Does ICT-Trade Openness ensure Energy and Environmental Sustainability? Empirical Evidence from selected South Asian Economies

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Abstract
Consumption of fossil fuels has triggered worldwide awareness to attain sustainability with respect to ensuring adequate energy access and mitigating environmental adversities, globally. Against this background, this paper aimed at investigating the impacts of enhancing ICT-trade openness on the transition from non-renewable to renewable energy use and carbon dioxide emissions in the context of six South Asian economies. The overall results from the econometric analyses confirm that greater openness to ICT-trade leads to greater consumption of renewable energy, reduces the intensity of energy-use and enhances the access to clean fuel and technology for cooking. However, although ICT trade is found to foster renewable energy consumption across South Asia, it fails to ensure renewable energy transition completely since greater openness to ICT-trade curbs the share of renewables in the aggregate energy consumption figures. Moreover, trade of ICT goods is found to reduce the levels of carbon emissions as well. Thus, these results impose key policy implications for the governments with respect to ensuring energy security alongside environmental sustainability across South Asia.

Keywords: ICT; renewable energy; non-renewable energy; carbon emissions; cross-sectional dependence
JEL classifications: O13; O14; P28; Q2; Q42

1. Introduction

Predominant dependence on the consumption of fossil fuels to source energy has eventually triggered worldwide awareness to attain sustainability with respect to ensuring adequate energy access and mitigating environmental adversities, globally. Combustion of these relatively environment-unfriendly Non-Renewable Energy (NRE) resources, has resulted in brisk exhaustion of their respective reserves, thus, jeopardizing the overall prospects of attaining energy security across the globe (Asif and Muneer 2007; Vivoda 2010). Besides, insufficient availability of the primary NRE sources has often compromised the reliability of secondary energy supplies, which has accounted for the global power generation volumes being below the corresponding installed capacities (Xue *et al.* 2014).

Apart from the gradual depletion of the NRE reserves, the aggravating energy demand worldwide has also had its toll on the global energy crises (Smil and Knowland 1980; Nematollahi *et al.* 2016). As a consequence, the underdeveloped economies, in particular, have obstinately been unable to match their respective demand for energy tapping their indigenous energy endowments. Thus, the need for enhancing the energy-use efficiency levels through the reduction in the intensities of energy employment has become a grueling concern for the energy planners worldwide (Herring 2006; Yang and Yu 2015).

On the other hand, NRE consumption had also played a stern role in the amplifying the pace of environment degradation (Omer 2008; Saboori and Sulaiman 2013). Environmental economists often allege the ignition of these resources to be responsible for stimulation of greenhouse emissions into the atmosphere which results in the exacerbation of the global temperatures and rapid meltdown of the glaciers (Hoel and Kverndokk 1996; Boden, Marland and Andres 2009). Hence, underscoring the necessity for countering and prolonging climate change worldwide, a transition from utilization of NRE to Renewable Energy (RE) resources is believed to be an effective strategy to decarbonize the global economy (Droge 2011; Murshed 2018). Furthermore, the gradual substitution of fossil fuels by renewable alternatives is also thought to complement the energy diversification policies of the energy-deficient economies across the world (Asif and Muneer 2007; Valentine 2011).

Therefore, taking the sustainability of the energy supply and the environment into cognizance, the United Nation (UN) has called out for international commitments to ensure greater access to affordable, reliable, sustainable and modern energy supplies worldwide[1]. The 7th Sustainable Development Goal (SDG) of the 2030 agenda of the United Nations specifically targets at substantially increasing the share of RE in the aggregate final energy consumption levels while simultaneously doubling the rates of energy-use efficiencies globally. However, attainment of these targets, especially from the perspective of the underdeveloped economies, is often impeded via multidimensional constraints, amongst which lack of technical know-how and technological backwardness are often acknowledged to be the major barriers to achieving the energy and environmental sustainability goals (Mirza *et al.* 2009; Urmee, Harries and Schlapfer 2009).

This is where trade of Information and Communications Technology (ICT) goods and services can exhibit a pivotal role in relieving the aforementioned technical barriers to facilitate the RE transition phenomenon which, in turn, is likely to restore the environmental harmony as well. Development of the ICT sector is also said to amplify the efficiency of energy use within the economy via ensuring better management of the energy consumption practices (Kramers *et al.* 2014; World Energy Council 2018). Incorporation of ICT into the global energy sector can potentially reduce the global energy demand by up to 6.3% by 2020 which implies that application of ICT can be an effective means of energy conservation worldwide (Rodríguez *et al.* 2005). Besides, ICT-based applications are also anticipated to complement the policies aimed at increasing the share of renewables in the total energy consumption figures through utilization of the renewable sources of energy.

For instance, the supply of most renewables sources of energy, particularly wind and solar, are believed to exhibit unpredictability due to largely being dependent on nature. Thus, ICT development can be imperative in this context via ensuring maximum harvestation at peak periods and facilitating the storage of electrical power generated from these RE sources (Ahmed, Naeem and Iqbal 2017). In addition, ICT applications can also aid in the conservation of electricity via smart gridding strategies which are key to negate the in-grid inefficiencies that account for system losses (Murshed 2019a). Import of ICT commodities is also expected to reduce the cost of renewable power generations within the developed economies which have relative disadvantages in producing these products locally. Furthermore, the greening of the ICT applications can also be decisive in reducing carbon emissions across the globe (Wang, Sanchez Rodriguez and Evans 2015).

Hence, keeping the enormous potentials of ICT development with respect to attainment of energy security and environmental stability into consideration, this paper aims at evaluating the

[1] For more information on goal 7 of the UN's Sustainable Development Goals see https://sustainabledevelopment.un.org/sdg7

impacts of enhancing openness to ICT-trade on the prospects of energy and environmental sustainability across selected South Asian regions namely Bangladesh, India, Pakistan, Sri Lanka, Nepal and Maldives.[2] Although a substantial number of earlier studies have probed into the overall trade openness and renewable energy transition nexus, the impact of ICT-trade openness in this regard is yet to be investigated. To the best of knowledge, this is the only paper that addresses the ICT-Energy-Environment nexus in the context of South Asia. The following questions are specifically addressed in this paper:

1. Does ICT trade elevate RE consumption In the South Asian region?
2. Can energy intensity be reduced via trade in ICT goods and services?
3. Does ICT trade account for reduction in carbon emissions?

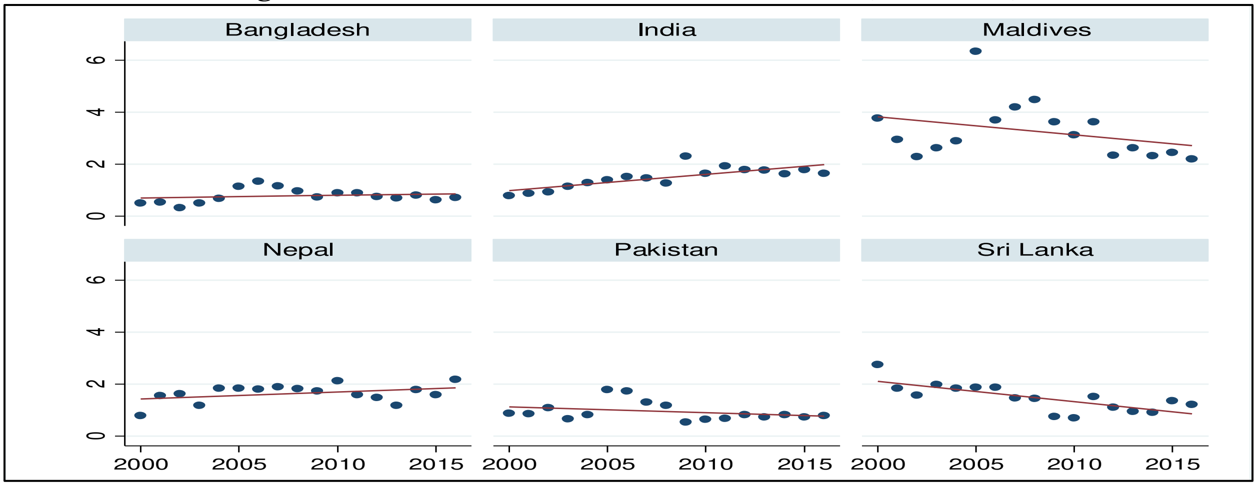
The remainder of this paper is arranged as follows. Section 2 provides a trend analysis of ICT trade in the selected South Asian economies and also sheds light on the relevant energy and environmental indicators. The literature study is critically analyzed in section 3. Information regarding the econometric modeling and the dataset used in this paper are shown in section 4 while section 5 briefly describes the methodology used. Section 6 discusses the findings from the econometric analyses and section 7 provides the concluding remarks.

2. Stylized facts on ICT trade, Energy consumption trends and CO2 emissions in South Asia

Figure 1 illustrates the trends in ICT goods trade in the six selected South Asian economies. It is evident from the fitted lines of the scatter plots that ICT trade as a percentage of GDP, also referred to as the ICT-trade openness, in India, Bangladesh and Nepal have exhibited positive trend on average between 2000 and 2015. In contrast Sri Lanka, Pakistan and Maldives registered a reverse trend. However, in comparison with the other five nations, the fluctuations in Nepal's ICT trade-GDP figures depicted most volatility. A particular reason behind this can be attributed to the nation's robust growth in ICT trade during the early 2000 period which reached its peak at around 2008 before having a sharp downfall. The average share of ICT goods traded in the respective GDPs for Bangladesh, India, Pakistan, Sri Lanka, Maldives and Nepal, between 2000 and 2015, were 0.77%, 1.47%, 0.95%, 1.49%, 3.27% and 1.65% respectively. It is to be noted that all these six South Asian economies have traditionally been net importers of ICT good which is important in the context of this paper which aims to predominantly analyze the impacts of ICT imports on the energy and environmental sustainability indicators.

[2] The selection of the South Asian countries is based on data availability.

Figure 1: ICT Goods Trade across South Asia (2000-2015)



Source: World Development Indicators (World Bank 2018)

The traditional dependence on NRE resources in most of the South Asian economies can be understood from Table 1. Nepal leads the other five nations in terms of its share of RE consumption in total final energy consumption, courtesy of the nation's vast potential of hydropower generation (Agrawala 2003). During the post-2000 period, the average RE share of Nepal in its total energy consumption stood at 88.08% followed by Sri Lanka, Pakistan, Bangladesh, India and Maldives having RE shares of 60.50%, 47.50%, 45.74%, 43.28% and 1.40%. The dismal RE share of Maldives points out towards the failure of this nation to undergo a renewable energy transition due to the vast reliance of the nation on imported petroleum for electricity generation purposes (van Alphen, van Sark and Hekkert 2007). The statistical figures reported in Table 1 also suggests that the shares of RE in the respective total final energy consumption levels of all the six nations have projected declining trends which makes the evaluation of the prospects of ICT trade enhancement on the renewable energy transition process, across South Asia, pertinent.

