, and the development of the value-added digital economy, developed and developing countries differ significantly from one another. As a result, the effect of the digital shift on carbon emissions reveals performance disparities between countries with different levels of development. Even though it is still in its early phases in BRICS countries, companies are beginning to use the knowledge for their distributed production, administration, and value-added trade. Since then, it has become clear that information globalization has a large favorable impact on the productivity of all factors affecting carbon emission. The empirical results of this study are in line with those earlier investigations such as Boutabba (2014) and Wang et al. (2019) as these studies confirmed that information globalization now has a more direct and wide-ranging impact on how dispersion of production and operations are conducted to the quick development of core technologies and tools as well as the continual improvement of infrastructure building. Machines and equipment are being improved, and business model innovation is still expanding. Similarly, Arce et al. (2016) has the same findings as ours such as they also found that the use of information globalization in management, R&D, value-added production, and other areas is growing in popularity.

## Test of robustness

In order to avoid the biased impact of time trend, this article splits the sample's time period into the same two sub-periods. Regression is then performed, assuring the reliability of the aforementioned empirical findings. Then, it is divided into several nations based on the characteristics of their GVC participation. The variable that was firstly explained is then replaced with the carbon intensity per unit of GDP. As in the previous regression, GVC participation is chosen as a key explanatory variable; the regression results in Table 7 demonstrate that the carbon reducing emission effect continues to be observed significantly after attainment the threshold of numerous indicators indicating the role of information globalization in modifying the impact of GVC participation on carbon emission in BRICS countries.

**Table 7** Results of robustness check

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Explanatory variable | 2000–2009 | 2010–2018 | Brazil | Russia | India | China | South Africa | $CO_2$ emission |
| GVC_0 | 0.5377*** (0.0670) | 0.6317 (0.3993) | 0.2551*** (0.0330) | 0.6092*** (0.0824) | 0.5772*** (0.0585) | 0.3016*** (0.0350) | | |
| GVC_1 | 0.5387*** (0.0675) | 0.3819*** (0.0701) | 0.2337*** (0.0325) | 0.4967*** (0.0815) | 0.4951*** (0.0590) | 0.2963*** (0.0555) | | 0.0861*** (0.0070) |
| ING_0 | −0.0117*** (0.0002) | −0.0190*** (0.0005) | −0.0316*** (0.0004) | | −0.0147*** (0.0006) | −0.0427*** (0.0001) | −0.0155*** (0.0015) | −0.0644*** (0.0083) |
| ING_1 | −0.0267*** (0.0023) | −0.0198*** (0.0001) | −0.0387*** (0.0024) | | −0.0326*** (0.0025) | −0.0493*** (0.0011) | −0.0187*** (0.0013) | −0.1118*** (0.0223) |
| Tipping point | DF ≤ 1.6935 | DJ ≤ 1.8635 | DJ ≤ 3.2852 | DF ≤ 1.8366 | DF ≤ 1.8112 | DF ≤ 1.8388 | DF ≤ 1.7706 | DF ≤ 0.3813 |
| | DJ > 1.6935 | DF > 1.8635 | DJ > 3.2852 | DF > 1.8366 | DF > 1.8112 | DF > 1.8388 | DF > 1.7706 | DF > 0.3813 |
| *GDPPC* | 0.3465*** (0.1306) | 0.1108 (0.1970) | | 0.1680 (0.1445) | 0.4499*** (0.1144) | | − 0.5263 (0.8595) | 0.9365*** (0.1885) |
| *URB* | 0.0370*** (0.0165) | − 0.0142 (0.0161) | | 0.0660*** (0.0140) | 0.0628*** (0.0123) | | −0.0596* (0.0424) | 0.0774*** (0.0212) |
| _cons | −1.2131*** (0.2037) | 0.1902(0.2562) | − 1.8420*** (0.0725) | − 1.4176*** (0.2180) | − 1.5763*** (0.1497) | −2.1001*** (0.4208) | 2.2994*** (1.2042) | 4.5376*** (0.2540) |
| Obs | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 500 |
| *R* squared | 0.8538 | 0.6476 | 0.5655 | 0.8431 | 0.8681 | 0.8665 | 0.2782 | 0.6465 |
| *F*-statistic | 122.80 | 99.98 | 739.95 | 244.01 | 287.31 | 260.55 | 46.58 | 166.04 |

