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RESEARCH ARTICLE

The relationship between urbanization, technology innovation, trade openness, and CO_2 emissions: evidence from a panel of Asian countries

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Abstract

This paper explores the dynamic relationship between CO_2 emissions, urbanization, trade openness, and technology innovation based on the panel data of 13 Asian countries over the period of 1985–2019. The STIRPAT model is used as a framework for the analysis. For estimation purpose, panel cointegration and FMOLS techniques are utilized. The causality between the concerned variables is also examined by estimating a panel VECM model. The results of panel cointegration reveal the presence of long-run relationship among the variables. FMOLS estimations show that energy consumption increases CO_2 emissions while technology change, urbanization, and trade openness compact it. Panel causality analysis indicates bidirectional causality between urbanization and emissions, technology and emissions, trade and emissions, and trade and technology in the long run. Overall findings support the idea that urbanization, technology innovation, and trade openness can play important role to achieve environmental sustainability.

Keywords Technology innovation · Trade · Urbanization · CO_2 emissions · STIRPAT · Dynamic panel · Asia

Introduction

Over the years, the increasing volume of greenhouse gases (GHGs) is a major factor behind environmental degradation worldwide (Seetanah et al. 2018). The global warming and environmental degradation arises as a result of increased energy pollution that adversely affects climate and human health (Adedoyin et al. 2020; Mardani et al. 2019). Being a main source of greenhouse gases, carbon dioxide (CO_2) emission has attracted greater attention from researchers over the past two decades. The CO_2 emissions contribute to 75% of greenhouse gas emissions (Abbasi and Riaz 2016). Furthermore, CO_2 emissions increased to 1.9% during 2018 as compared to 1.2% in 2016 which is quite high (EDGAR 2019). This sharp rise in global temperature and its impact on the climate prompted the origination of the United Nations Framework Convention on Climate Change in 1992. Later, the “Kyoto Protocol” in 1997 and the “Paris Contract” in 2015 were established with the purpose to alleviate the global warming. Asian countries actively participate in competitions to improve production, but policies to protect the environment failed to mitigate CO_2 emissions, as carbon emissions in the Asian region account for 47% of that worldwide (Hanif et al. 2019). Thus, prompt actions are required to mitigate CO_2 emission from the major Asian countries.

In order to analyze the factors that lead to increased CO_2 emissions, urbanization is considered as a main indicator that causes increased CO_2 emissions. With substantial increase in economic growth and development, the labor force is moving from agriculture to industrial sector that is mostly located in urban zones. Consequently, the movement from agriculture to industrial sector dramatically affects the settlement patterns, and thus contributes to increasing CO_2 emissions (Al-mulali et al. 2015; Salim et al. 2019). According to the United Nations report, about 54% of the world’s population is living in urban areas, which expands to 66% by 2050 (United Nations 2018). With fast-paced urbanization, CO_2 emissions are increasing dramatically (WDI 2019). According to

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International Energy Agency (IEA), about 70% of the increasing CO_2 emissions is caused by urbanization and it will increase to 76% by 2030 (IEA 2019). The growth of urbanization in Asia is reported 64% which is much faster than in other regions in the world.

The present study aims to introduce the role of technology innovation (TI) that plays a substantial role in mitigating CO_2 emissions in Asian countries. Several existing studies (see, e.g., Santra 2017; Hasanbeigi et al. 2012; Goulder and Mathai 2000) have emphasized that modern technology adoption has potential to reduce CO_2 emissions by improving energy efficiency without limiting economic growth trends. For instance, environmental policies affect CO_2 emissions in two ways. On the one hand, it affects the prices of carbon-based fuels by imposing energy taxes that directly discourage energy use and reduce pollution emissions, while on the other hand, such policies may also encourage firms to purchase or invent new technology in order to bring alternative fuels that emit less carbon (Santra 2017; Carraro and Siniscalco 1994). Therefore, energy efficiency technologies such as renewable energy and minimization of wastes and residues during production, transmission, and distribution systems are important to reduce energy sector emissions (Jiaqiang et al. 2017; Sohag et al. 2015; Apergis and Danuletiu 2014; Madsen et al. 2010; Pao and Tsai 2010). However, it is also argued that technology advancement contributes toward depletion of resources as well as environmental degradation by the rebound effect. The use of technology in industrial sector tends to increase production activities that require more raw materials and energy resources which harm environmental quality (Khan et al. 2017; Greening et al. 2000). There is, however, not much empirical work available that indicates the relationship between technological innovation and CO_2 emissions. This paper, therefore, contributes to the existing literature by examining whether or not environment-related technological innovation helps to mitigate CO_2 emissions. Thus, this study helps policymakers to implement efficient policies for environmental sustainability.