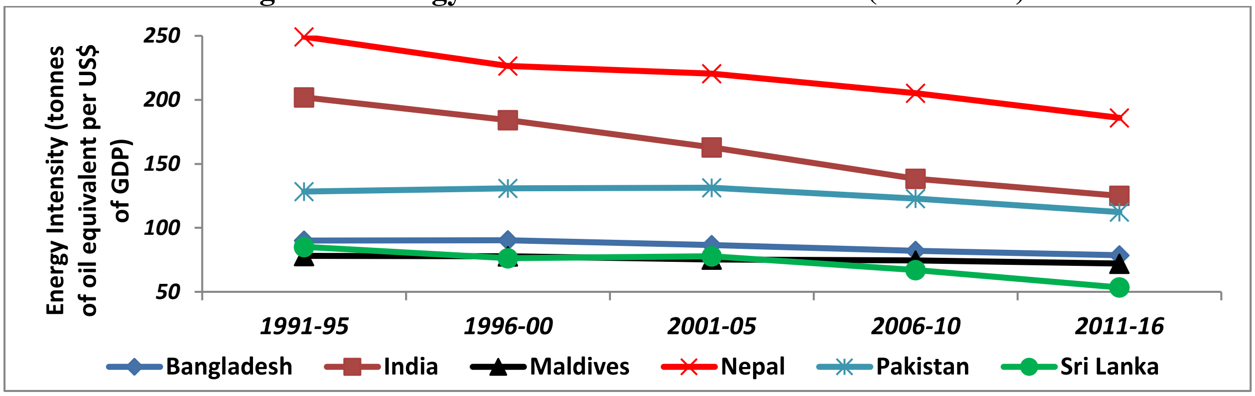
Table 1: The Renewable Energy Share in Total Final Energy Consumption (2000-2016)

Year	India	Bangladesh	Nepal	Pakistan	Sri Lanka	Maldives
2000-04	50.90	54.78	89.14	50.12	62.42	1.86
2005-08	46.38	48.19	90.64	46.07	61.00	1.49
2009-12	39.39	40.70	86.97	46.27	61.32	1.15
2013-16	36.84	37.05	85.30	46.85	56.78	0.98

Source: World Development Indicators (World Bank 2018)

The average intensities of energy employment across South Asia, as depicted in figure 2, state that all the selected South Asian countries have managed to raise their respective energy-use efficiencies between 1991 and 2016. Sri Lanka currently tops the list in terms of ensuring the most efficient use of energy across South Asia. The nation's average level of energy-use intensity was around 86 tonnes of oil equivalent per US dollar of its GDP which went down to almost 53 by the end of 2016, implying a 37% efficiency gain. In contrast, Nepal has unfortunately languished behind its regional neighbors and accounted for the most inefficient use of energy resources all throughout the aforementioned time period. On the other hand, India, despite not matching Nepal with respect to the level of energy-use efficiency, was the forerunner outpacing all the other five nations with respect to the rate of improvement in its efficiency of energy utilization. As oppose to Nepal's 37% efficiency gain, India managed to improve its efficiency level by almost 39% while the corresponding energy-use efficiencies in Nepal, Bangladesh, Pakistan and Maldives on average improved by 25.4%, 12.71%, 12.53% and 7.66%, respectively.

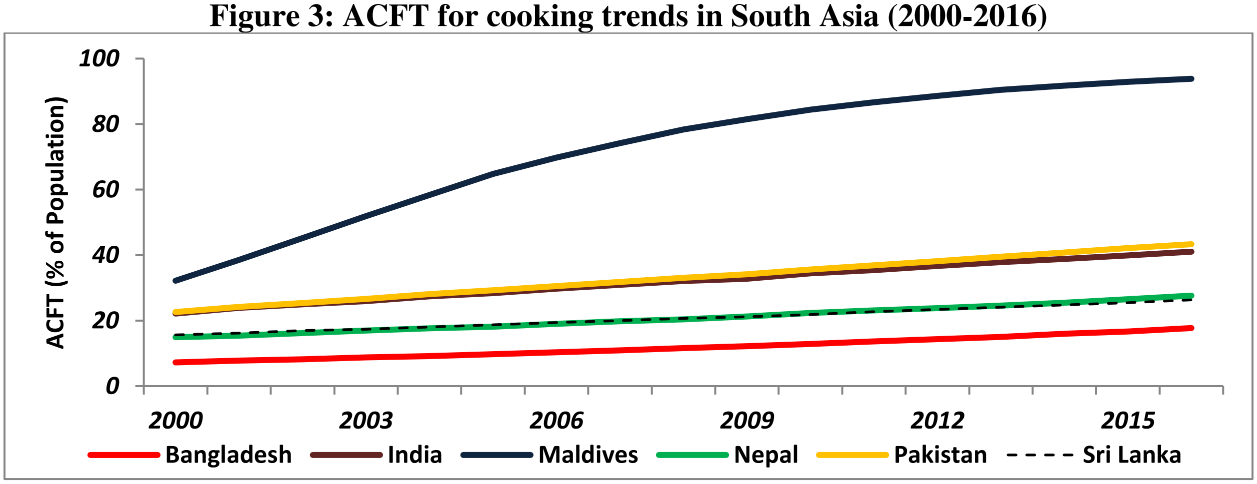
Figure 2: Energy-use Intensities in South Asia (1991-2016)



Source: World Development Indicators (World Bank 2018)

Figure 3 illustrates the Access to Clean Fuel and Technologies (ACFT) for cooking trends between 2000 and 2016. It is evident from the respective line plots that both India and Pakistan have managed to project identical projections in their respective ACFT for cooking while the corresponding trends in ACFT for cooking in Nepal and Sri Lanka also coincided for a large period between 2000 and 2016. In contrast, Maldives has demonstrated significant improvement in ensuring ACFT for cooking, registering an almost three-fold increase during the post-2000 period. However, Bangladesh has been the least successful of the six South Asian nations in ensuring greater access to ACFT for cooking. Between 2000 and 2016, the average ACFT for cooking in Bangladesh was merely 11.9%, much lower than all five of its neighbors.

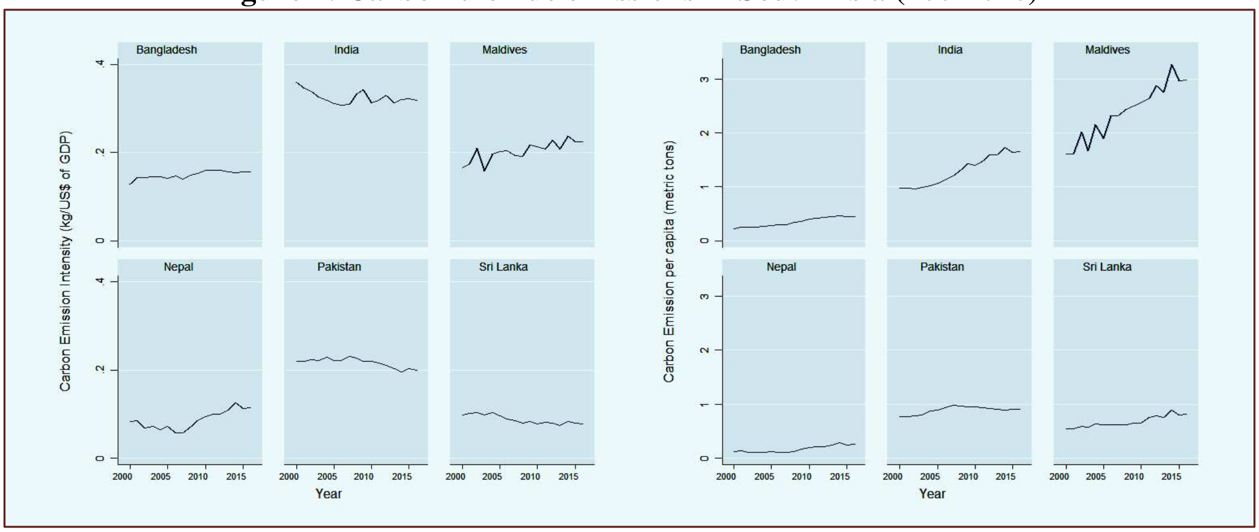
Figure 3: ACFT for cooking trends in South Asia (2000-2016)



Source: World Development Indicators (World Bank 2018)

Carbon emissions trends in South Asia are graphed in figure 4. As far as carbon dioxide emission-intensities are concerned, India is perceived to be the most polluted South Asian economy, followed by Maldives and Pakistan. However, Pakistan seems to have done well in mitigating its intensity of CO_2 emissions, in recent times, which is not the case for Maldives in which a progressive trend can be witnessed. In contrast, Sri Lanka and Nepal have done considerably well in limiting their respect intensity level of CO_2 emission. On the other hand, the per capita CO_2 emissions in Bangladesh and Nepal are the lowest amongst the six South Asian countries. However, the per capita CO_2 emission in Bangladesh can be attributed to the nation's high rate of population growth while for Nepal it could be because of the nation's predominant use of RE resources. Conversely, Maldives and India are the two top per capita CO_2 emitters within the South Asian belt.

