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RESEARCH ARTICLE

# Renewable and non-renewable energy consumption—impact on economic growth and $CO_2$ emissions in five emerging market economies

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## Abstract

In a neo-classical aggregate production and Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) modeling framework, the paper attempts to explore the relationship between disaggregated energy consumption, economic growth, and carbon dioxide emissions in case of five emerging market economies—Brazil, Russia, China, India, and South Africa (BRICS) over the period 1992 to 2016. The study applied the robust unit root, cointegration, and long-run elasticity estimation methods like Pooled Mean Group and differenced panel generalized method of moments for empirical exercise. Having detected the panel heterogeneity and cross-sectional dependence, the cointegration tests documented the evidence of a long-run association among the variables. In the long-run, capital, labor, and non-renewable energy consumption are found to affect the economic growth positively. On the contrary, the impact of renewable energy consumption on the economic growth is found be positive but statistically insignificant. Moreover, population, per-capita income, and non-renewable energy consumption are found to increase the emissions whereas renewable energy consumption decreases them. Therefore, along with a proper emissions controls, BRICS countries should design and implement effective support policies so as to ensure the economic growth along with environmental sustainability.

**Keywords** Renewable energy · Non-renewable energy · $CO_2$ emissions · Economic growth · BRICS

## Introduction

The energy consumption in all forms has been considered imperative to complement the other factor inputs like labor and capital in the production processes (power generation, industry use, transportation use, residential use, etc.) of the economies. Many countries across the globe have been confronting the problem of inadequate energy supplies to meet the growing energy demand, while at the same time, struggle with the issues of environmental sustainability. Some energy-importing countries are even concerned about the energy security (Hednenus et al. 2010) due to the monopolized control of energy sources in the politically unstable geographical locations and high and volatile energy prices (Gnansounou 2008). Researchers have been continuously cautioning about the deleterious repercussions of energy supply and its usage (Stern 2007; Adamantiades and Kessides (2009); DeCanio 2009; Reddy and Assenza 2009). Unless substantial policy initiatives are executed, world economy at large would be unsustainable—economically, environmentally, and socially. International energy report (IEA 2009a) has asserted that if appreciable decisive policies are not undertaken, energy-related carbon dioxide ($CO_2$) emissions will get doubled by 2050 and increasing trends of oil demand will trigger the energy security issues even higher.[1]

Increasing dependence on non-renewable energy sources, energy insecurity and alarming climate change has mandated (forced) many countries across the globe to find alternative energy sources. Renewable energy sources have been

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[1] Nobuo Tanaka, Executive Director (IEA 2009b), emphasized this prognosis as follows: "The message is simple and stark: if the world continues on the basis of today's energy and climate policies, the consequences of climate change will be severe. Energy is at the heart of the problem—and so must form the core of the solution (Apergis et al. 2010).

recognized as the excellent substitute in the global energy consumption mix.[2] As reported in Fig. 1, in 2015, of the total global final energy consumption, renewable energy consumption (REC) constituted about 19.3% and out of this 9.1% belongs to traditional biomass and 10.2% to modern renewables (REN21 2017[3]). Figure 2 shows that by the end of 2016, renewables comprised about 30% of the world's power-generating capacity—enough to supply 24.5% of global electricity, with hydropower contributing about 16.6%.

It is important to note that the share of REC in the overall energy consumption has increased only marginally in the recent period, even though renewable energy sector has witnessed tremendous growth, particularly for solar PV and wind power. This could be attributed to the consistently strong demand for overall energy (with an exception of temporary 2009 pull-back due to the economic recession) and the substantial use of traditional biomass for heat (making up to half of all renewable energy use) (REN21 2017).

However, the renewable share of world electricity generation is expected to increase from 18% in 2007 to 23% in 2035 with a relative contribution of 54% and 26% of hydroelectricity and wind energy, respectively (Apergis and Payne 2012). Although the substantial growth projections and geographical extensions of renewable energy can be ascribed partly to government policies,[4] continued decline in prices of renewable energy technologies, and rising energy demand, there has also been a positive response from general public to adopt the renewable energy (REN21 2017; Kaygusuz et al. 2007; Kaygusuz 2007; Sovacool 2009).

Given that renewable energy has been considered as a panacea for a sustainable energy future, it would certainly be important to understand the relationship dynamics between REC and economic growth on the one hand and between REC and $CO_2$ emissions in order to assess the likely impact on environment. This study is an attempt to address the above issues in case of five emerging market economies, popularly known as BRICS (Brazil, Russia, China, India, and South Africa) for the period 1992–2016.[5] While the nature of association between overall energy consumption, economic growth, and $CO_2$ emissions has been examined at length (Ozturk 2010; Payne 2010a,b), studies investigating the influence of disaggregated energy consumption, i.e., both renewable (REC) and non-renewable energy consumption (NREC), on the growth performance and environmental impact have not been conducted exhaustively and the evidence reported so far remained inconclusive. The focus of this study is to contribute to the existing literature by scrutinizing the simultaneous effect of REC and NREC in order to identify properly the energy mix of BRICS countries which would be conducive for growth enhancements and environmental sustainability. To the best of author's knowledge, this is one of the first studies which simultaneously examined the impact of REC and NREC on both economic growth and environmental impact in case of BRICS countries. BRICS countries are chosen for the analysis due to their substantial contribution in global $CO_2$ emissions and active participation towards renewable energy.

According to EDGAR database created by the European Commission and Netherlands Environmental Assessment Agency, in 2016, China tops the list again with a share of 29.18% in total $CO_2$ emissions across the globe, India (7.07%) holds the rank three after USA followed by Russia (4.65%) at rank four, Brazil (1.29%) at rank twelve, and South Africa (1.09%) at rank fifteen among top twenty $CO_2$ emitters across the world.[6] As can be seen from Fig. 3, the countries are quite progressive in the renewable energy generation and as on 2016 the respective share of BRICS countries in the renewable energy power production is 81.2%, 17.4%, 15.0%, 25.7%, and 4.2% (Global Energy Statistical Year book 2017). Though, however, the status of renewable energy is not very advanced (except Brazil where renewables are expected to reach to 43.8% of total energy mix in 2016[7]), the pace of development towards it is growing appreciably over the years.

The present study will contribute to the growing literature in the following ways. Unlike the previous studies, the present paper applied the robust unit root, cointegration, and long-run elasticity estimation methods which will take care of panel heterogeneity along with cross-sectional dependence. Incorporating the issues of heterogeneity and cross-sectional dependence is quite imperative to ensure a valid empirical exercise and reach to reliable policy implications. This is important because the energy policies established at the international level can also affect the individual countries simultaneously, in addition to other exogenous shocks. Secondly, doing away with the OLS, DOLS, and FMOLS largely used in the previous studies, the present study applied the pooled mean group estimator (PMG) developed by Pesaran and Smith (1995), Pesaran et al. (1999) and differenced panel GMM (generalized method of moments) developed by Arellano and Bond (1991) to undertake the empirical exercise and to ensure the robustness. Third, the selection of the panel is not random. The countries chosen for the empirical investigation are potential contributors to global $CO_2$ emissions along with

[2] Renewable energy is projected to be the fastest growing world energy source (International Energy outlook 2010).

[3] Renewable Energy Policy Network for the twenty-first century.

[4] Like renewable energy tax credits, installation rebates for renewable energy systems, renewable energy portfolio standards, and the creation of markets for renewable energy certificates.

[5] The time period between 1992 and 2016 covers the period when most of the renewable initiatives have been implemented across countries.