However, the implementation of various energy saving measures and the pattern of energy consumption (EC) also depend on the economic activities in a country. Economic growth (EG) is likely to be more energy intensive with greater tendency of economic activities which are largely fossil fuel driven and cause environmental deterioration. Moreover, increasing economic growth causes to improve technology, promote alternative energy sources and rely on these renewable energy sources (for instance, geothermal, hydropower, biomass, wind, solar, and marine energies) for production, and expand the tertiary and services sector which helped to contain carbon emissions (Kaika and Zervas 2013). Several studies have demonstrated that the scale of economic activities (commonly measured by GDP per capita) is positively associated with EC and thus increases CO_2 emissions (Omri 2013; Shahbaz et al. 2013; Marrero 2010; Chebbi and Boujelbene 2008). On the other hand, higher EG is also needed to improve energy efficiency that ultimately reduces CO_2 emissions. The countries with higher level of GDP use resources more efficiently and can also devote more resources to invent or import energy-efficient technologies to reduce pollution emissions (Lapinskienė et al. 2017).

Another important factor affecting energy CO_2 emissions is trade openness (TO). Recent studies have shown that TO might affect energy CO_2 emissions through different channels such as income, economies of scale, technique, and composition effects (Wan et al. 2015; Sadorsky 2010; Feridun et al. 2006; Frankel and Rose 2005; Antweiler et al. 2001). It is argued that international trade is an essential component of EG, and a rise in TO is associated with higher economic activities, energy demand, and CO_2 emissions (Sadorsky 2012; Jalil and Feridun 2011). On the other hand, international trade linkage is also a source of advance technology spillovers from developed countries to developing ones. The diffusion of more sophisticated technology increases productivity of energy use and thus lowers carbon emissions (Nasreen and Anwar 2014; Antweiler et al. 2001).

Therefore, it is important to examine the dynamics between urbanization, technology, trade, and CO_2 emission for policymakers because of its direct implications for sustainable environment and economic development. This paper contributes to the literature by extending the analysis of causal dynamics between CO_2 emissions, technology innovation, and trade openness by controlling for several important variables such as energy use, economic development, and population to a panel data of 13 Asian countries over the period of 1985–2019. Limited to our knowledge, there has thus far been no attempt to examine the relationship between these variables within a multivariate framework across these 13 Asian countries. It is well known that Asia is a region of the world's largest economies, with more than half of the world's total population size. The choice of Asia is also motivated by the fact that this region accounts for over one quarter (28%) of the global primary energy demand and more than half (53%) of the world's total coal consumption, which are among the major sources of CO_2 emissions (Nasreen and Anwar 2014; Bloch et al. 2012). According to Asia/World Energy Outlook (2018), energy conservation and pollution reduction efforts in Asian countries have important implications for the future of global environmental sustainability because of the larger share of this region in global energy consumption and pollution emissions, especially in China and India, which will account for 32% of the world's total energy consumption by 2040. Thus, the relationship between TI, TO, and CO_2 emissions in such a heavily populated and rapidly growing region is the focus of our study.

The present study utilizes Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model. To examine the long-run co-movement and the causal relationship among the variables, we utilized

(Baltagi 2009; Pedroni 1999, 2004; Im et al. 2003; Maddala and Wu 1999; Kao 1999) panel cointegration tests (Levin et al. 2002) and panel fully modified OLS (FMOLS) technique. FMOLS corrects the standard OLS for bias induced by endogeneity and serial correlation. Moreover, we estimated a panel vector error correction model (VECM) that is appropriate for heterogeneous panel to detect the direction of causality between the variables. The results of this study indicate the presence of cointegration among the variables such as EC, TI, TO, EG, and CO_2 emissions. Long-run elasticity estimation results of FMOLS report that EC and EG increase emission level while TI and TO reduce it in our sample of Asian countries. The Granger causality analysis provides further evidence on the long-run relationship among the variables and reveals bidirectional long-run causality between emissions and energy consumption, emissions and technology change, emissions and trade openness, and trade and technology. These findings may yield new avenues for policymakers to design a comprehensive energy, technology, and trade and environmental policy to attain sustainable economic development.

The rest of the paper is organized as follows: "Literature review" provides literature review; "Econometric model and data collection" describes model, estimation techniques, and data source; "Analytical framework" presents results of empirical estimations; and finally, "Panel cointegration tests" concludes the whole discussion.