Figure 4: Carbon dioxide emissions in South Asia (200-2016)



Source: World Development Indicators (World Bank 2018)

3. Literature Study

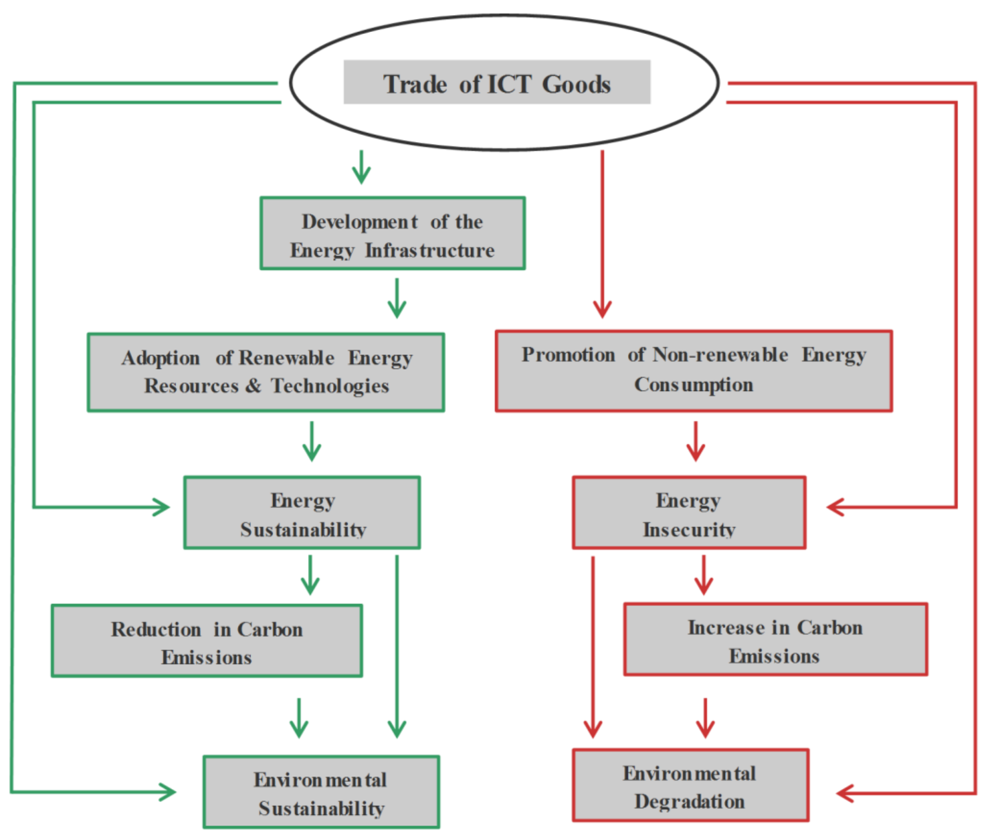
This section is classified into two subsections with the former analyzing the conceptual foundations behind the ICT trade, Energy and Environment relationships while the latter shedding light on the relevant empirical evidence documented in the literature.

3.1.Theoretical Framework

The rationale behind the liberalization of trade barriers, in general, can be understood from the Heckscher-Ohlin-Vanek theory of trade proposed by Vanek (1968). This theory postulates that keeping the relative factor endowments across two countries into cognizance, a country will be a net exporter of those goods which intensively employ its relatively abundant factors while being a net importer of those goods which intensively employ the relatively less-abundant factors. Hence, liberalization of the barriers to ICT goods trade would ideally facilitate the flows of ICT commodities into the countries that have relatively less comparative advantages in producing them via their indigenous resources. Moreover, enhancing openness to ICT-trade would also lead to the development of the ICT sector within the developing economies in particular which, in turn, is anticipated to improve their energy infrastructure in order to facilitate the adoption of RE technologies. It is acknowledged in the literature that inappropriate energy infrastructure often bottlenecks the prospects of RE transition within the underdeveloped countries (Murshed 2019c). Furthermore, green ICT commodities are believed to have the capacity to incorporate renewable power which can be effective in elevating the overall RE demand within the economy (Andreopoulou 2012). ICT applications can also account for inefficient consumption of electric power through the smartening of the conventional grids to curb energy wastages to a large extent (Panajotovic, Jankovic and Odadzic, 2011). The use of ICT is also linked to off-grid electrification through employment of RE resources which could be beneficial in relieving pressure off the national grid to some extent (Alstone, Gersheenson and Kammen 2015).

On the other hand, incorporation of RE into the national energy-mix, through the application of ICT in particular, could also reduce the intensity of carbon emissions into the atmosphere. Although trade of ICT goods may at times trigger carbon emissions further particularly via boosting the consumption of energy sourced from the NRE sources, it is believed that green ICT products can reverse this trend via improving the overall efficiency of energy use and also through facilitation of RE consumption within the economy (Despins *et al.* 2011). Hence, greater trade of ICT commodities across the national boundaries can be expected to foster the transition from consumption of the traditional fossil fuels to consumption of the modern renewable alternatives which, in turn, could exhibit critically important roles in ensuring energy security and also mitigating environmental degradation. Figure 5 presents a graphical illustration of the theoretical framework.

Table 5: The Conceptual Framework



Source: Author's own

3.2. Literature on ICT and RE transition

Although the trade of ICT goods and services is envisioned to display critically important roles in promoting RE consumption within the economy, not many existing studies have empirically explored the specific impacts of ICT-trade on the employment of RE resources. However, a plethora of studies in the literature did document the impacts of rising trade openness on the adoption of RE technologies within the developing economies in particular (Murshed 2018; Amri 2019). Hence, considering ICT-trade as a subset of the overall volume of international trade between countries, these existing studies can be expected to provide an understanding of the dynamic association between ICT-trade and the RE transition phenomenon across the globe.

In a study by Alam and Murad (2020) on 25 Organization for Economic Co-operation and Development (OECD) countries, the authors conclude in favor of international trade openness, along with economic growth and technological progress, being responsible for greater use of RE resources within these economies. Hence, trade of ICT goods could be expected to facilitate technological spillover across the technologically-backward economies which, in turn, could be efficient in inducing RE consumption within these economies. In addition, Alam and Murad (2020) also referred to the long-run dynamics between trade openness and RE-use being similar for all the countries while some country-specific variation in the nature of this nexus was also observed from the econometric analyses. Likewise, Murshed (2019c) found statistical evidence in favor of trade openness accounting for higher RE consumption in low-income economies but not in the context of countries belonging to the lower and upper middle-income groups. In addition, the author also opined trade liberalization as a key policy intervention that helps to enhance the energy consumption efficiency levels across all the three income groups while elevating the access to clean fuels and technologies within the lower middle-income nations. On the other hand, in a study on the determinants of China's renewable electricity output, Lin, Omoju and Okonkwo (2016) refer to trade openness to undermine the share of renewable electricity in the nation’s aggregate electricity output.

Although the role of promoting ICT-trade has received nominal attraction amidst the energy and environmental economists, the role of ICT applications with respect to harnessing the potential adoption of RE technologies has been extensively documented in the existing literature. Ahmed, Naeem and Iqbal (2017) probed into the ways in which RE resources can be exemplary in ensuring the eco-sustainability of the world economy. The authors also shed light in the context of several ICT products and devices being employed within the energy sector which cumulatively account for conservation of energy to ensure energy security to a large extent. In addition, the authors also opine in favor of ICT sector development complementing to RE transition particularly via facilitation of harvest and storage, distribution, and incorporation of RE sources into the existing energy systems and networks. Linking ICT development as a contemporary tool to ensure smattering of the conventional power systems within buildings, Abid, Lghoul and Benhaddou (2017) analyzed the potential ways through which ICT applications can integrate RE resources into the energy systems to make buildings more energy-efficient. Likewise, Stallo *et al.* (2010) explored the multifaceted channels through which applications of ICT can fuel the development of the RE sector. Among the two main modes identified by the authors, ICT can be tapped to generate power from renewable sources, which includes sunlight, wind, geothermal and water, while it can also be used to complement the existing renewable power generation process in order to complement the global green-energy initiatives. In a similar paper by Arnone *et al.* (2013), the authors highlighted the importance of building an ICT-based energy management system for RE generation from photovoltaic and wind sources.

In contrast to ICT applications triggering RE generation and consumption within the economy, many studies have also advocated in favor of renewable power supply exhibiting a crucial role in the sustainability of the ICT sector, especially within the rural areas. Ikwaba Paul and Uhomoibhi (2013) investigated the impacts of solar electricity generation on the application of ICT for sustainable development across Africa. The authors refer to the lack of in-grid electric power supply as a major factor bottlenecking development of the African economy whereby generation of power from solar resources could be effective in improving the reliability of power supply for the ICT sector to flourish. Thus, keeping the possible bidirectional causal association between ICT and RE employment into consideration, it is pertinent to explore the nexus between these variables with respect to ensuring energy security as well as to achieving sustainability of the ICT sector.

3.3. Literature on ICT and Carbon Emissions

Emission of carbon into the atmosphere is not a problem confined to a particular nation or region responsible for the emission but it affects the global environment as well. Hence, reducing carbon and other greenhouse gaseous emission is critically pertinent keeping the environmental and ecological sustainability into consideration. Although the impacts of ICT-trade on the environment are yet to be extensively documented in the existing literature, many studies have highlighted the dynamic association between consumption of ICT goods and carbon emissions (Lee and Brahmasrene 2014; Park, Meng and Baloch 2018).

The nexus between the use of ICT products and carbon emissions has exhibited ambiguity in the existing literature. For instance, Khan *et al.* (2018) found statistical evidence regarding the negative impacts of ICT on the environment for the next 11 emerging economies. The estimate results showed that the consumption of ICT products in the form of internet usage increases carbon dioxide emissions across these nations. In addition, when interacted with financial development, the negative impact of ICT seems to be accentuated. However, at higher levels of economic growth, the interacted impact of ICT is found to reduce carbon dioxide emissions which implied that economic growth leads to greening of the ICT sector which in turn could be effective in curbing the associated emission to a large extent.

Similarly, in a study comprising of 116 developing and 26 developed economies across the world, Higón, Gholami and Shirazi (2017) concluded that application of ICT impedes environmental sustainability in the early stages, thus, emitting carbon into the atmosphere. However, with time, the relationship is reciprocated whereby in the latter stages ICT can be tapped to control the quantity of carbon emissions and, therefore, mitigate the associated environmental degradation issues. The statistical estimates from the regression analyses provided statistical evidence in favor of a non-linear inverted-U shaped association between consumption of ICT goods, which included fixed telephone subscriptions, mobile cellphone subscriptions, personal computer users, internet use, and fixed broadband subscriptions, and per capita carbon emissions.

In a study on the five BRICS countries, Haseeb *et al.* (2019) opined in favor of ICT having a positive impact on the environment through the mitigation of carbon dioxide emissions. Using internet use and mobile subscriptions to proxy for ICT products, the authors found that 1% increase in the number of internet users and mobile phone subscribers, per 100 people, attributed to reduction in the per capita carbon dioxide emissions within the BRICS countries by 40 and 66 percentage points, respectively. However, the results from the country-specific analyses depicted heterogeneity since both the ICT goods were found to reduce carbon dioxide emissions in Brazil and Russia only while for India and China the results seemed to statistically validate the adverse impacts of ICT on carbon dioxide emissions. On the other hand, internet use and mobile subscription were found to respectively reduce and elevate the per capita carbon dioxide emissions in South Africa. In a similar study by Zhang, Wang and Latif (2019), the authors concluded in favor of the consumption of the two aforementioned ICT commodities being effective in reducing carbon dioxide emissions within high and middle-income countries while increasing the carbon dioxide emission within economies belonging to the low-income group.