[6] https://en.wikipedia.org/wiki/List_of_countries_by_carbon_dioxide_emissions

[7] https://renewablesnow.com/news/renewables-to-reach-438-of-brazils-energy-mix-in-2017-563742/

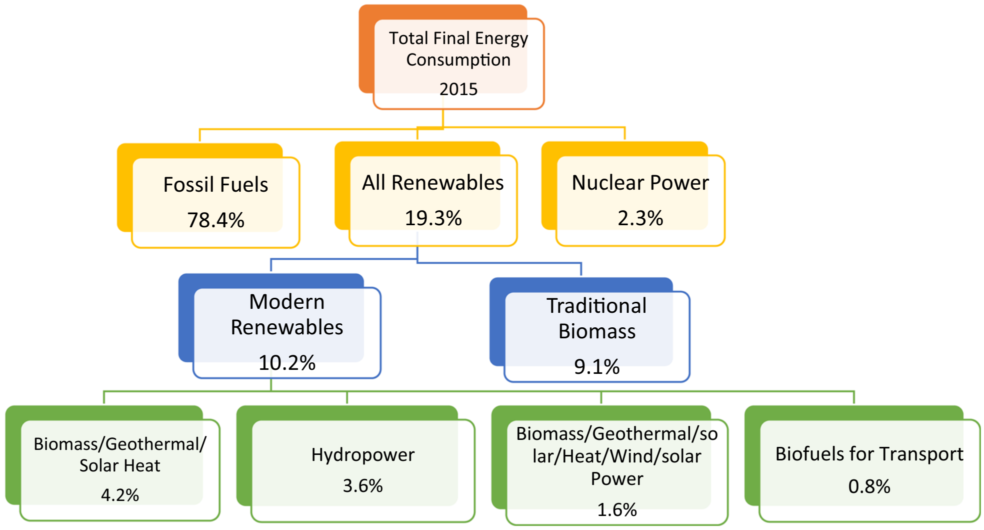


**Fig. 1** Estimated renewable energy share of total final energy consumption 2015 (REN21. 2017 Report)

triggering energy demands. Further, to avoid the omitted variable bias (Lutkepohl 1982), along with conventional factor inputs like labor and capital, the study incorporated a neo-classical production function approach and STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology)-derived environmental model (Ehrlich and Holdren 1971) to investigate the impact of REC and NREC on economic growth and environmental impact of BRICS countries. Finally, the study provide estimates of long-run elasticities which reflect both the time dimensions and the cross-sectional nature of the panel and provide appreciable power relative to the studies involving only the time series analysis.

The rest of the article is organized as follows: the "Literature review" section provides a critical review of the existing literature. The "Analytical framework" section presents the analytical framework. The econometric methodology and estimation strategy are given in the "Econometric methodology" section. The "Results and discussion" section deals with results and discussion. Finally, the "Conclusion" section the article provides relevant policy implications.

## Literature review

There exist a plethora of studies which have examined the casual nexus between economic growth, energy consumption, and $CO_2$ emissions (Alper and Oguz 2016) either in an individual country setting or in a panel data framework, incorporating both balanced and unbalanced panels, homogenous and heterogeneous panels, developed, emerging, less developed, or a mixture of all the three types. No consensus has emerged from these studies.[8] We refrain from the voluminous literature here.[9] Further, of the two basic categories of overall energy consumption, the impact of non-renewable energy consumption (NREC) on the growth performance and environmental impact has been scrutinized quite exhaustively with only a few studies are conducted to investigate the impact of renewable energy consumption (REC) on the said variables. Therefore, to ensure the relevance of the surveyed literature, it will be confined to renewable energy studies and is divided into two sub-categories, namely (i) association between REC and economic growth and (ii) association between REC and $CO_2$ emissions (Environmental Impact).

### Economic growth and renewable energy consumption

The nature of association between energy consumption and economic growth has been explained along the four theoretical paradigms, namely growth hypothesis (unidirectional causal relationship between renewable energy consumption and economic growth), conservation hypothesis (economic growth causes energy consumption), feedback hypothesis (bidirectional causality between the two), and neutrality hypothesis (no relationship) (Alper and Oguz 2016). The empirical studies conducted so far found the relevance with any of the four hypothesis. Applying the Data Envelopment Analysis (DEA) methodology Chien and Hu (2007) examined the impact of REC in case of a mixed panel of 45 developed and developing countries over the period 2001–2002. The study reported the significant impact of REC on capital stock and real GDP in case of non-OECD countries. In another study, Sadorsky (2009b) found that a 1% hike in per-capita income leads to approximately 3.5% rise in REC in case of 18 emerging market economies. The study also reported a price elasticity of − 0.70 for the REC. In a multivariate panel data framework, Apergis and Payne

[8] According to Ozturk (2010), using different data sets, alternative econometric methodologies and different country's characteristics are the main reasons of the conflicting result.

[9] Refer to Ozturk (2010) for a detailed survey.

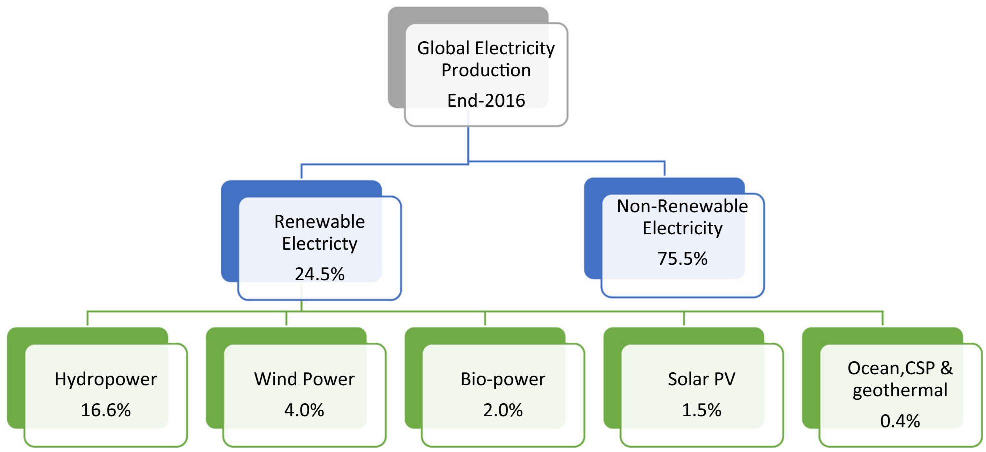


**Fig. 2** Estimated renewable energy share of global electricity production, end 2016 (Source—REN21. 2017 Report

(2010a, 2010b, 2011a, 2011b, and 2012) examined the impact of REC on the growth performance of different groups of countries. Applying various panel cointegration and causality approaches, the authors found that increase in REC increases the economic growth in various groups of countries. The authors further reported the validity of feedback hypothesis in a heterogeneous panel cointegration setting. Fang (2011) in an individual country analysis for China documented the evidence of growth hypothesis over the period 1978–2008. Using the variance decomposition approach (VDC), Tiwari (2011a) also supported the growth hypothesis while analyzing the data of Indian economy over the period 1960–2009. Similarly, Tiwari (2011b) found that growth rate of NREC has a negative impact and that of REC has a positive impact on growth performance of European and Eurasian countries over the period 1965–2009.

Applying the autoregressive distributed lag model (ARDL) and vector error correction model (VECM) to the data period 1980–2009, Bildirici (2012) found the evidence of bidirectional causality between biomass energy consumption and economic growth (feedback hypothesis) in case of seven developing and emerging economies. In an ARDL framework, Tugcu et al. (2012) found both the renewable and non-renewable are determining factors of growth. Similarly, analyzing the data for 108 countries during 1980–2009, Al-mulali et al. (2013) found the evidence of feedback hypothesis for 79% of the examined countries and conservation and neutrality hypothesis in case of 2% and 19%, respectively. Pau and Fu (2013a, b) examined the impact of various types of energies on the real GDP in case of Brazil for the period 1980–2009. Using VECM and Granger causality, the authors reported the evidence of feedback hypothesis in case of total REC and real GDP, non-hydroelectric renewable energy and real GDP, and nuclear energy and real GDP. The authors also found the evidence of growth hypothesis between hydroelectric energy and real GDP. Using ARDL, Sebri and Ben-Salha (2014) reported the evidence of feedback hypothesis in case of three countries (Brazil, India, and South Africa) of BRICS panel for 1971–2010. Likewise, Salim et al. (2014) investigating the data of OECD countries reported the evidence of bidirectional causality between industrial output