Literature review

The last two decades have seen an emergence of research on the link between environmental degradation and human activities. The earlier studies examining the relationship between output growth and environmental pollution mainly concentrate on environmental Kuznets curve (EKC), which suggests an inverted U-shaped relationship between EG and pollution emission. The EKC hypothesis implies that at first, economic development increases pollution level but beyond a turning point, pollution level decreases with a rise in income due to increasing environmental awareness, regulations, and public spending on environment protection (Shahbaz et al. 2013). Starting with the pioneering work of Grossman and Krueger (2004), numerous studies have been devoted to empirically testing EKC hypothesis, which yields mixed results (Halicioglu 2009; Dinda 2004; Shahbaz et al. 2012; Al-mulali et al. 2015; Alam et al. 2016; Kwakwa and Adu 2016; Aboagye 2017; Dong et al. 2018; Sinha and Shahbaz 2018). Another group of studies concentrates on energy consumption-economic growth (EC-EG) nexus (Sarkodie et al. 2019; Mardani et al. 2019; Dogan et al. 2020), which suggests that economic development and energy consumption might be determined jointly because economic development is both a cause and a consequence of energy consumption. Moreover, the higher economic development requires more energy consumption, and more efficient energy use needs a higher level of economic development (Lapinskienė et al. 2017). Starting from the seminal work of (Kraft and Kraft 1978), the relation between EC and EG has been investigated extensively (Halicioglu 2009; Narayan and Narayan 2008; Wolde-Rufael 2006; Masih and Masih 1996). The findings of empirical research, however, appear to be inconsistent.

The latest literature on this issue combines both approaches and also includes some new variables like population, trade openness, technology development, and other country-specific factors that are likely to affect environmental quality. Empirical results of these studies mainly depend on the variables included in the empirical model, data frequency, and econometric techniques used in the analysis. Several studies have been conducted to show that EC, EG, and CO_2 emissions are interrelated but the results of empirical studies are mixed. For instance, Chebbi and Boujelbene (2008) investigated the relationship between these three variables using time series data during 1971–2004 for Tunisia. The results revealed that output induces higher energy use and the resulting energy consumption leads to CO_2 emissions. Pao and Tsai (2010) by using panel data of four BRIC countries (Brazil, Russia, India, and China) investigated the dynamics of EC, GDP growth, and CO_2 emissions. The results indicate that EC increases CO_2 emissions while the relationship between GDP growth and CO_2 emissions follows EKC hypothesis. Furthermore, the results also indicate bidirectional long-run causality between EC, GDP growth and CO_2 emissions, and unidirectional short-run causality from emissions to EC and output, respectively. By using panel data of 27 EU countries, Marrero (2010) reported positive effects of EC and EG on CO_2 emissions. Pao and Tsai (2011) extended this idea by examining the association between GDP growth, EC, and CO_2 emission for Brazil by using the gray prediction model and found that emissions are more sensitive to energy consumption than output while supporting the EKC hypothesis. Long-run association between EC, EG, and CO_2 emissions is also confirmed by Omri (2013) for 14 MENA countries and Shahbaz et al. (2015) for a panel of 99 countries. However, empirical findings provided by Baek (2015) are different about growth-pollution nexus. The study utilized panel data of seven Arctic countries (namely Canada, Denmark, Iceland, Finland, Norway, Sweden and USA) using panel ARDL and generalized least square methods. The results showed positive impact of EC on CO_2 emissions but an inverse relationship between GDP growth and CO_2 emissions.

Like EC and EG, international trade also helps explain the dynamics of CO_2 emissions. The effect of TO can be classified into scale, technique, and composition effects (Antweiler et al. 2001). Many believe that trade deteriorates environment quality (Ertugrul et al. 2016). Race to the bottom is the most widely discussed hypothesis, according to which the true effects of openness depend on the environmental policies in a country (Machado 2000). Less developed economies adopt weaker environmental regulations and decrease energy prices to stay competitive in international markets. Weaker regulations and cheaper energy reduce energy efficiency which could have a negative effect on environment quality (Wan et al. 2015; Antweiler et al. 2001). Frankel and Rose (2005) noted that free trade may also result in importing of polluted goods in poor countries having low environmental standards, i.e., the so-called pollution haven countries. Similar arguments are presented by Shahbaz et al. (2013) who argued that free trade and movement of production factors may shift dirty industries toward pollution haven countries where environmental regulations are mere formalities. Some other studies which concluded harmful impact of trade on environment are Al-mulali et al. (2015), Kasman and Duman (2015), Jalil and Feridun (2011), Nasir and Rehman (2011), Cole et al. (2000), and Machado (2000).