4. Model Specification and Data

This paper modifies the econometric model used by Murhsed (2018) to evaluate the impacts of trade of ICT goods on energy and environmental sustainability across South Asia. The model used in the study by Murshed (2018) considered the overall trade openness index as the principal regressor of interest. However, since this paper aims to specifically address the impact of ICT trade, the ICT trade openness index is used instead. In addition, this paper also assesses the impacts of ICT trade on carbon emissions in separate models as well. The regression models used in this paper can be shown as:

$$lnREC_{it} = \partial_0 + \partial_1 IOPEN_{it} + \partial_{jt} X_{j,it} + \varepsilon_{it} \quad (1)$$

$$RES_{it} = \delta_0 + \delta_1 IOPEN_{it} + \delta_{jt} X_{j,it} + \varepsilon_{it} \quad (2)$$

$$lnEI_{it} = \theta_0 + \theta_1 IOPEN_{it} + \theta_{jt} X_{j,it} + \varepsilon_{it} \quad (3)$$

$$ACFT_{it} = \alpha_0 + \alpha_1 IOPEN_{it} + \alpha_{kt} Y_{k,it} + \varepsilon_{it} \quad (4)$$

where the subscripts i, t and ε refer to the individual cross-sectional units (countries), time periods (years) and the error terms, respectively. ∂, δ, θ and α are the elasticity parameters to be estimated. The dependent variables used in models 1, 2, 3 and 4 are used as indicators of RE transition in the economy. REC refers to renewable energy consumption in terms of terajoules while RES stands for the percentage share of RE consumption in total energy consumption levels. EI is the abbreviation for the intensity of energy-use which is expressed as the amount of energy used to produce one unit of GDP. This particular variable captures the efficiency of energy employment within the economy whereby higher values of EI refers to lower energy-use efficiency levels and vice-versa. Finally, ACFT is the short form for access to clean fuels and technologies for cooking which is given by the percentage of the population having access to these.

The principal regressor of interest IOPEN denotes ICT-trade openness which is measured in terms of the sum of imports and exports of ICT goods as a percentage share in the GDP of the respective economies. A higher value of this index can be interpreted as higher amounts of ICT trade by the selected South Asian economies and vice-versa. X is set of *j* (*j*=1, 2, …, 7) control variables that are believed to influence REC, RES and EI which includes carbon emissions (CO_2) in metric tons per capita, world crude oil price (OIL) in US dollars per barrel, net inflows of foreign direct investments (FDI) in constant 2010 US dollars, net official development assistance (NODA) received in terms of 2010 constant US dollars, international remittance inflows (REMIT) in 2010 constant US dollars, Gross National Product (GNI) per capita (GNIPC) measured in terms of 2010 constant US dollars and consumer price index (CPI) to proxy for the domestic inflationary rates. Y is a vector of *k* (*k*=1, 2, …, 5) control variables that are expected to affect ACFT which includes CO_2, OIL, CPI, life expectancy at birth (LIFE) and secondary school enrolment rates (SSE).

In addition, in order to estimate the impacts of ICT-trade on the environment, the per capita carbon dioxide emissions (CO_2) is considered as an indicator of environmental welfare. The econometric models in this regard are given by:

$$\boldsymbol{lnCO2_{it} = \mu_0 + \mu_1 IOPEN_{it} + \mu_2 lnREC_{it} + \mu_3 (IOPEN * lnREC_{it}) + \mu_4 lnOIL_{it} + \mu_5 GNIPC_{it} + \mu_6 GNIPC2_{it} + \varepsilon_{it}} \quad \textbf{(5)}$$

$$\boldsymbol{lnCO2_{it} = \pi_0 + \pi_1 IOPEN_{it} + \pi_2 lnNREC_{it} + \pi_3 (IOPEN * lnREC_{it}) + \pi_4 lnOIL_{it} + \pi_5 GNIPC_{it} + \mu_6 {GNIPC^2}_{it} + \varepsilon_{it}} \quad \textbf{(6)}$$

where μ and π are the elasticity parameters to be estimated. NREC refers to NR energy consumption measured in terms of terajoules. In both models 5 and 6, REC and NREC are interacted with IOPEN to assess the combined impacts of higher openness to ICT-trade and energy consumption on carbon dioxide emissions which is pertinent to understand the heterogeneity of the impacts with respect to the type of energy resource consumed. $GNIPC^2$ is the squared term of the per capita GNI figures which is used to account for possible the non-linear relationship between economic growth and carbon emissions. The squared term is also tapped to test the validity of the Environmental Kuznets Curve (EKC) hypothesis.[3]
All the variables have been transformed into their natural logarithms for the ease of conditional bivariate elasticity estimations. Annual time-series data from 2000 to 2006 is compiled in the context of all the six selected South Asian economies. The crude oil price data has been sourced from the British Petroleum Statistical Review of World Energy (British Petroleum 2018) while data for the rest of the variables are generated from the World Development Indicators database of the World Bank (2018).

5. Methodology

5.1. Cross-sectional dependency analysis

The problem of cross-sectional dependence leads to biased and inconsistent outcomes. Hence, prior to investigating the stationarity and the cointegrating properties, it is pertinent to investigate whether the cross-sections are independent or not. Cross-sectional dependence usually arises when one economic data of a particular country is influenced via the same economic data in another country whereby the countries within the panel dataset are either globally or regionally

[3] For more information on the EKC hypothesis see Pata (2018).

associated. This paper taps the Pesaran Cross-sectional Dependency (CD) and the Breusch-Pagan Lagrange Multiplier (LM) tests, respectively introduced by Pesaran (2004) and Breusch and Pagan (1980), for this purpose. Both the tests spit out a test statistic that is tested under the null hypothesis of cross-sectional independence against the alternative hypothesis of otherwise. For a model comprising of *N* number of cross-sections for the time period *T*, the test statistics of the CD and LM tests can be given by:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\, \hat{\rho}_{ij}^{2} \rightarrow N(0,1) \quad (7)$$

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\, \hat{\rho}_{ij}^{2} \rightarrow \chi^{2} \frac{N(N-1)}{2} \quad (8)$$

The panel unit root analysis follows the cross-sectional dependency investigations.

5.2. Panel unit root analysis

In the context of the panels being interlinked, the application of the first generation panel data unit root estimation techniques is no longer appropriate due to these tests not being able to account for cross-sectional dependence. Thus, the second generation panel unit root tests that are robust to handling cross-sectional dependency in the data are used. This paper uses the Cross-sectionally Augmented Dickey-Fuller (CADF) and the Cross-sectionally augmented Im, Pesaran and Shin (CIPS) unit root estimation techniques proposed by Pesaran (2007). The CADF statistic can be obtained from the regression given below:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{s} d_{ij}\, \Delta\bar{y}_{t-j} + \sum_{j=1}^{s} \delta_{ij}\, \Delta\bar{y}_{i,t-j} + e_{it} \quad (9)$$

where $\bar{y}$ and $\overline{\Delta y}$ are the cross-sectional averages of lagged levels and first differences, respectively, at time T for all countries. The estimated t-statistic from equation (9) is then used to compute the CIPS statistic which can be shown as:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i \quad (10)$$

where $CADF_i$ is the t-statistic estimated from the CADF regression model shown in equation (9). Both the CADF and CIPS tests are performed under the null hypothesis of non-stationarity of the variables against the alternative hypothesis of otherwise. The panel cointegration analysis follows the unit root tests.

5.3. Panel Cointegration analysis

Likewise, the first generation panel unit root tests, the conventional panel cointegration estimator such as the Pedroni (1999) residual-based cointegration technique does not take the cross-sectional dependency within the panels into account. Thus, the Westerlund (2007) panel cointegration analysis, which is robust to handling cross-sectionally dependent panel dataset, is employed to investigate the long run associations between the variables. Cross-sectional dependency is accounted for via estimation of the probability values of the test statistics via bootstrapping methods. A total of two group-mean tests and two panel tests are performed under the null hypothesis of no cointegration against the alternative hypothesis of cointegration among at least one cross-sectional unit or cointegration among the whole panel, respectively. The Westerlund (2007) tests are structured in the context of an error-correction model which can be expressed as:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i\left(y_{i,t-1} - \beta_i' x_{i,t-1}\right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{-q_i}^{p_i} \gamma_{ij} \Delta \mathrm{x}_{i,t-j} + e_{it} \quad \mathbf{(11)}$$

where d_t stands for the deterministic components and p_i and q_i are the lag lengths and lead orders which vary across individual cross-sections. The two group-mean test statistics G_t and G_a and the two panel test statistics P_t and P_a within the Westerlund (2007) cointegration analysis can be shown as:

$$G_t = \frac{1}{N} \sum_{i=1}^{N} \frac{\widehat{\alpha_i}}{SE(\widehat{\alpha}_i)} \quad \mathbf{(12)}$$

$$G_a = \frac{1}{N} \sum_{i=1}^{N} \frac{T\widehat{\alpha_i}}{\widehat{\alpha}_i(1)} \quad \mathbf{(13)}$$

$$P_t = \frac{\widehat{\alpha_i}}{SE(\widehat{\alpha}_i)} \quad \mathbf{(14)}$$

$$P_a = T\widehat{\alpha} \quad \mathbf{(15)}$$

The Stata command *xtwest* (Persyn and Westerlund 2008) is considered in this analysis.

5.4. Panel regression analysis

This paper employs the Continuously Updated Fully Modified (CUP-FM) and the Continuously Updated Bias Corrected (CUP-BC) panel cointegrating regression estimators, proposed by Bai, Kao and Ng (2009) to estimate the long-run elasticities of the energy and environmental sustainability indicators with respect to ICT-trade openness in the presence of key macroeconomic control variables. Both these techniques are said to generate robust results in the presence of endogeneity and cross-sectional dependency issues with the dataset and can also accommodate mixed order of integration among the variables in the respective models. The regression function of a CUP-FM and CUP-BC model can be shown as:

$$\left(\widehat{\beta}_{CUP}, \widehat{F}_{CUP}\right) = argmin \frac{1}{nT^2} \sum_{i=1}^{n} (y_i - x_i\beta)' M_F (y_i - x_i\beta) \quad \mathbf{(16)}$$

where $M_F = I_T - T^{-2}F\acute{F}$, and I_T and F are the identity of matrix dimension T, and the error term assumes a latent common factor. In the context of the continuously biased estimators being consistent, asymptotic bias may arise from the endogeneity and the cross-sectional dependency problems. Although both the CUP-FM and the CUP-BC correct for this asymptotic bias, the difference between these two estimators is that the CUP-FM estimator corrects for the bias correction only in the final stage of the iteration while the CUP-BC corrects it at each stage of the iteration. For robustness check, this study also taps the Feasible Generalized Least Squares (FGLS) estimator as well.