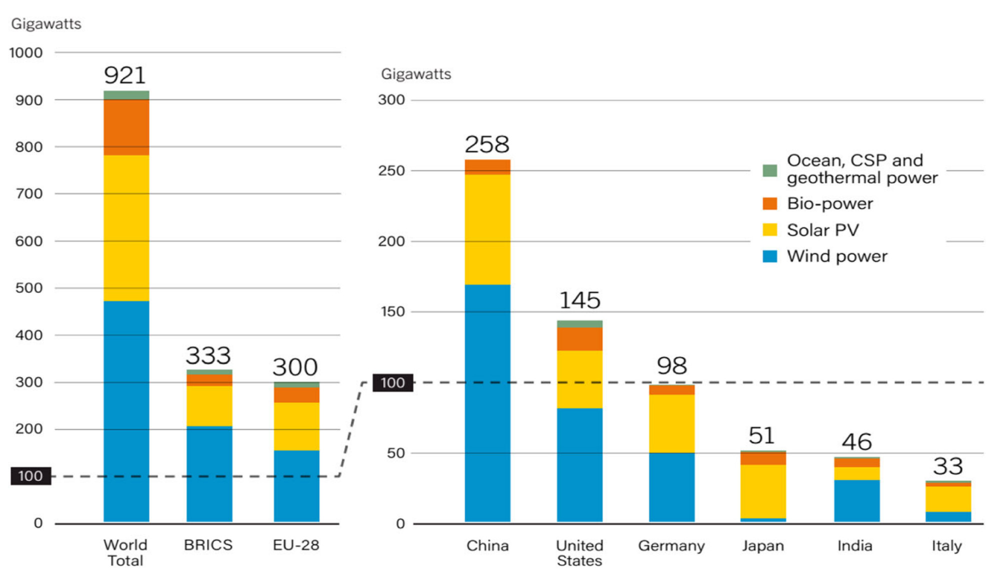


**Fig. 3** Renewable power capacities in World, BRICS, EU-28, and top six countries, 2016. Not including hydropower. Distinction is made because hydropower remains the largest single component by far of renewable power capacity and, thus, can mask developments in other renewable energy technologies if included

and both renewable and non-renewable energies in short run and long run. In addition, the authors found the evidence of bidirectional causality between economic growth and the non-renewable energy; however, only a unidirectional causality between economic growth and renewable energy is documented. Bhattacharya et al. (2016) found that out of 38 top renewable energy-consuming countries, REC has a significant positive impact on the economic output for 57% of our selected countries. Ozturk and Bilgili (2015) found the direct impact of biomass consumption on GDP growth for 51 sub-Saharan African countries during 1980–2009 in a heterogeneous panel framework. Dogan (2015) found that REC has an insignificant impact on economic growth while NREC has a significant positive effect on it in case of Turkey. Examining the data for 12 European economies over the period 1990–2014, Saad and Taleb (2018) reported the evidence of unidirectional causality from economic growth to REC in the short run and feedback hypothesis is found in long run.

### $CO_2$ emissions and renewable energy consumption

The causal connection between $CO_2$ emissions and total energy consumption in general and REC in particular has been examined scantly in the field of energy economics. Initially, Sadorsky (2009a) documented that a 1% increase in real GDP per person increases per capita REC by 8.44%, while a 1% increase in $CO_2$ per person increases per capita REC by 5.23% in case of G7 countries. Investigating the USA economy over the period 1960–2009, Menyah and Wolde-Rufael (2010) reported the absence of causality from REC to $CO_2$ emissions; however, a feedback causality is observed between nuclear energy consumption and $CO_2$ emissions. Examining the data from 1984 to 2007, Apergis et al. (2010) found that in the long run, nuclear energy affects the emissions negatively and emissions affect REC positively in case of a mixed panel of 19 countries. Following the structural vector autoregressive (SVAR) approach, Silva et al. (2012) found that renewable energy sources on electricity generation affects the $CO_2$ emissions negatively in case of four countries during 1960–2004. Analyzing the data of OECD countries over the period 1980–2011, Shafiei and Salim (2014) document that NREC increases $CO_2$ emissions whereas REC decreases them. The study also highlighted the existence of environmental Kuznets curve (EKC) between $CO_2$ emissions and urbanization. In a panel cointegration and error correction setup, Apergis and Payne (2014) found the evidence of feedback relationship between REC and economic growth and between REC and $CO_2$ emissions in case of 25 OECD countries. Using a panel Granger causality framework, Zeb et al. (2014) documented the evidence of neutrality hypothesis between electricity production from renewables, $CO_2$ emissions, natural resource depletion, GDP, and poverty in case of five SAARC countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) during 1975–2010. However, the evidence of growth hypothesis is found when FMOLS approach was used. More recently, Apergis and Payne (2015) found the statistically positive impact of REC on output growth and statistically negative impact on $CO_2$ emissions in case of 11 South American countries. The study also reported the case of feedback causality among the variables. Dogan and Seker (2016a, b) also found that $CO_2$ emissions are negatively impacted by REC along with trade-openness and financial development; however, NREC increases the emissions. Here again, the case of bidirectional causality is reported between REC and $CO_2$ emissions and EKC is also validated. Similarly, Paramati et al. (2017) found that REC affects the economic output positively and has a negative impact on $CO_2$ emissions during 1990–2012 for the next 11 developing economies.

From the above surveyed literature, it can be asserted that the scholars have considered various geographical locations, different sets of explanatory variables, and different data periods. However, the evidence reported about the nature of relationship between economic growth and REC on the one hand and that of $CO_2$ and REC on the other remained scanty and largely inconclusive. Although, Brazil, Russia, India, China, and South Africa have been included (in one's or two's) in the earlier studies, but except for Sebri and Ben-Salha (2014), no other study has examined the case of BRICS countries as a separate panel. Recognized as the major emerging national economies[10] and due to their significant influence on regional affairs, the analysis of BRICS countries related to the influence of NREC and REC on the economic growth and environmental impact is highly warranted. Secondly, the econometric methodology has largely remained confined to OLS, DOLS, and FMOLS to measure the long-run elasticity of respective coefficients. The application of additional methodologies like PMG and panel GMM would check the sensitivity of established results of the various studies and to ensure the robustness.

## Analytical framework

The paper tried to explore the influence of REC and NREC on the economic growth and $CO_2$ emissions, across BRICS countries. To serve the purpose, the study followed the existing literature and applied the neoclassical growth model specification and IPAT-derived environmental model (Ehrlich and Holdren 1971), respectively. Regarding the influence on growth dynamics of an economy, the energy as a separate input factor in the production function has been denied the importance owing to its lower share in the overall cost structure of the economy compared to other

[10] In 2015, the combined nominal GDP of BRICS countries equals around US$16.6 trillion, equivalent to approximately 22% of the gross world product.

inputs like labor and capital (Ghali and El-Sakka 2004; Lee et al. 2008). However, Moroney's[11] Moroney (1992) assertion, recognized in the recent times, made the research fraternity to review its perception about the role of energy in the production process, and it is being treated now at par with other factor inputs. Subsequently, a plethora of studies have included energy input as an additional factor of production process and analyzed its importance in explaining the growth performance of an economy (Beaudreau 2005; Ghali and El-Sakka 2004; lee and Chang 2008; Lee et al. 2008; Narayan and Smyth 2008; Oh and Lee 2004; Sari and Soytas 2007; Soytas and Sari 2006; Stern 2000; Yuan et al. 2008; Wolde-Rufael 2009; Paramati et al. 2017). Following these studies, the paper examined the impact of renewable and non-renewable energy consumption on the economic growth in a neo-classical aggregate production framework as:

$$Q_{it} = f(K_{it}, N_{it}, REC_{it}, NREC_{it}) \quad (1)$$

where $Q$ denotes economic output; $K$—capital stock; $N$—labor employment; $REC$—renewable energy consumption; and $NREC$—non-renewable energy consumption, respectively. The subscripts $i$ and $t$ indicate the country ($i = 1, 2, 3, 4\ldots N$) and time period ($t = 1, 2, 3, 4\ldots T$) of the panel. The estimable linear log form of Eq. 1 can be derived as:

$$LQ_{it} = \theta_0 + \theta_1 LK_{it} + \theta_2 LN_{it} + \theta_3 LREC_{it} + \theta_4 LNREC_{it} + \mu_{it} \quad (2)$$

The $\theta' s$ as usual refer to the elasticity coefficients of respective inputs.