The values in the brackets are standard errors

*$p<0.1$, **$p<0.05$, ***$p<0.01$

## Conclusions and policy implications

This study examines the influencing factors of carbon emissions in BRICS economies based on the predefined approach of carbon neutrality and digitized GVC-based trade. This paper empirically examines the relationship between the GVC participation and information globalization on the measure of carbon emission by choosing the cross-sectional data of BRICS countries of the last 19 years and develop a panel threshold regression model. The findings from various aspects of the regression analysis show that when the two parameters of information globalization—the de facto measure and the de jur measure—cross each threshold value (4.02 and 1.81), respectively, the modifying effect of GVC participation on carbon emissions tends to decrease. These findings demonstrate the participation in GVCs significantly reduces $CO_2$ emissions when the optimum levels of information globalization, one of the key factors of green value-added production, are exceeded.

In light of the existing literature and novelty in providing the policymakers in BRICS economies with thresholds for avoidable $CO_2$ emissions and complementary thresholds for information globalization and GVC participation for complementary policies, the policy implications of the findings are evident. While enjoying the advantages of a sophisticated framework and an open economy, developed economies should actively uphold their obligations, take the initiative to assist the nations under analysis in accelerating the design of circular cleaner energy production systems, and jointly promote global emission reduction by utilizing available funds and digital technologies to create a threshold level of information globalization across the nations. In light of the differences in national endowments and the effect of the digitized value-added trade on carbon emissions, it is necessary to slow down the development of the digital economy, remove trade restrictions and international trade barriers, and promote international coordination of digital economy governance through information ladder.

In accordance with the findings of the study, it is essential for BRICS countries to increase the use of digitalization in value-added trade and lessen the environmental impact of that trade and encourage the conventional production sectors to use modern technology, information flow via the GVC chain, and digitization in manufacturing activity dispersion to increase their energy efficiency. Technology and technique innovation promote the creation of adaptive, low-carbon digital infrastructure in order to stop high-carbon economic growth and make it easier to achieve carbon neutrality targets while promoting the new “Internet plus” paradigm of technological innovation and digital GVC-based trade. Threshold level of information globalization can increase the impact of energized digital technology on emission reduction by promoting efficiency reform, lowering the use of production resources, and speeding up the coverage, dispersion, and connectivity of sensing devices, digital phones, and electronic communications in both forward and backward GVC participation. Future studies may focus on investigating the relationship between environmental quality, participation in GVCs, and information globalization at the level of the specific country in question.

## Appendix

**Table 8** BRICS countries and their codes

| Code | Country |
|---|---|
| 1 | Brazil |
| 2 | Russia |
| 3 | India |
| 4 | China |
| 5 | South Africa |

**Author contribution** All authors contributed to the study conception and design. Material preparation, literature search, and analysis were performed by Tingting Liu and Muhammad Nadeem. The first draft of the manuscript was written by Muhammad Nadeem, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Muhammad Nadeem: conceptualization, methodology, investigation, literature search, visualization, software, and validation, Tingting Liu: writing—original draft and writing—review and editing. Zilong Wang: resources, supervision, and writing—review and editing.

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**Data availability** Data is available with the authors and repository given at the time of submission.

## Declarations

**Ethical approval** We declare that manuscript is original and has not been sent to any other journal.

**Consent to participate** This study has not directly/indirectly involved human and/or animals.

**Consent for publication** The manuscript was reviewed, and all authors consented to publish.

**Conflict of interest** The authors declare no competing interests.

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