5.5. Panel causality analysis

The newly developed Dumitrescu-Hurlin panel causality estimation technique developed by Dumitrescu and Hurlin (2012) is applied to investigate the causal dynamics between openness to ICT-trade and the energy and environment indicators considered in this paper. The conventional Granger (1969) causality test inappropriate assumes homogeneity across the cross-sections whereby the test statistic is estimated using the null hypothesis that Granger causality does not exist between a pair of stationary variables belonging to all the cross-sections against the homogenous alternative hypothesis of Granger causality existing between these variables in all the cross-sections. Thus, this method does not take the heterogeneity across the cross-sections into consideration which results in biased causality estimates. In contrast, the Dumitrescu-Hurlin causality technique allows for heterogeneity across the cross-sections to estimate the Z-bar statistic using the null hypothesis that there does not exist a Granger causality between a pair of stationary variables in all the cross-sections, referred to as the Homogenous Non-Causality (HNC) null hypothesis, against the non-homogenous alternative hypothesis of Granger causality existing between these variables in at least one of the cross-sections. The mean statistic used to test the HNC null hypothesis can be given as:

$$\boldsymbol{W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}} \quad \textbf{(17)}$$

where $W_{N,T}^{HNC}$ is the mean value of the individual Wald statistic $W_{i,t}$. According to Dumitrescu and Hurlin (2012), under the assumption that the individual residuals are independently distributed across all the cross-sections and their covariances are equal to zero, the mean statistic sequentially converges to the equation below when T and N tend to approach infinity:

$$\boldsymbol{Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}}\left(W_{N,T}^{HNC} - K\right)\underset{T,N\to\infty}{\overset{\vec{d}}{}} N(0,1)} \quad \textbf{(18)}$$

where $Z_{N,T}^{HNC}$ is the z-statistic, N is the number of cross-sections and K is the optimal lag length. According to Dumitrescu and Hurlin (2012), if T tends to infinity, the individual Wald statistics are independently identically distributed with the mean individual Wald statistic being equal to K and its variance being equal to 2K. A standardized Z-statistic ($\boldsymbol{\overline{Z}_{N,T}^{HNC}}$) is then approximately calculated for the mean Wald statistic of the HNC null hypothesis which can be shown as:

$$\boldsymbol{\overline{Z}_{N,T}^{HNC} = \frac{\sqrt{N}}{\sqrt{Var(\widetilde{W}_{i,T})}}\left[W_{N,T}^{HNC} - E\widetilde{W}_{i,T}\right]} \quad \textbf{(19)}$$

The statistical significance of the standardized Z-statistic determines the causality between a pair of stationary variables in at least one of the cross-sections. For robustness check, the Granger (1969) causality and the Geweke's (1982) measure of instantaneous feedback techniques are also tapped to deduce the causal associations.

6. Results and Discussion

At first, the analysis starts off with the investigation of cross-sectional dependency among the panels. Table 2 reports the corresponding results from all the cross-sectional dependency estimation methods. The statistically significant test statistics reject the null hypothesis of cross-sectional independence to confirm the presence of cross-sectional dependence in all the six models considered in this paper. Since there is evidence of cross-sectional dependence, the second generation panel unit root tests are applied. Table 3 presents the results form the unit root analyses. Both the CAPS and CADF tests suggest all the variables are non-stationary at their respective level forms. However, the variables do become stationary at their first differences, thus, evidencing a common order of integration between the variables. These imply that the variables are mean-reverting which fulfills the requirements for performing the regression analyses to follow.

Table 2: Cross-sectional Dependency Analysis

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	**$lnREC_t$**	**RES_t**	**$lnEI_t$**	**$ACFT_t$**	**$lnCO2_t$**	**$lnCO2_t$**
CD-Tests	-1.731***	1.851**	-1.617***	-1.472***	-1.172**	3.163*
	(0.084)	(0.042)	(0.061)	(0.078)	(0.041)	(0.002)
LM-Tests	52.517*	50.012*	39.970*	42.880*	64.903*	55.112*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)

*Note: the optimal lags are based on Schwarz Information Criterion (SIC); The probability values are reported within the parentheses. *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 3: The second generation panel unit root test results

Variables	**CIPS**		**CADF**	
	Level, I(0)	**1st Difference, I(1)**	**Level, I(0)**	**1st Difference, I(1)**
$lnREC_t$	-2.013	-5.299*	-2.388	-3.798*
RES_t	-2.004	-4.238*	-1.219	-2.389***
$lnEI_t$	-2.154	-5.149*	-2.001	-3.634*
$ACFT_t$	-1.854	-4.775*	-2.149	-3.287*
$IOPEN_t$	-2.634	-5.152*	-2.281	-3.346*
$lnCO2_t$	-2.164	-4.825	-1.307	-3.302*
$lnOIL_t$	1.719	4.701*	1.700	3.107*
$lnFDI_t$	-2.618	-4.133*	-2.436	-3.364*
$lnNODA_t$	-2.578	-5.658*	-2.819	-3.561*
$lnREMIT_t$	-1.969	-3.169**	-2.512	-3.430*
$lnGNIPC_t$	-2.298	-2.760***	-1.461	-3.590*
CPI_t	-2.408	-3.928*	-2.236	-3.685*
SSE_t	-1.897	-3.088**	-1.355	-3.304*
$LIFE_t$	-1.181	-4.723*	-2.218	-4.067*
$lnTEC_t$	-1.084	-4.431*	-2.410	-3.640*
$IOPEN_t*lnREC_t$	-1.991	-5.247*	-2.248	-3.476*
$IPOEN_t*lnNREC_t$	-1.688	-5.437*	-2.314	-3.482*
$lnGNIPC2_t$	-1.278	2.813**	-1.449	-3.781*

*Note: The estimates are calculated considering trends and the optimal lags are based on SIC; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Next, the second generation panel cointegration test is employed to check the long run associations between the variables. The results from the Westerlund (2007) panel cointegration test, which accounts for the cross-sectionally dependent panels in the dataset, are reported in table 4. It can be seen that the majority of the estimated statistics are statistically significant which reject the null hypothesis of no cointegration at 1% and 5% significance levels. Thus, it can be said that there are long-run associations between the variables considered in this paper.

Table 4: Westerlund (2007) Cointegration analysis

Model	Statistic	Value	Z-Value	P-Value
(1)	G_t	-5.614	-7.627	0.000
	G_a	-5.706	3.349	0.000
	P_t	-5.136	2.067	0.006
	P_a	-3.543	2.285	0.007
(2)	G_t	-4.124	-3.799	0.000
	G_a	-6.519	3.620	0.000
	P_t	-9.159	-3.087	0.001
	P_a	-6.690	3.021	0.000
(3)	G_t	-1.800	2.175	0.057
	G_a	-13.939	-4.233	0.000
	P_t	-10.723	-2.956	0.000
	P_a	-10.516	-3.662	0.000
(4)	G_t	-10.419	3.135	0.000
	G_a	-13.434	4.083	0.000
	P_t	-2.861	2.731	0.387
	P_a	-4.245	2.078	0.026
(5)	G_t	-4.500	-3.911	0.000
	G_a	-3.978	2.213	0.023
	P_t	-3.593	2.119	0.029
	P_a	-4.026	-3.112	0.000
(6)	G_t	-4.721	-2.918	0.009
	G_a	-4.417	2.118	0.041
	P_t	-3.994	2.981	0.039
	P_a	-1.776	2.804	0.198

*Note: The optimal lags are based on SIC; * and ** denote statistical significance at 1%, and 5%levels respectively*

After confirmation of cointegration among the variables, the next step involves the estimation of the long-run elasticities using the appropriate panel regression estimators that account for cross-sectional dependence across the panels. The FGLS, CUP-FM and CUP-BC regression techniques are tapped to unearth the long-run relationships. The elasticity estimates in the context of models 1, 2 and 3 are reported in table 5. The estimates, in general, portray the robustness of the results to the different regression techniques which is evident from the similarity of the predicted signs of the estimated elasticities.

In the context of model 1, the statistically significant long-run elasticities advocate in favor of a positive association between the trade of ICT goods and consumption of RE within the concerned South Asian nations. It is found that a 1% rise in ICT-trade openness attributes to a rise in the RE consumption figures by 0.04%-0.11%, on average, *ceteris paribus.* Hence, it can be asserted that liberalization of the barriers that impede the trade of ICT commodities could be ideal in augmenting RE resources into the national energy-mix across South Asia. Moreover, it can be also said that the cross-border flows of ICT goods could also account for the technological constraints within the South Asian nations that have traditionally bottlenecked the transition from consumption of NRE to RE resources across this region. Thus, promoting ICT trade and development across the selected South Asian economies can be effective ensuring energy sustainability as well since the ICT trade-induced RE consumption can complement the existing NRE resources with respect to meeting the persistent growth in South Asia's demand for energy. Besides, the other results from the regression analyses indicate RE consumption is also positively influenced by higher economic growth, rising carbon emissions, inflows of international remittances, hikes in world crude oil prices and domestic inflation. On the other hand, another interesting finding from the analyses validates the pollution haven hypothesis[4] in the context of the South Asian economies which is perceived from the negative and statistically significant elasticity parameter attached to $lnFDI_t$.

However, despite rising openness to ICT-trade being associated with higher levels of RE consumption across the selected South Asian economies, it does not quite guarantee the transition from the use of NRE to RE resources. This can be clearly understood from the negative signs estimated RE consumption elasticities in the context of model 2. It is found that a 1% rise in openness to ICT goods trade reduces the share of RE in the total energy consumption levels by 0.62%-0.68%, on average, *ceteris paribus*. This implies that trade of ICT commodities not only enhances the consumption of RE, but it also boosts the overall consumption of NRE as well, thus, elevating the share of NRE in the aggregate energy consumption levels across South Asia. Consumption of ICT products is known to enhance the demand for electricity, whereby the conventional fossil fuel-generated electric power is often tapped to meet the surging energy demand. As a result, the consumption of NRE can be expected to simultaneously go up alongside the imports of ICT commodities which could have possibly attributed to the negative nexus between ICT-openness and RE share in aggregate energy consumption levels. This is a key finding from the perspective of policy implications regarding the greening of the ICT goods that are traded. Hence, it is better off to reduce the trade barriers relatively more in the context of those ICT commodities that have the capacity to employ the RE resources rather than relaxing tariffs on conventional ICT commodities that intensively use electricity sourced from the NRE resources.