Similarly, to analyze the impact of human activities on environment proxied by $CO_2$ emissions, IPAT identity has been applied quite comprehensively (Stern 1992; Harrison and Pearce 2000; York et al. 2002; Shafiei and Salim 2014; Paramati et al. 2017). Originally, the identity was introduced by Ehrlich and Holdren (1971) and Holdren and Ehrlich (1974) as a multiplicative product of environmental impact ($I$), population ($P$), income ($A$), and technology ($T$) as:

$$I = P \times A \times T \quad (3)$$

The obvious advantage of the identity three is that it assigns parsimoniously the mathematical relationship between key driving forces and environmental impact (Dietz and Rosa 1997; York et al. 2003). In order to gain some additional insights, Waggoner and Ausubel (2002) extends it to ImPACT (by segregating $T$ into consumption per unit of GDP ($C$) and impact per unit of consumption ($T$)) and Schulze (2002) to I=PBAT (by adding the behavior factor $(B)$[12]). Despite being parsimonious, non-rigid and lucid in indicating the effects of key driving forces on the environment, IPAT and ImPACT are criticized for the assumption of proportionality between the key determinants and no allowance for non-monotonic or non-proportional impact of the driving forces (York et al. 2003).

To do away with these limitations, Dietz and Rosa (1994, 1997) developed a stochastic version of the basic model commonly known in the literature as STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology). It is no longer an identity and is even more flexible to allow for non-proportional options as well. The basic representation of a STIRPAT model is given by:

$$I_i = \delta P_i^{\alpha} A_i^{\beta} T_i^{\gamma} \varepsilon_i \quad (4)$$

Taking logarithm of Eq. 4, we get:

$$Ln\ I_{it} = Ln\ \delta + \alpha\ Ln\ (P_{it}) + \beta\ Ln\ (A_{it}) + \gamma\ Ln\ (T_{it}) + Ln\ \varepsilon_{it} \quad (5)$$

where $\delta$ is a constant; $\alpha$, $\beta$, and $\gamma$ represent the elasticity coefficients of $P$, $A$, and $T$, respectively; $\varepsilon$ is error term, $t$ represent time, and $i$ is the cross-sectional unit. Following York et al. (2003), additional terms can be entered into the basic STIRPAT model in the form of segregated components of technology term ($T$). Since $T$ denotes the environmental impact per unit of economic activity, it is decomposed into two components which highlight the difference in the economic structure of each country according to the type of energy consumed, i.e., renewable and non-renewable energy. Following Shafiei and Salim (2014) and Paramati et al. (2017), the estimable equation which portrays the impact of REC and NREC on the environmental impact, proxied by $CO_2$ emissions, along with population and affluence (economic activity or GDP per capita) is as follows:

$$Ln\ I_{it} = Ln\ \delta + \alpha\ Ln\ (P_{it}) + \beta\ Ln\ (A_{it}) + \gamma\ Ln\ (REC_{it}) + \sigma\ Ln\ NREC_{it} + Ln\ \varepsilon_{it} \quad (6)$$

Here again, $I$, $P$, $REC$, and $NREC$ denote the environmental impact ($CO_2$ emissions), population size, GDP per capita, renewable consumption, and non-renewable energy consumption, respectively. $\varepsilon$, $t$, and $i$ have the same meanings described in Eq. 5.

[11] Moroney (1992: 337) rightly argues: "It is one thing to correctly cite energy's small cost share in GNP, but an error to conclude, on this account, that energy plays a secondary role. Its role is primary, coequal with capital formation."

[12] Diesendorf (2002) and Roca (2002), however, criticized the inclusion of behavior factor ($B$) on account of its existing representation in each term on the right hand side of Eq. 3 and difficulty in quantification.

## Econometric methodology

### Data

Data used in the study is related to five major emerging economies of the world namely Brazil, Russia, China, India, and South Africa. The study employs a panel data set with an annual frequency over the period 1992–2012 (25 observations per cross-sectional unit). The name of the variables used in empirical exercise, their description, units of measurement, and the data source is given in Table 1. As can be observed from Table 1, the units of measurement vary across variables, like the economic growth (*Q*), capital (*K*), and per-capita income (*A*) are measured in constant 2010 US$, labor (*N*) and population (*P*) in numbers, renewable energy consumption (*REC*) in Terajoules (Tj), non-renewable energy consumption (*NREC*) in Quadrillion British thermal Units (Qd. Btu), and carbon dioxide emissions (*I*) in million metric tons (MMT); it would therefore be imperative to convert them into a uniform scale of measurement before proceeding for empirical analysis. Following previous studies (Bhattacharya et al. 2016; Paramati et al. 2017), all the variables are converted into natural logarithms in order to overcome the problems associated with distributional properties of data series and, more importantly, to interpret the estimated coefficients in terms of elasticities.

### Panel heterogeneity and cross-sectional dependence

From Fig. 4, it can be observed that the countries to be analyzed in the study portray a different pattern of their GDP growth performance and, therefore, provide an indication of inherent heterogeneity of individual cross-sectional units. The average annual growth rate of Brazil, Russia, India, China, and South Africa over the period 1992–2016 is reported to be 2.54, 1.06, 6.85, 9.87, and 2.62, respectively. In addition, the cross-sectional units differ in terms of their rate of capital formation, population growth rate, REC, and NREC.

Due to the appreciable economic and financial integration of economies, cross-sectional dependence across the BRICS countries will be an important issue to account for. These economies are interconnected through common global shocks[13] (like the Asian financial crisis, global recession, trade relations, energy, fiscal and monetary policies), having a contagious effect on one another. Disregarding the cross-sectional dependence among the panel members is believed to lead to severe fallacies like biased results of standard unit root tests and loss of estimation efficiency.[14] However, if accounted, it will allow the estimation of unobserved common factors that otherwise is not feasible in a single equation time series framework.

To test whether cross-sectional dependence is present in the BRICS panel, the study applied Lagrange multiplier (LM) test, developed by Breusch and Pagan (1980), since the test performs better in case of panels featured with $T > N$. However, to augment the results of LM test, Pesaran (2004) cross-sectional dependence (CD) test is also applied.[15] As can be seen from Table 2, null of cross-sectional independence is rejected for all the variables incorporated into the analysis.

### Unit root tests analysis

To understand the stationarity properties of variables under investigation, the study applied a battery of panel unit root tests.[16] Levin et al. (2002) developed a panel ADF test (LLC), assuming homogeneity in the dynamics of autoregressive coefficients for all the panel units. On the contrary, Im et al. (2003) test (IPS) allows for the heterogeneity in the dynamics of the autoregressive coefficients for all the panel units. The non-parametric unit root tests of Maddala and Wu (1999) which combine the *p* values from the individual unit root tests are also applied using Fisher-ADF and Fisher-PP tests. These tests also allow for panel heterogeneity. Null of non-stationarity is tested again—an alternative of stationary series in case of all the above tests.

Applying the suitable functional forms of the unit root tests, Table 3 shows that all the variables are I (1) at levels and I (0) at the first differences except few cases like N is stationary at the level according to Fisher ADF and PP tests and I is stationary at level according to LLC test.

### Panel cointegration tests

Having confirmed that all the variables are integrated of order one, the study proceeded to test for the presence of long-run cointegration relationship among them. Pedroni (1999, 2004) residual-based heterogeneous panel cointegration test, which allows for cross-section interdependence with different individual effects, is estimated to serve the purpose. The choice is motivated by the heterogeneous nature of BRICS panel. To test the null of no cointegration, Pedroni (1999, 2004) develops seven test statistics with first four

[13] Technically cross-sectional dependence may arise due presence of common shocks and unobserved components that ultimately become part of the error term, spatial dependence, and idiosyncratic pairwise dependence in the disturbances with no particular pattern of common components or spatial dependence (De Hoyos and Sarafidis 2006).

[14] if there is sufficient cross-sectional dependence in the data and this is ignored in estimation, the decrease in estimation efficiency can become so large that, in fact, the pooled (panel) least-square estimator may provide little gain over the single-equation ordinary least squares (Phillips and Sul, 2003).

[15] The test is usually applied where $T < N$, a panel situation where the LM test statistic enjoys no desirable statistical properties in that it exhibits substantial size distortions (Pesaran 2004). In addition, the test can be applied in both balanced and unbalanced panels.

[16] To conserve space, the details of the panel unit root and stationarity tests have been omitted.