Other key findings reveal that rising carbon emissions into the atmosphere tend to induce urgency in undergoing a RE transition which can be seen from the positive relationship between carbon dioxide emissions and RE shares in total energy consumption figures across South Asia. The corresponding elasticity estimates in the context of model 2 shows that a 1% rise in carbon dioxide emissions is accompanied by an increment in the RE shares by 3.13%-5.96%, on average, *ceteris paribus.* Similar impacts are also witnessed with respect to rising crude oil prices in the world market resulting in a rise in the share of RE. In addition, the inflow of FDIs is also found to aggravate the relative use of NRE resources which further establishes the validity of the pollution haven hypothesis in the context of the concerned South Asian economies. On the other hand, inward foreign development assistances and international remittances seem to be conducive to enhancing the share of RE within this region. As far as economic growth is concerned, it can be seen that rising income levels across South Asia are affecting the RE

[4] For more information on the pollution haven hypothesis see Cole (2004).

transition process since the marginal growth effects on RE shares are found to be negative which is a matter of concern.

In the context of model 3, it can be asserted that enhancing the trade of ICT goods can effectively enhance the efficiency of energy use in South Asia. The negative estimated elasticity parameters imply that a 1% rise in ICT-openness curbs the intensity of energy use by 0.09%-0.22%, on average, *ceteris paribus.* Hence, from the perspective of energy conservation, liberalizing barriers to facilitate cross-border flows of ICT goods can be ideal in reducing the overall level of energy consumption without compromising the overall energy demand in the economy. A plausible explanation in this regard could be made in the sense that development of the ICT sector is often associated with smart-gridding of the traditional national power-grid whereby appropriate applications of smart-gridding technologies can counter the inefficient-use and wasting of electricity and can also reduce the system losses stemming from transmission and distribution irregularities.[5]

Table 5: Regression analyses in context of models (1), (2) and (3)

Model	**(1)**	**(1)**	**(1)**	**(2)**	**(2)**	**(2)**	**(3)**	**(3)**	**(3)**
Estimator	**CUP-FM**	**CUP-BC**	**FGLS**	**CUP-FM**	**CUP-BC**	**FGLS**	**CUP-FM**	**CUP-BC**	**FGLS**
Regressors									
$IOPEN_t$	0.109**	0.061*	0.043***	-1.761*	-1.680*	-0.615**	-0.188*	-0.223*	-0.13**
	(0.050)	(0.012)	(0.019)	(0.329)	(0.268)	(0.006)	(0.016)	(0.041)	(0.050)
$lnCO2_t$	0.115**	0.132	0.038***	3.133**	3.422**	5.959*	-0.103*	-0.306*	-0.220*
	(0.049)	(0.088)	(0.002)	(1.305)	(1.579)	(0.908)	(0.023)	(0.040)	(0.027)
$lnOIL_t$	0.102	0.429*	0.271*	1.486	6.115*	3.851*	0.07**	0.436*	0.035
	(0.096)	(0.130)	(0.068)	(2.565)	(2.933)	(1.241)	(0.026)	(0.079)	(0.053)
$lnFDI_t$	-0.08***	-0.373*	-0.196*	-4.356*	-6.489*	-3.559*	0.027	0.043	0.145
	(0.047)	(0.052)	(0.051)	(1.267)	(0.905)	(0.882)	(0.020)	(0.039)	(0.117)
$lnNODA_t$	-0.519	-0.051	-0.017	-5.320*	-4.339***	-2.180**	-0.020	-0.206*	-0.030
	(0.716)	(0.149)	(0.049)	(2.038)	(2.013)	(0.898)	(0.017)	(0.063)	(0.050)
$lnREMIT_t$	0.458*	0.458*	0.439*	11.877*	11.443*	10.415*	0.049*	0.139*	0.055*
	(0.036)	(0.052)	(0.022)	(0.965)	(1.000)	(0.467)	(0.011)	(0.030)	(0.009)
$lnGNIPC_t$	0.641*	0.544*	0.263*	-28.576*	-5.182**	-10.279*	-4.484*	1.149*	0.379*
	(0.139)	(0.082)	(0.101)	(3.719)	(2.001)	(1.758)	(0.030)	(0.114)	(0.048)
CPI_t	0.015	0.047*	0.018*	0.239	0.754*	0.305**	-0.004*	-0.013	-0.008
	(0.011)	(0.009)	(0.007)	(0.286)	(0.166)	(0.120)	(0.001)	(0.008)	(0.006)
Constant	15.135*	3.726	2.822*	171.351*	119.58**	101.942*	-2.865*	-9.529*	-2.954*
	(1.554)	(2.602)	(1.017)	(45.651)	(51.02)	(17.948)	(0.361)	(1.278)	(0.912)
Wald Chi^2			2030.1*			1365.6*	2334.9*		
Adj. R^2	0.773	0.805		0.707	0.781			0.680	0.727
Observations	101	101	102	101	101	102	102	101	101

*Note: The standard errors are reported within the parentheses; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 6 reports the regression results in the context of model 4. It is visible that the trade of ICT goods results in greater access to clean fuel and technologies for cooking across South Asia. The marginal effect of rising openness to ICT trade contributes to a rise in the clean cooking fuel and technology access by 5.05%-6.72%, on average, *ceteris paribus.* This is an interesting finding because conventional dependence on the traditional sources of cooking fuels not only affects the environmental balance but it also triggers health adversities among the women in particular. Hence, ICT-openness positively influencing the adoption of the cleaner alternatives would simultaneously harmonize the environmental balance and also improve the health conditions of

[5] For more information on the prospects and benefits of smart gridding the national power-grid see Murshed (2019b).

the women who are the major stakeholders of the health-adversities linked to the combustion of the relatively unclean cooking-fuels. This is also supported by the positive nexus found between access to clean fuel and technologies for cooking and the average life expectancies at birth within South Asia. Moreover, the adoption of such cooking fuel and technologies is also seen to be positively influenced by the rising carbon emissions. In addition, secondary school enrolment rates also stimulate clean cooking fuel adoption across this region which implies that better education generates awareness in understanding the negative impacts of combusting traditional cooking fuels and, in turn, replacing them with the relatively cleaner alternatives.

Table 6: Regression analysis in the context of models (4)

Model	(4)	(4)	(4)
Estimator	**CUP-FM**	**CUP-BC**	**FGLS**
Regressors			
$IOPEN_t$	6.717*	5.054**	6.541*
	(1.513)	(1.750)	(0.562)
$lnCO2_t$	9.966*	8.891*	6.923*
	(0.701)	(0.421)	(0.604)
$lnOIL_t$	4.511	3.726	2.911
	(4.878)	(2.771)	(2.735)
$LIFE_t$	2.901*	1.773*	1.630*
	(0.688)	(0.414)	(0.177)
SSE_t	2.002*	2.090*	1.089*
	(0.083)	(0.057)	(0.241)
CPI_t	-0.125	-0.284	-0.229
	(0.217)	(0.210)	(0.140)
$lnGNIPC_t$	18.310*	17.517*	21.972*
	(2.843)	(1.283)	(1.750)
Constant	-50.369*	-10.459*	-50.314*
	(20.134)	(2.009)	(10.881)
Wald Chi^2			1121.02*
Adj. R^2	0.674	0.749	
Observations	101	101	102

*Note: The standard errors are reported within the parentheses; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

The conditional impacts of openness to ICT trade on the environment are evaluated via its impact on the magnitude of carbon dioxide emissions. The regression results in the context of models 5 and 6 are reported in table 7. It is evident from the elasticity estimates that the overall impacts of enhancing ICT-trade openness on carbon emissions are conditional on the nature of the energy resource consumed across the selected South Asian economies. These can be understood from the statistically significant elasticity parameters attached to the interaction terms which tend to implicate that higher openness to ICT trade is effective in reducing carbon emissions provided the level of RE consumption goes up as well. On the other hand, ICT-openness, along with rising levels of NRE consumption, is found to contribute to higher carbon emissions. Hence, it is pertinent to facilitate cross-border trade of ICT goods that have the capacity to employ RE which, in turn, can effectively reduce the carbon emissions within South Asia. These results conform to the conclusions made by Inglesi-Lotz and Dogan (2018) for ten Sub-Saharan African nations.

Other important results show that carbon dioxide emissions across the selected South Asian economies are sensitive to exogenous shocks to world crude oil prices which can be perceived from the statistical significance of the associated estimated elasticity parameters. The results indicate that a 1% rise in crude oil prices, holding all else constant, reduces carbon dioxide emissions on average by 0.30%-0.70%. Moreover, controlling for ICT-openness, RE consumption, NRE consumption and crude oil price, the results also provide statistical support to validate the environmental Kuznets curve hypothesis. This is evident from the positive and negative signs of the estimated elasticity parameters attached to GNI per capita and its squared terms, respectively. Hence, it can be said that at initial phases of economic development there is a trade-off between economic and environmental welfares whereby carbon emissions are found to rise to degrade the environment. However, beyond a certain level of development, the trade-off tends to be phased off to establish a complimentary association between economic and environmental development whereby carbon emissions tend to go down. Since RE resources are relatively cleaner sources of energy, greater consumption of renewables can be associated with lower carbon emissions as well. Keeping this RE-carbon emission nexus into consideration, it can be asserted that higher openness to the trade of RE-intensive ICT goods and services can play a key role in influencing the turning point of the environmental Kuznets curve at lower levels of per capita GNI.