**Table 1** Variable description

| | Symbol | Description | Units | Source |
|---|---|---|---|---|
| Economic growth | Q | Gross-domestic product at market prices | Constant 2010 US$ | WDI |
| Capital | K | Gross fixed capital formation | Constant 2010 US$ | WDI |
| Labor | N | Total working population who are aged 15 and above | | WDI |
| Population | P | Total population, regardless of legal status or citizenship | | WDI |
| Per-capita income | A | Gross domestic product per head of population | Constant 2010 US$ | WDI |
| Renewable energy | REC | Sum of hydro, modern and traditional biomass, wind, solar, liquid biofuels, biogas, geothermal, marine, and waste resource | Terajoule (Tj) | SEFA/WB |
| Non-renewable energy | NREC | Sum of coal, gas, and petroleum | Quadrillion Btu (Qd. Btu) | US-EIA |
| Carbon dioxide emissions ($CO_2$) | I | Total carbon dioxide emissions from the consumption of energy | Million metric tons (MMT) | US-EIA |

*WDI* world Development Indicators, *SEFA/WB* Sustainable Energy for All published by World Bank, *US-EIA* United States Energy Information Agency

(panel $v$ statistic, panel $\rho$ statistic, panel PP statistic (nonparametric), and panel ADF statistic (parametric)) are known as *within-dimension* panel cointegration tests[17] and the other three (group $\rho$ statistic, group PP statistic (nonparametric), and group ADF statistic (parametric)) as group mean panel cointegration,[18] *between-dimension*, tests. All the seven statistics are distributed asymptotically as standard normal. Of these seven tests, with the exception of $v$ statistic, all the remaining six are left-sided tests where large negative values reject the null of no cointegration.[19] To authenticate the results of Pedroni (1999, 2004) tests, Kao (1999) and Fisher-type cointegration tests, developed by Maddala and Wu (1999), were also applied.

Table 4 reports that out of seven test statistics, as incorporated in Pedroni (1999, 2004), the evidence of cointegration is found in five out of seven tests, when the cointegration is examined among $Q$, $K$, $N$, $REC$, and $NREC$. Similarly, Table 5 reports that null of no cointegration is rejected in case of four out of seven tests, when variables like $I$, $P$, $A$, $REC$, and $NREC$ were tested for cointegration. The results Kao (1999), as shown in lower panels of both the tables, again validate the existence of cointegration among two sets of variables. The cointegration test results of Maddala and Wu (1999) also corroborate the results of Pedroni (1999, 2004) and Kao (1999). However, the results are not reported to save the space. Thus, it can be concluded that there exists a long-run cointegration relationship among the variables.

## Long-run elasticity coefficients

Equations 2 and 6 are estimated by applying the dynamic panel techniques namely *Pooled Mean Group* estimation (PMG) developed by Pesaran and Smith, 1995; Pesaran et al., 1999) and *differenced panel* GMM (generalized method of moments) developed by Arellano and Bond (1991).

The PMG estimator, basically an extension of ARDL (Autoregressive Distributed Lag) model to the panel data, has the advantage of taking care of panel heterogeneity by allowing the short-run coefficients to vary across the cross-sectional units along with intercepts and error variances. However, it restricts the long-run coefficients to be equal across cross sections.[20] In addition, the PMG estimator portrays the dynamic adjustment from any short-period deviation towards the long-run cointegrating association. The dynamic specifications of the different cross-sectional units are permitted to vary with differences in error correction terms due to the heterogeneity of short-run coefficients. Using the lags of various variables in the error correction specification, the estimator also takes care of possible endogeneity. The error correction specification of a PMG model is given by:

[17] In these test statistics, autoregressive coefficients are pooled across different countries to check for the stationarity or otherwise of estimated residuals by taking cognizance of common time factors and heterogeneity of cross sections.
[18] These statistics are based on averages of the individual autoregressive coefficients associated with the unit root tests of the residuals for each country in the panel.
[19] Conversely, the large positive values reject the null of no cointegration in case of $v$ test. For further details, refer to Pedroni (1999, 2004).

[20] There are three dynamic estimators of this family available in the literature like dynamic fixed effects (DFE), mean group (MG) given by Pesaran and Smith (1995), and Pooled Mean Group (PMG) developed by Pesaran and Smith, 1995, Pesaran et al., 1999. The first one completely avoids the heterogeneity and only intercepts, and error variances are allowed to vary. In the second one, intercepts, slope coefficients (both short and long run), and error variances are allowed to vary. And finally, PMG estimator allows the intercepts, error variances, and short-run slope coefficients to vary across groups; however, the long-run parameters are assumed to be the same. The choice for the appropriate estimator is decided by the Hausman 1978 test. As reported in Tables 5 and 7, Hausman test favors the null of "difference in long-run coefficients not systematic," and hence, PMG is applied in both the cases of economic growth and $CO_2$ emission analysis.
[0] If $\varphi_i = 0$, then there is an evidence of no cointegration.

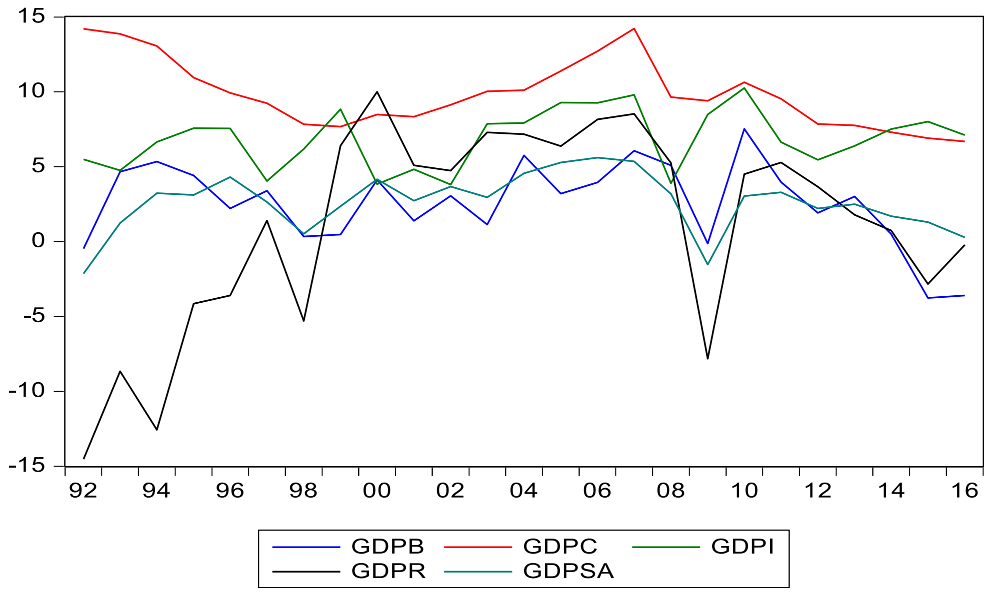


**Fig. 4** GDP growth rates of BRICS countries

$$\Delta y_{it} = \varphi_i \left( y_{i,t-1} - \omega_i^{'} x_{i,t-1} \right) + \sum_{j=0}^{m-1} \partial_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=0}^{n-1} \rho_{ij}^{'*} \Delta x_{i,t-j} + \varnothing_i + \pi_{it} \quad (7)$$

Here, $y$ represents the dependent variable ($Q$ and $I$, respectively), $\left( y_{i,t-1} - \omega_i^{'} x_{i,t-1} \right)$ portrays the magnitude of deviation from the long-run equilibrium relationship, at any period $t = 2,3 \ldots T$, for any cross-sectional unit $i = 1,2,3, \ldots N$. $\varphi_i$ is the associated error correcting speed of adjustment term. This coefficient is assumed to be significantly negative under a prior expectation of a long-run association.[21] The vector $\omega_i^{'}$ constitutes the long-run elasticity coefficients of respective dependent variables with respect to each respective regressors denoted by $x_{i,\ t-1}$. Vector $\rho$ denote the short-run coefficients; $\varnothing_i$ is an unobserved time invariant country-specific effect; and finally, $\pi_{it}$ is an observation-specific error term. The PMG estimator is quite appealing when studying small sets of countries rather than large diverse macro panels.