Table 7: Regression analyses in context of models (5) and (6)

Model	(5)	(5)	(5)	(6)	(6)	(6)
Estimator	**CUP-FM**	**CUP-BC**	**FGLS**	**CUP-FM**	**CUP-BC**	**GFLS**
Regressors						
$lnIOPEN_t$	0.349**	0.339**	0.310	0.321**	0.361**	0.214
	(0.162)	(0.151)	(0.292)	(0.151)	(0.152)	(0.182)
$lnREC_t$	-3.246*	-0.924*	-3.930*	-	-	-
	(0.850)	(0.100)	(0.054)			
$lnIPOEN_t$*$lnREC_t$	-0.144***	-0.125*	-0.100*	-	-	-
	(0.087)	(0.026)	(0.008)			
$lnNREC_t$	-	-	-	1.191*	1.138*	1.131*
				(0.035)	(0.211)	(0.003)
$lnIOPEN_t$*$NREC_t$	-	-	-	0.024*	0.011**	0.001***
				(0.009)	(0.006)	(0.001)
$lnOIL_t$	-0.617**	-0.374*	-0.364*	-0.697*	-0.239**	-0.299***
	(0.307)	(0.111)	(0.083)	(0.164)	(0.115)	(0.057)
$lnGNIPC_t$	350.253*	350.357*	87.873*	36.070*	3.959**	10.859*
	(37.21)	(39.89)	(21.271)	(3.297)	(2.010)	(2.826)
$lnGNIPC2_t$	-398.146*	-403.728*	-101.498*	-39.830*	-3.599*	-11.606*
	(55.819)	(82.991)	(32.119)	(35.118)	(0.318)	(1.317)
Constant	-0.966*	-0.912	-0.923	-13.526*	-10.730*	-10.840)
	(0.028)	(1.219)	(0.846)	(1.287)	(2.100)	(0.289)
Wald Chi^2			494.79*			3466.1*
Adj. R^2	0.828	0.888		0.873	0.881	
Observations	101	101	102	101	101	102

*Note: The standard errors are reported within the parentheses; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Finally, the Dumitrescu-Hurlin heterogeneous causality analysis is conducted. Tables 8 and 9 report the corresponding results. It is apparent from the overall estimates that unidirectional causalities stem from ICT-trade openness to RE consumption, energy-use intensity levels and access to clean fuels and technologies for cooking purposes in the context of the selected South Asian nations. However, a feedback causal association is found to be existing between the trade of ICT goods and share of RE in aggregate energy consumption figures. Hence, keeping the modes of causation into cognizance and linking them with the corresponding elasticity estimates from the regression analyses, it can be asserted that liberalization of barriers to trade of ICT goods could be effective in boosting the consumption of RE resources and also improve the efficiency of energy consumption within the concerned nations. However, the policymakers have to be cautious in reducing the trade barriers on ICT goods that make intensive use of NRE resources since liberalizing these barriers could backfire to trigger the consumption of NRE resources at a faster rate than the consumption of the RE resources. Therefore, the ultimate transition from consumption of NRE to RE resources ultimately would be conditional on appropriate taxation policies which should ideally facilitate the cross-border flows of green ICT-goods and services into the South Asian nations.

On the other hand, statistical evidence regarding bidirectional association between trade of ICT goods and carbon dioxide emissions is found which implies that not only does cross-border movements of ICT goods affect the emissions of carbon dioxide into the atmosphere, the intensity of such emissions also play a critical role in instigating movements in the ICT-trade openness indices within the South Asian economies. Thus, linking to the positive sign of the elasticity estimate, it can be said that enhancing openness to the trade of ICT goods degrades the environment through greater emission of carbon dioxide. However, it can be expected that rising volumes of carbon within the atmosphere could also give rise to awareness to boost the trade of green ICT goods and services which would account for the environmental adversities associated with ICT trade. Moreover, a unidirectional causality running from RE consumption to carbon dioxide emissions is also witnessed which further calls for effective energy sector reforms to ensure replacement of NRE resources via the renewable alternatives in order to reduce the intensity of carbon emissions within the selected South Asian nations. Once again, liberalization of barriers to trade of green ICT goods and services, which profusely employ RE resources, should be a policy intervention from the associated governments keeping the sustainability of the environment into cognizance. The results from the Granger (1969) and the Geweke (1982) causality estimates are reported in tables 10, 11, 12 and 13 in the appendix. The overall results show that these techniques are inferior compared to the Dumitrescu-Hurlin causality estimation method; which can be perceived from the failure of these methods to statistically establish causal linkages between the concerned variables.

Table 8: Dumitrescu and Hurlin (2012) heterogeneous panel causality test results

Model (1)			Model (2)			Model (3)		
Dep. Var.	**Indep. Var.**	**Z-Stat**	**Dep. Var.**	**Indep. Var.**	**Z-Stat**	**Dep. Var.**	**Indep. Var.**	**Z-Stat**
$lnREC_t$	**$IOPEN_t$**	5.371*	**RESt**	**$IOPEN_t$**	5.471*	**lnEIt**	**$IOPEN_t$**	3.438*
$IOPEN_t$	**$lnREC_t$**	-0.068	**$IOPEN_t$**	**RESt**	4.211*	**$IOPEN_t$**	**lnEIt**	0.582
$lnREC_t$	**$lnCO2_t$**	3.323*	**RESt**	**$lnCO2_t$**	7.626*	**lnEIt**	**$lnCO2_t$**	0.189
$lnCO2_t$	**$lnREC_t$**	0.275	**$lnCO2_t$**	**RESt**	1.335	**$lnCO2_t$**	**lnEIt**	2.712*
$lnREC_t$	**$lnOIL_t$**	3.140*	**RESt**	**$lnOIL_t$**	6.684*	**lnEIt**	**$lnOIL_t$**	5.103*
$lnOIL_t$	**$lnREC_t$**	0.638	**$lnOIL_t$**	**RESt**	-1.241	**$lnOIL_t$**	**lnEIt**	0.503
$lnREC_t$	**$lnFDI_t$**	-0.052	**RESt**	**$lnFDI_t$**	2.774*	**lnEIt**	**$lnFDI_t$**	0.386
$lnFDI_t$	**$lnREC_t$**	0.869	**$lnFDI_t$**	**RESt**	2.285**	**$lnFDI_t$**	**lnEIt**	4.720*
$lnREC_t$	**$lnNODA_t$**	2.248**	**RESt**	**$lnNODA_t$**	3.541*	**lnEIt**	**$lnNODA_t$**	1.298
$lnNODA_t$	**$lnREC_t$**	4.492*	**$lnNODA_t$**	**RESt**	6.311*	**$lnNODA_t$**	**lnEIt**	7.454
$lnREC_t$	**$lnREMIT_t$**	6.003*	**RESt**	**$lnREMIT_t$**	7.786*	**lnEIt**	**$lnREMIT_t$**	1.97**
$lnREMIT_t$	**$lnREC_t$**	19.956*	**$lnREMIT_t$**	**RESt**	1.357	**$lnREMIT_t$**	**lnEIt**	22.08*
$lnREC_t$	**$lnGNIPC_t$**	8.268*	**RESt**	**$lnGNIPC_t$**	2.69***	**lnEIt**	**$lnGNIPC_t$**	6.567*
$lnGNIPC_t$	**$lnREC_t$**	1.052	**$lnGNIPC_t$**	**RESt**	3.101*	**$lnGNIPC_t$**	**lnEIt**	1.510
$lnREC_t$	**INF_t**	1.501	**RESt**	**INF_t**	1.91***	**lnEIt**	**INF_t**	-1.031
INF_t	**$lnREC_t$**	0.311	**INF_t**	**RESt**	-0.096	**INF_t**	**lnEIt**	0.617

*Note: The estimated z-statistics are reported; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 9: Dumitrescu and Hurlin (2012) heterogeneous panel causality test results

Model (4)			Model (5) and (6)		
Dep. Var.	**Indep. Var.**	**Z-Stat**	**Dep. Var.**	**Indep. Var.**	**Z-Stat**
ACFTt	$\mathbf{IOPEN_t}$	5.428*	$\mathbf{lnCO2_t}$	$\mathbf{IOPEN_t}$	8.031*
$\mathbf{IOPEN_t}$	**ACFTt**	1.150	$\mathbf{IOPEN_t}$	$\mathbf{lnCO2_t}$	2.012**
ACFTt	$\mathbf{lnCO2_t}$	-0.715	$\mathbf{lnCO2_t}$	$\mathbf{lnREC_t}$	4.275*
$\mathbf{lnCO2_t}$	**ACFTt**	3.755*	$\mathbf{lnREC_t}$	$\mathbf{lnCO2_t}$	3.324*
ACFTt	$\mathbf{lnOIL_t}$	-0.401	$\mathbf{lnCO2_t}$	$\mathbf{IOPEN_t*lnREC}$	4.265*
$\mathbf{lnOIL_t}$	**ACFTt**	-0.464	$\mathbf{IOPEN_t*lnREC_t}$	$\mathbf{lnCO2_t}$	1.116
ACFTt	$\mathbf{lnLIFE_t}$	-0.001	$\mathbf{lnCO2_t}$	$\mathbf{lnNREC_t}$	8.191*
$\mathbf{lnLIFE_t}$	**ACFTt**	271.48*	$\mathbf{lnNREC_t}$	$\mathbf{lnCO2_t}$	13.272*
ACFTt	$\mathbf{lnSSE_t}$	0.001	$\mathbf{lnCO2_t}$	$\mathbf{IOPEN_t*lnNREC_t}$	1.278
$\mathbf{lnSSE_t}$	**ACFTt**	0.129	$\mathbf{IOPEN_t*lnNREC_t}$	$\mathbf{lnCO2_t}$	1.980**
ACFTt	$\mathbf{INF_t}$	3.453*	$\mathbf{lnCO2_t}$	$\mathbf{lnOIL_t}$	2.119**
$\mathbf{INF_t}$	**ACFTt**	-1.023	$\mathbf{lnOIL_t}$	$\mathbf{lnCO2_t}$	-1.041
ACFTt	$\mathbf{lnGNIPC_t}$	-0.177	$\mathbf{lnCO2_t}$	$\mathbf{lnGNIPC_t}$	4.848*
$\mathbf{lnGNIPC_t}$	**ACFTt**	2.595	$\mathbf{lnGNIPC_t}$	$\mathbf{lnCO2_t}$	3.665*
			$\mathbf{lnCO2_t}$	$\mathbf{lnGNIPC2_t}$	4.901*
			$\mathbf{lnGNIPC2_t}$	$\mathbf{lnCO2_t}$	3.604

*Note: The estimated z-statistics are reported; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

7. Conclusion

Attainment of energy security within the economy, particularly through phasing out of the traditional dependence on the consumption of fossil fuels and the adoption of RE resources, has been a key policy agenda amidst governments all around the world. In addition, ensuring environmental sustainability, particularly via mitigation of carbon and other greenhouse emissions, has also become a development goal within the global economy. Keeping both these targets into cognizance, liberalizing barriers to trade of ICT goods is hypothesized to complement the underlying strategies aimed at achieving these goals. Against this milieu, this paper aimed at investigating the role of enhancing ICT-trade openness with respect to the initiation of the RE transition and mitigation of carbon dioxide emission in the context of selected South Asian economies. The results indicate that greater flows of ICT goods facilitate consumption of RE, enhance the efficiency of energy use and increase access to clean fuel and technologies for cooking. However, in spite of such positive impacts, enhancing ICT-trade openness is unable to elevate the share of renewables in the aggregate energy consumption figures across the South Asian countries. This implies that liberalization of the relevant barriers trade barriers, despite contributing to higher levels of RE consumption, stimulates the cross-border flows of the ICT goods that intensively consume NRE resources as well. Hence, it is recommended that trade barriers should only be reduced in the context of green ICT commodities that have the capacity to employ the RE resources. On the other hand, a rise in the ICT-trade openness indices is also found to be curbing the levels of per capita carbon dioxide emissions across South Asia. This further call for effective policy interventions to be undertaken to facilitate the cross-border flows of the relatively greener ICT goods which, along with ensuring RE transition, would be ideal in prolonging the climate change adversities linked to carbon emissions stemming from the combustion of the fossil fuels.