The dynamic panel GMM methodology enables to exploit the dynamic specification of the data by employing the suitable lag length of instrumented variables to develop the internal instruments and also incorporates the pooled attribute of the underlying panel. The methodology adopted in this paper, known as Arellano and Bond (1991) difference GMM estimator, first proposed by Holtz-Eakin et al. (1988), has several additional advantages, which makes it more suitable for the dynamic panel data analysis.[22] The difference GMM avoids the problem of endogeneity by making use of appropriate instruments of (both pure exogenous and lagged endogenous) endogenous variables and also eliminates the possibility of likely association between time-invarying country characteristics and explanatory variables (Mileva 2007). This panel econometric technique eliminates the problem of autocorrelation by instrumenting the lagged autoregressive term with its suitable past levels. In addition, Sarafidis and Robertson (2009) mentioned that if there exist a cross-sectional dependence among the panel members, all estimators that rely on instrumental variables (2SLS) and GMM like those by Anderson and Hsiao (1981), Arellano and Bond (1991) and Blundell and Bond (1998) tend to give the inconsistent estimates in case $N$ grows sufficiently large for a fixed $T$. Since $N$ is relatively lower in this study, the use of Arellano and Bond (1991) in presence of cross-sectional dependence as reported in Table 2 is justified. However, this methodology has the limitation of assuming slope homogeneity and allowing only the intercept terms to vary. The basic formulation of first differenced panel GMM is given as follows:

$$\Delta y_{i,t-1} = \tau \Delta y_{i,t-1} + \vartheta \Delta x_{it} + \varnothing_i + \epsilon_{it}; i = 1, 2, 3, \ldots N; t = 2, 3, \ldots T \quad (8)$$

where $\Delta y$ is the first differenced dependent variable; $\Delta$x is a first differenced vector of explanatory variables used in Eqs. 2 and 6. $\varnothing_i$ is an unobserved time invariant country-specific effect, and finally, $\epsilon_{it}$ is an observation-specific error term.

[21] If $\varphi_i = 0$, then there is an evidence of no cointegration.

[22] There are two versions of panel GMM—first differenced and system GMM. The first differenced GMM uses the entire data in first differences in a single equation framework. However, system GMM uses the level equation to obtain a system of two equations: one differenced and one in levels. By adding the second equation, additional instruments can be obtained. Because system GMM uses more instruments than the difference GMM (to gain more efficiency), it may not be appropriate to use system GMM with a data set with a small number of countries, which in this study is only 5. So difference GMM is applied instead of system GMM.

**Table 2** Test for cross-sectional Dependence

| | Variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *Q* | *K* | *N* | *REC* | *NREC* | *P* | *A* | *I* |
| BP-LM test | 229.12* | 187.67* | 195.72* | 165.26* | 120.31* | 229.06* | 225.80* | 134.43* |
| *P* value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Pesaran CD | 15.12* | 13.54* | 13.79* | 5.47* | 9.08* | 3.78* | 15.01* | 10.71* |
| *P* value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Indicates the rejection of null of cross-sectional independence at 1% level of significance

## Results and discussion

### Economic growth and energy consumption

Table 6 portrays the long-run impact of *K*, *N*, *NREC*, and *REC* on the *Q* using the PMG estimation procedure. It can be observed that capital (*K*) and labor (*N*) followed the standard route of being the principle factor inputs to enhance the growth/output (*Q*) performance of an economy. One percent increase in *K* and *N* leads to 0.23% and 0.46% increase in economic growth, respectively. Regarding the impact of non-renewable energy, it is observed that a 1% increase in *NREC* increases *Q* by a magnitude of about 0.14%. These findings are in line with those of Apergis and Payne (2011a), Bhattacharya et al. (2016), and Paramati et al. (2017) etc. Thus, *NREC* like *K* and *N* played an important role in increasing the economic output of BRICS economies.

The impact of renewable energy consumption on the economic growth is found be positive but statistically insignificant. The finding is opposite to those of Apergis and Payne (2011b) and Paramati et al. (2017). While it is beyond the scope of present study to elucidate the underlying causes for the insignificance of renewable energy as a potential determinant of economic growth in BRICS countries, however, some suggestive reasons are outlined as follows.

Firstly, the examined countries have been unable to make an effective and appreciable use of renewable energy sources in enhancing their growth performance (Bhattacharya et al. 2016). Secondly, the share of renewable energy consumption in the overall energy mix is low relative to conventional energy consumption.[23] This may in turn lead to slow deployment process with no significant impact on growth performance (Bhattacharya et al. 2016). The appreciable use of renewable energy requires substantial research and development (R&D) investments to ensure the proper learning of the new technology (Sims 2004); however, a significant reduction in R&D investment levels have been observed in a number of

**Table 3** Panel unit root tests (1992–2016)

| Variables | Panel test | Levels | First differences |
|---|---|---|---|
| *Q* | LLC | − 0.18 | − 3.54* |
| | IPS | 2.63 | − 3.35* |
| | Fisher-ADF | 3.33 | 28.77* |
| | Fisher-PP | 3.87 | 28.46* |
| *K* | LLC | − 0.45 | − 5.07* |
| | IPS | − 1.54 | − 3.85* |
| | Fisher-ADF | 17.57 | 35.48* |
| | Fisher-PP | 13.41 | 38.56* |
| *N* | LLC | − 0.24 | − 1.96** |
| | IPS | 2.21 | − 2.04** |
| | Fisher-ADF | 40.61* | – |
| | Fisher-PP | 35.36* | – |
| *NRE* | LLC | 1.66 | − 3.69* |
| | IPS | 0.79 | − 4.51* |
| | Fisher-ADF | 10.48 | 39.29* |
| | Fisher-PP | 5.80 | 38.87* |
| *RE* | LLC | 1.25 | − 6.20* |
| | IPS | 2.52 | − 5.87* |
| | Fisher-ADF | 5.04 | 46.86* |
| | Fisher-PP | 4.70 | 45.85* |
| *P* | LLC | 2.82 | − 6.03* |
| | IPS | 0.25 | − 1.54*** |
| | Fisher-ADF | 1.17 | 42.17* |
| | Fisher-PP | 3.86 | 74.26* |
| *A* | LLC | 0.64 | − 3.59* |
| | IPS | − 0.11 | − 2.18* |
| | Fisher-ADF | 10.35 | 20.58* |
| | Fisher-PP | 6.04 | 19.86* |
| *I* | LLC | − 1.88 | – |
| | IPS | − 0.27 | − 2.14** |
| | Fisher-ADF | 8.96 | 24.39* |
| | Fisher-PP | 8.67 | 35.28* |

*, **, and *** denote the rejection of null of non-stationary against an alternative of stationary at 1, 5, and 10% level of significance

[23] "The Indian energy sector is predominantly coal-based (69%), with 5% non-hydro renewables and 12% hydropower. Financing and coordination between renewable resource–rich states (Tamil Nadu, Gujarat, and Rajasthan) and the rest of the country are major challenges for grid-integration purposes," Bhattacharya et al. 2016. Similarly, Brazil, Russia, and South Africa are also underdeveloped so far as the relative percentage of REC in total energy consumption is concerned. However, china has been moving quite increasingly towards renewable energy adoption. Since China was home to more than one-quarter of the world's renewable power capacity in 2016 (REN21 2017).

**Table 4** Panel cointegration tests (*Q*, *K*, *N*, *REC*, and *NREC*)

a. Pedroni test

| | Statistic | Prob. | Weighted Statistic | Prob. |
|---|---|---|---|---|
| Alternative hypothesis: common AR coefs. (within-dimension) | | | | |
| Panel $v$ statistic | 4.68 | 0.02** | 5.48 | 0.00* |
| Panel $\rho$ statistic | 2.22 | 0.98 | 1.81 | 0.96 |
| Panel PP statistic | − 6.53 | 0.00* | − 8.38 | 0.00* |
| Panel ADF statistic | − 5.85 | 0.00* | − 7.33 | 0.00* |
| | Statistic | Prob. | | |
| Alternative hypothesis: individual AR coefs. (between-dimension) | | | | |
| Group $\rho$ statistic | 2.73 | 0.99 | | |
| Group PP statistic | − 7.71 | 0.00* | | |
| Group ADF statistic | − 8.15 | 0.00* | | |
| b. Kao test | | | | |
| | | $t$ statistic | Prob. | |
| ADF | | − 1.66 | 0.04** | |

* and ** denote rejection of null of no cointegration at 1% and 5% level of significance

developed and emerging economies (Nemant and Kammen 2007; REN21 2017). From 2015 to 2016, the total world investment in renewable power and fuels has decreased by 23% from 312 billion USD to 247 billion USD (REN21 2017). In 2016, China's investment in renewables is down by 32% compared to 2015 (lowest since 2013), Brazil also witnessed lower investment levels compared to 2015, South Africa saw investment fall up to 75% compared to 2015, and India witnessed a more or less stable investment level of 9.7 billion USD (REN21 2017).

The development of renewable energy sector has not explored largely due to restricted size of domestic markets for the new technology in the infancy stages of the development in developing countries (Jäger-Waldau, 2007; Lewis and Wiser 2007). In addition, the fall in price of alternative energy sources like natural gas has also contributed to the reduced attention towards renewable energy (Martinot et al., 2005). Further, there is a need for strongly incentivizing the renewable energy exploration, however, which is very dismal in most countries (International Energy Agency, 2009a). The recent financial crisis of 2007–2008 has also affected the renewable energy sector very badly by lowering the investment levels (IEA 2009a, REN21 2017). Moreover, the technological standards and availability of required fuels for renewable energy is lacking along with uncertainties about the rates at which particular investment cost of renewables could be reduced (De Vries et al. 2007).

The short-run results portrays the positive and significant impact of *K* and *NREC* and the insignificance of *REC* and *N* on economic output.[24] In addition, the error correction term is both negative and statistically significant at 1% significance level, validating again the already established result of the existence of a long-run cointegration relationship between *Q* and *K*, *N*, *REC*, and *NREC*. The speed of adjustment to disequilibrium is about − 0.45%/year which is equal to adjustment towards equilibrium time period of about 2.22 years.[25]

In order to ensure the accuracy of the results reported via PMG estimation, the study applied the differenced panel GMM Arellano–Bond estimations. The results documented in Table 7 highlight that the impact of all the four explanatory variables on *Q* is completely consistent with the estimated results of PMG estimator. Though relative to PMG estimators, the magnitudes are different, but between the coefficients themselves, the relative impact of *N* is again higher than *K* and that of *NREC* is positive and significant unlike that of *REC*. The Sargan test accepted the null of strong instruments and Arellano–Bond AR (2) test accepted the null of no autocorrelation, respectively.[26] In addition, to ensure the precision of Sargan test, the stability condition of keeping the number of instruments less or equal to number of groups is also satisfied.[27]

[24] The sign of *N* changed from positive to negative, and this may be due to diminishing returns to variable factor which in the short-run is labor.

[25] Calculated as the inverse of the absolute value of the error correction term (ECT), (Apergis et al. 2010)

[26] The test for AR (1) process, however, in first differences usually rejects the null hypothesis of no autocorrelation (Mileva 2007).

[27] In this case, five instruments were used.

**Table 5** Panel cointegration tests (*I*, *A*, *P*, *REC*, and *NREC*)

| a. Pedroni test | | | | |
|---|---|---|---|---|
| | Statistic | Prob. | *W* statistic | Prob. |
| Alternative hypothesis: common AR coefs. (within-dimension) | | | | |
| Panel *v* statistic | 1.38 | 0.08 | − 2.43 | 0.99 |
| Panel *ρ* statistic | 0.08 | 0.53 | 0.44 | 0.67 |
| Panel PP statistic | − 3.92 | 0.00* | − 6.19 | 0.00* |
| Panel ADF statistic | − 4.28 | 0.00* | − 4.70 | 0.00* |
| | Statistic | Prob. | | |
| Alternative hypothesis: individual AR coefs. (between-dimension) | | | | |
| Group *ρ* statistic | 1.04 | 0.85 | | |
| Group PP statistic | − 8.00 | 0.00* | | |
| Group ADF statistic | − 4.76 | 0.00* | | |
| | | *t* statistic | Prob. | |
| ADF | | − 2.87 | 0.00* | |

*Denotes rejection of null of no cointegration at 1% level of significance

## $CO_2$ emissions and energy consumption

Table 8 portrays the impact of *A*, *P*, *NREC*, and *REC* on the $CO_2$ emissions using the PMG estimation procedure. The coefficients are found statistically significant and theoretically plausible. Both *P* and *A* affect the $CO_2$ emissions positively; however, the estimated influence of population is found to be greater than that of per-capita GDP. Therefore, a 1% increase in both *P* and *A* in the long run will lead to more emissions from the former than due to the hike in later. This finding is in conformity with many other studies like those of Fan et al. (2006), Poumanyvong and Kaneko (2010), Liddle (2011), and Shafiei and Salim (2014). The more sensitivity of environmental impact to the changes in population growth than to changes in per-capita incomes in the long run occurs mainly due to accelerated consumption of energy and, hence, appreciable pollutant emissions (Liddle 2011). With respect to the possible influence of renewable and non-renewable energy consumption, it can be seen from Table 8 REC has a negative and statistically significant impact on $CO_2$ emissions,

**Table 6** Error correction model-2 (PMG estimations, 1992–2016)

| Dependent variable: *D*(*Q*) | | | |
|---|---|---|---|
| Selected model: ARDL (3,1,1,1,1) | | | |
| Long-run equation | | | |
| Variables | Coeff. | Std. | Prob. |
| *K* | 0.23 | 0.04 | 0.00* |
| *N* | 0.46 | 0.24 | 0.05*** |
| *NREC* | 0.14 | 0.08 | 0.07*** |
| *REC* | 0.10 | 0.07 | 0.14 |
| Short-run equation | | | |
| Error correction | − 0.45 | 0.08 | 0.00* |
| *D*(*Q*(− 1)) | 0.05 | 0.10 | 0.59 |
| *D*(*Q*(− 2)) | − 0.04 | 0.10 | 0.65 |
| *D*(*K*) | 0.10 | 0.05 | 0.08*** |
| *D*(*N*) | − 1.81 | 1.71 | 0.29 |
| *D*(*NREC*) | 0.01 | 0.03 | 0.00* |
| *D*(*REC*) | 0.23 | 0.28 | 0.40 |
| Constant | 4.97 | 0.99 | 0.00* |
| Trend | 0.00 | 0.00 | 0.01** |
| Obs. | 110 | | |
| Log likelihood | 368.79 | | |
| JB statistics | 5.19 (0.07) | | |
| Hausman test | [dfe vs. pmg] | [mg vs. pmg] | |
| | 1.29 (0.86) | 0.67 (0.90) | |

*p* values and any subsequent tests do not account for model selection. *, **, and *** denote statistical significance of respective coefficients at 1, 5, and 10% level

**Table 7** Differenced panel GMM Arellano–Bond estimations

| Dependent variable: *Q* | | | |
|---|---|---|---|
| Long-run equation | | | |
| Variables | Coeff. | Std. | Prob. |
| *Q*(− 1) | 0.79 | 0.03 | 0.00* |
| *K* | 0.11 | 0.02 | 0.00* |
| *N* | 0.21 | 0.03 | 0.00* |
| *NREC* | 0.06 | 0.02 | 0.00* |
| *REC* | 0.20 | 0.22 | 0.76 |
| Obs. | 115 | | |
| F(5, 110) | 10,074.55 (0.00*) | | |
| AR(2) test | − 0.76 (0.44) | | |
| Sargan test | 1.27 (0.94) | | |

*p* values and any subsequent tests do not account for model selection. * denotes significance at 1% significance level

**Table 8** Error correction model-1 (PMG estimations, 1992–2016)

| | | | |
|---|---|---|---|
| Dependent variable: *D*(*I*) | | | |
| Selected model: ARDL (2,1,1,1,1) | | | |
| Long-run equation | | | |
| Variables | Coeff. | Std. | Prob. |
| *A* | 0.55 | 0.08 | 0.00* |
| *P* | 1.97 | 0.37 | 0.00* |
| *NREC* | 0.91 | 0.05 | 0.00* |
| *REC* | − 0.12 | 0.06 | 0.04** |
| Short-run equation | | | |
| Error correction | − 0.90 | 0.31 | 0.00* |
| *D*(*I*(− 1)) | 0.01 | 0.10 | 0.90 |
| *D*(*A*) | − 0.26 | 0.14 | 0.06*** |
| *D*(*P*) | − 12.92 | 11.59 | 0.26 |
| *D*(*NREC*) | 0.22 | 0.22 | 0.32 |
| *D*(*REC*) | − 0.40 | 0.32 | 0.04** |
| Constant | − 33.30 | 11.10 | 0.00* |
| Trend | − 0.03 | 0.01 | 0.00* |
| Obs. | 115 | | |
| Log likelihood | 314.59 | | |
| JB statistic | 2.10 (0.35) | | |
| Hausman test | [dfe vs. pmg] 0.82 (0.93) | [mg vs. pmg] 8.14 (0.08) | |