As part of the future scope of research, this analysis can be extended to conduct country-specific studies in order to identify the possible heterogeneity of the findings. Moreover, other greenhouse emissions can also be included to assess the impacts of ICT-trade on environmental sustainability. Moreover, this study can be replicated incorporating the possible structural breaks in the data for robustness checks of the estimated results. Finally, a disaggregated analysis using the consumption of different types of ICT goods can also be undertaken to assess their respective impacts on RE transition and carbon dioxide emissions.

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Appendix

Table 10: Panel Granger causality test results

Model (1)			Model (2)			Model (3)		
Dep. Var.	**Indep. Var.**	**Chi^2-Stat**	**Dep. Var.**	**Indep. Var.**	**Chi^2-Stat**	**Dep. Var.**	**Indep. Var.**	**Chi^2-Stat**
$lnREC_t$	**$IOPEN_t$**	1.993***	**RESt**	**$IOPEN_t$**	0.812	**lnEIt**	**$IOPEN_t$**	1.985
$IOPEN_t$	**$lnREC_t$**	1.239	**$IOPEN_t$**	**RESt**	1.631	**$IOPEN_t$**	**lnEIt**	4.153
$lnREC_t$	**$lnCO2_t$**	0.664	**RESt**	**$lnCO2_t$**	12.855*	**lnEIt**	**$lnCO2_t$**	1.954
$lnCO2_t$	**$lnREC_t$**	1.267	**$lnCO2_t$**	**RESt**	1.505	**$lnCO2_t$**	**lnEIt**	0.885
$lnREC_t$	**$lnOIL_t$**	0.427	**RESt**	**$lnOIL_t$**	5.637***	**lnEIt**	**$lnOIL_t$**	14.065*
$lnOIL_t$	**$lnREC_t$**	0.286	**$lnOIL_t$**	**RESt**	1.976	**$lnOIL_t$**	**lnEIt**	0.194
$lnREC_t$	**$lnFDI_t$**	0.086	**RESt**	**$lnFDI_t$**	6.479**	**lnEIt**	**$lnFDI_t$**	0.546
$lnFDI_t$	**$lnREC_t$**	11.657*	**$lnFDI_t$**	**RESt**	9.489*	**$lnFDI_t$**	**lnEIt**	12.757*
$lnREC_t$	**$lnNODA_t$**	1.758	**RESt**	**$lnNODA_t$**	2.563	**lnEIt**	**$lnNODA_t$**	0.802
$lnNODA_t$	**$lnREC_t$**	1.792	**$lnNODA_t$**	**RESt**	6.661***	**$lnNODA_t$**	**lnEIt**	1.929
$lnREC_t$	**$lnREMIT_t$**	1.068	**RESt**	**$lnREMIT_t$**	6.585**	**lnEIt**	**$lnREMIT_t$**	4.588***
$lnREMIT_t$	**$lnREC_t$**	16.449*	**$lnREMIT_t$**	**RESt**	17.113*	**$lnREMIT_t$**	**lnEIt**	3.811
$lnREC_t$	**$lnGNIPC_t$**	0.324	**RESt**	**$lnGNIPC_t$**	9.750*	**lnEIt**	**$lnGNIPC_t$**	2.743
$lnGNIPC_t$	**$lnREC_t$**	3.129*	**$lnGNIPC_t$**	**RESt**	0.525	**$lnGNIPC_t$**	**lnEIt**	5.613***
$lnREC_t$	**INF_t**	6.403*	**RESt**	**INF_t**	10.263	**lnEIt**	**INF_t**	1.252
INF_t	**$lnREC_t$**	1.049	**INF_t**	**RESt**	5.882***	**INF_t**	**lnEIt**	0.672

*Note: The estimated Chi^2-statistics are reported; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 11: Panel Granger causality test results

Model (4)			Model (5)			Model (6)		
Dep. Var.	**Indep. Var.**	**Chi^2-Stat**	**Dep. Var.**	**Indep. Var.**	**Chi^2-Stat**	**Dep. Var.**	**Indep. Var.**	**Chi^2-Stat**
ACFTt	**$IOPEN_t$**	1.966	**$lnCO2_t$**	**$lnREC_t$**	1.675	**$lnCO2_t$**	**$lnTEC_t$**	1.232
$IOPEN_t$	**ACFTt**	2.196	**$lnREC_t$**	**$lnCO2_t$**	1.443	**$lnTEC_t$**	**$lnCO2_t$**	1.160
ACFTt	**$lnCO2_t$**	4.111	**$lnCO2_t$**	**$lnREC_t$*IOPEN**	1.502	**$lnCO2_t$**	**$lnTEC_t$*IOPEN**	3.134
$lnCO2_t$	**ACFTt**	3.110	**$lnREC_t$*$IOPEN_t$**	**$lnCO2_t$**	6.818**	**$lnTEC_t$*$IOPEN_t$**	**$lnCO2_t$**	1.726
ACFTt	**$lnOIL_t$**	7.472**	**$lnCO2_t$**	**$lnOIL_t$**	5.269***	**$lnCO2_t$**	**$lnOIL_t$**	3.402
$lnOIL_t$	**ACFTt**	0.219	**$lnOIL_t$**	**$lnCO2_t$**	1.036	**$lnOIL_t$**	**$lnCO2_t$**	1.255
ACFTt	**$lnLIFE_t$**	5.372***	**$lnCO2_t$**	**$lnGNIPC_t$**	0.914	**$lnCO2_t$**	**$lnGNIPC_t$**	0.940
$lnLIFE_t$	**ACFTt**	33.258*	**$lnGNIPC_t$**	**$lnCO2_t$**	5.103***	**$lnGNIPC_t$**	**$lnCO2_t$**	1.058
ACFTt	**$lnSSE_t$**	5.398***	**$lnCO2_t$**	**$lnGNIPC2_t$**	0.891	**$lnCO2_t$**	**$lnGNIPC2_t$**	0.936
$lnSSE_t$	**ACFTt**	1.167	**$lnGNIPC2_t$**	**$lnCO2_t$**	5.189***	**$lnGNIPC2_t$**	**$lnCO2_t$**	1.053
ACFTt	**INF_t**	0.541						
INF_t	**ACFTt**	4.998***						
ACFTt	**$lnGNIPC_t$**	2.589						
$lnGNIPC_t$	**ACFTt**	9.307*						

*Note: The estimated Chi^2-statistics are reported; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 12: Geweke's (1982) Measure of Instantaneous Feedback results

Model (1)		Model (2)		Model (3)	
Null Hypothesis[a]	**Chi^2 stat.**	**Null Hypothesis[a]**	**Chi^2 stat.**	**Null Hypothesis[a]**	**Chi^2 stat.**
$lnREC_t$ and $IOPEN_t$	0.425	**RES_t and $IOPEN_t$**	0.946	**$lnEI_t$ and $IOPEN_t$**	2.177
$lnREC_t$ and $CO2_t$	1.168	**RES_t and $CO2_t$**	1.240*	**$lnEI_t$ and $CO2_t$**	0.364
$lnREC_t$ and $lnOIL_t$	0.306	**RES_t and $lnOIL_t$**	0.025	**$lnEI_t$ and $lnOIL_t$**	16.125*
$lnREC_t$ and $lnFDI_t$	0.312	**RES_t and $lnFDI_t$**	7.714*	**$lnEI_t$ and $lnFDI_t$**	0.002
$lnREC_t$ and $lnREMIT_t$	0.266	**RES_t and $lnREMIT_t$**	0.015	**$lnEI_t$ and $lnREMIT_t$**	0.815
$lnREC_t$ and $lnNODA_t$	0.130	**RES_t and $lnNODA_t$**	2.564***	**$lnEI_t$ and $lnNODA_t$**	0.953
$lnREC_t$ and $lnGNIPC_t$	3.531***	**RES_t and $lnGNIPC_t$**	0.176	**$lnEI_t$ and $lnGNIPC_t$**	2.013
$lnREC_t$ and INF_t	0.004	**RES_t and INF_t**	1.134	**$lnEI_t$ and INF_t**	4.132

*Note: a denotes the Null Hypothesis of the presence of instantaneous feedback; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*

Table 13: Geweke's (1982) Measure of Instantaneous Feedback results

Model (4)		Model (5)		Model (6)	
Null Hypothesis[a]	**Chi^2 stat.**	**Null Hypothesis[a]**	**Chi^2 stat.**	**Null Hypothesis[a]**	**Chi^2 stat.**
$ACFT_t$ and $IOPEN_t$	0.944	**$lnCO2_t$ and $lnREC_t$**	2.037	**$lnCO2_t$ and $lnREC_t$**	3.670***
$ACFT_t$ and $CO2_t$	0.002	**$lnCO2_t$ and $lnREC_t$*$IOPEN_t$**	0.409	**$lnCO2_t$ and $lnREC_t$*$IOPEN_t$**	0.629
$ACFT_t$ and $lnOIL_t$	1.834	**$lnCO2_t$ and $lnOIL_t$**	5.166**	**$lnCO2_t$ and $lnOIL_t$**	6.751*
$ACFT_t$ and $lnLIFE_t$	6.835*	**$lnCO2_t$ and $lnGNIPC_t$**	5.273**	**$lnCO2_t$ and $lnGNIPC_t$**	3.210***
$ACFT_t$ and $lnSSE_t$	1.440	**$lnCO2_t$ and $lnGNIPC2_t$**	5.228**	**$lnCO2_t$ and $lnGNIPC2_t$**	3.179***
$ACFT_t$ and $lnGNIPC_t$	0.188				
$ACFT_t$ and INF_t	1.433				

*Note: a denotes the Null Hypothesis of the presence of instantaneous feedback; *, ** and *** denote statistical significance at 1%, 5% and 10% levels respectively*