*p* values and any subsequent tests do not account for model selection. *, **, and *** denote statistical significance of respective coefficients at 1, 5, and 10% level

implying that in the long run, a 1% hike in *REC* lowers the $CO_2$ emissions by around 0.12%. This finding is in conformity with Shafiei and Salim (2014) and Paramati et al. (2017) but, contrasts with Menyah and Wolde-Rufael (2010) and Apergis et al. (2010). NREC, on the other hand, affects the $CO_2$ emissions positively and 1% increase in former affects the latter by a magnitude of 0.91%. It can be observed that the positive impact of NREC is relatively more than the negative impact of REC, and this may be due to the infancy stage of renewable energy consumption and a substantial proportion of NREC in the overall energy consumption.

The short-run dynamics as shown in lower part of Table 8 again highlight the important role of REC in reducing the $CO_2$ emissions; also, although NREC reported a positive relationship with emissions, it lacks the statistical significance in short run. In addition, the error correction term is both negative and statistically significant at 1% significance level, validating the existence of a long-run cointegration relationship between $CO_2$ and *A*, *P*, *REC*, and *NREC*. The speed of adjustment to disequilibrium is about − 0.90%/year which is equal to adjustment towards equilibrium time period of about 1.1 years.

For the robustness purposes, here again, the study applied the differenced panel GMM Arellano–Bond estimation. The results documented in Table 9 highlight that PMG estimators are completely consistent with the estimated results of GMM

**Table 9** Differenced panel GMM Arellano–Bond estimations

| | | | |
|---|---|---|---|
| Dependent variable: *I* | | | |
| Long-run equation | | | |
| Variables | Coeff. | Std. | Prob. |
| *I*(− 1) | 0.19 | 0.04 | 0.00* |
| *A* | 0.02 | 0.18 | 0.25 |
| *P* | 0.15 | 0.05 | 0.00* |
| *NREC* | 0.82 | 0.03 | 0.00* |
| *REC* | − 0.13 | 0.03 | 0.00* |
| Obs. | 115 | | |
| F(5, 110) | 4375.04 (0.00*) | | |
| AR(2) test | 1.05 (0.29) | | |
| Sargan test | 3.63 (0.30) | | |

*p* values and any subsequent tests do not account for model selection. * denote statistical significance at 1% level of significance

estimator.[28] Though relative to PMG estimators, the magnitudes are different, but between the coefficients themselves, the relative impact of *P* is again higher than *A* and that of NREC is again higher than REC. The Sargan test accepted the null of strong instruments and Arellano–Bond AR (2) test accepted the null of no autocorrelation, respectively. In this case as well, the stability condition as required for precision of Sargan test is fulfilled.[29]

## Conclusion

Many countries across the globe have been confronting the problem of inadequate energy supplies to meet the growing energy demand, while at the same time struggle with the issues of environmental sustainability. Unless substantial policy initiatives are executed, world economy at large would be unsustainable—economically, environmentally, and socially. Increasing dependence on non-renewable energy sources, energy insecurity, and alarming climate change has mandated (forced) many countries across the globe to find alternative energy sources. Renewable energy sources have been recognized as the excellent substitute in the global energy consumption mix and a panacea for a sustainable energy future. Applying the robust unit root tests, heterogeneous cointegration, and long-run elasticity estimation methods in the case of BRICS (Brazil, Russia, China, India, and South Africa) countries for the period 1992–2016, the study investigated the relationship dynamics between renewable energy (REC) and economic growth and between

[28] Except for GDP per-capita, with an impact of only 0.02 (positive) but statistically insignificant

[29] In this case, as well, number of instruments used equals to the number of cross-sectional units involved in the analysis.

REC and carbon dioxide ($CO_2$) emissions along with other control variables including non-renewable energy (NREC).

Having detected the panel heterogeneity and cross-sectional dependence, the cointegration tests documented the evidence of a long-run association between economic growth (*Q*), capital (*K*), labor (*L*), *REC*, and *NREC* on the one hand and between $CO_2$ emissions (*I*), population (*P*), per-capita income (*A*), *REC*, and *NREC* on the other. In the long run, capital, labor, and non-renewable energy consumption are found to affect the economic growth positively. One percent increase in *K* and *N* leads to 0.23% and 0.46% increase in economic growth, respectively, and a 1% increase in NREC increases *Q* by a magnitude of about 0.14%. On the contrary, the impact of renewable energy consumption on the economic growth is found be positive but statistically insignificant. Though it is beyond the scope of present study to elucidate the insignificance of REC on the economic growth, however, the factors like insufficient implementation of renewable energy in the production process, lower share of REC in the overall energy mix, significant reduction in research and development investments needed for awareness and more exploration of renewables, restricted size of domestic markets for new technology, fall in the price of alternative energy sources like natural gas, inadequate incentivization towards renewable energy exploration, recent pull-back due to global financial crisis, lack of technological standards, unavailability of required fuels, and uncertainties about renewable investments might be the regarded as the compelling reasons.

Similarly, regarding the $CO_2$ emissions, both *P* and *A* affect positively; however, the estimated influence of population is found to be greater than that of per-capita income. One percent increase in both *P* and *A* in the long run will lead to more emissions from the former than due to the hike in later. With respect to the possible influence of renewable and non-renewable energy consumption, REC has a negative and statistically significant impact on $CO_2$ emissions, implying that in the long run, a 1% hike in REC lowers the $CO_2$ emissions by around 0.12%. NREC on the other hand affects the $CO_2$ emissions positively, and 1% increase in former affects the latter by a magnitude of 0.91%. The positive impact of NREC is relatively more than the negative impact of REC, and this may be due to the infancy stage of renewable energy consumption and a substantial proportion of NREC in the overall energy consumption. Finally, the speed of adjustment to disequilibrium is about − 0.45%/ year (equal to time period of about 2.22 years) in case of economic growth and about − 0.90%/year (equal to time period of about 1.1 years) in case of $CO_2$ emission.

The interdependence between renewable and non-renewable energy consumption and economic growth implies that both the sources constitute important ingredients of the growth trajectory of the examined economies. However, the two types of energy act contrarily when it comes to the question of carbon emissions. The presence of substitutability between renewable and non-renewable energy consumption tempts for the enhanced and effective use of government policies that are executed to enhance appreciably the renewable energy sector as well as explore the possibility of implementing carbon taxes to combat the use of non-renewable energy consumption and the associated $CO_2$ emissions. Therefore, BRICS countries should design and implement effective support policies like renewable energy production tax credits, installation rebates for renewable energy systems, renewable energy portfolio standards, and the creation of markets for renewable energy certificates to promote investment in renewable technology and increase the share of renewable energy in the overall energy mix, so that it reaches the threshold of being an effective contributor to both growth dynamics and environmental sustainability. Further, the regulation in the form of a carbon tax for reducing the emissions from the non-renewable energy consumption is also warranted. In addition, the substantial exploration of renewable energy sector may constitute an opportunity for the modernization of energy sector in order to abide with the objectives of sustainability as established by the policy makers across countries (Kaygusuz et al. 2007; Aspergis and Payne 2010a).

At the international level, as pointed out by Hirschl (2009), policy makers should design a multilateral mechanism to promote the renewable energy and ensure the energy efficiency across countries. Appropriate incentive measures for the development and market accessibility of renewable energy should be executed and implemented across the globe. Cooperation on the development of renewable energy markets between the public and private sector stakeholders in terms of on-going projects, technological advancements, and ways of financing the project investments would again constitute imperativeness for the substantial exploration of renewable energy sector.

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