On the other hand, supporters of *gain from trade theory* claim that international trade increases competition between countries and promotes efficient use of scarce resources and facilitates transfer of cleaner technologies in order to combat environmental pollution (Shahbaz et al. 2013; Frankel and Rose 2005; Yanikkaya 2003; Helpman 1998). The positive impacts of trade on environmental quality are reported by many researchers using both country-specific and panel data (Wan et al. 2015; Shahbaz et al. 2012; Grether et al. 2007; Frankel and Rose 2005; Antweiler et al. 2001; Ferrantino 1997; Birdsall and Wheeler 1993; Shafik and Bandyopadhyay 1992). For instance, Antweiler et al. (2001) provided empirical evidences from a panel of 43 countries to show that trade-induced technique and scale effects have positive impact on environment quality. Frankel and Rose (2005) investigated trade-pollution nexus using cross country data and revealed that trade openness reduces three measures of environment pollution namely SO_2, NO_2, and particulate matter. A recent study by Wan et al. (2015) provides useful insights on trade-facilitated technology spillovers and energy productivity convergence across 16 EU countries. The analysis revealed that trade helps reduce energy productivity gap by encouraging common environmental regulations and accelerating technology spillovers.

With respect to technology-pollution nexus, several researchers have emphasized that environmental quality and technology innovation are connected (Santra 2017; Hasanbeigi et al. 2012; Lantz and Feng 2006; Berndt et al. 1993; Sterner 1990; Jorgenson and Fraumeni 1981). Adoption of advance technology has potential to reduce energy consumption and pollution level without limiting GDP growth trend (Santra 2017; Hasanbeigi et al. 2012). Recent studies utilized both country-specific and panel data to provide empirical evidences on the relationship between technology innovation and environmental sustainability. For example, Ang (2009) utilized Chinese data to examine the effect of R&D expenditure and technology transfer on CO_2 emissions. The results indicated that both the R&D and technology transfer have reduced emissions in both the long run and short run in China. By using panel data of 20 OECD countries, Wong et al. (2013) argued that technology adoption has played an important role to gain greater energy efficiency and economic growth in OECD countries. Sohag et al. (2015) used Malaysian Data to investigate the effect of technology innovation on energy consumption. The results showed a negative impact of technology innovation on energy consumption in Malaysia. Park et al. (2017) collected data from China and Korea to investigate the relationship between residential CO_2 emissions and technology use. The results indicated a reduction in residential CO_2 emissions due to the use of efficient technologies in both countries. Santra (2017) extends this idea to show that technological innovation has positively helped BRICS countries, namely, Brazil, Russia, India, China, and South Africa, to increase energy productivity and environmental quality. Furthermore, environmental regulations like pollution taxes can stimulate the firms to purchase or invent new technologies in order to combat pollution emissions without reducing their output level. By using high-tech industries data from China, Xu and Lin (2016) reported that high-tech industries are beneficial to control CO_2 emissions. Moreover, the emission reduction performance of the central and western regions is better than of the eastern region, which is mainly because of greater R&D expenditure and technology endowments of the formers.

Material and methods

The current paper makes use of STIRPAT model of Dietz and Rosa (1994) and extends it further by incorporating other variables (CO_2 emissions per capita, population, economic growth, energy consumption per capita, technology innovation, and trade openness) for empirical estimation. The STIRPAT model is an extension of well-known IPAT model and provides a framework to empirically estimate the effects of anthropogenic activities on environmental change. In general form, the STIRPAT model can be formulized as follows:

$$It = bP_t^c A_t^d T_t^e \varepsilon_t \tag{1}$$

where I represents environmental effects or energy pollution; P, A, and T denote population size; affluence or economic activities per capita, usually measured by real per-capita GDP (RGDPP); and technology level, respectively. The b is an intercept term while the c, d, and e are the coefficients of the environmental effects of P, A, and T respectively. The term t stands for the year and ε_t is the usual random error term. Since logarithmic transformation of all the variables can avoid possible heteroscedasticity and also linearize the model that makes elasticity calculations easier as the estimated coefficients capture the percentage changes in the underlying variables. Thus, Eq. (1) is rewritten as

$$\ln I_t = b + c \ln P_t + d \ln A_t + e \ln T_t + \varepsilon_t \quad (2)$$

where ln(.) is natural logarithm and I, P, A, and T are the same as in above Eq. (1). The STIRPAT model permits to incorporate other factors that affect environmental pressure. Dietz and Rosa (1994) argued that other factors affecting the relationship can be replaced by the term T in the original specification. Based on the discussion in "Introduction" and "Literature review", we extend this model by including energy consumption, trade openness, and technology innovation. The extended STIRPAT model can be expressed as

$$\ln CO_{it} = \alpha_0 + \alpha_1 URB + \alpha_2 \ln P_{it} + \alpha_3 \ln A_{it} + \alpha_4 \ln EC_{it} + \alpha_5 \ln T_{it} + \alpha_6 \ln TO_{it} + \varepsilon_{it} \quad (3)$$

where CO is CO_2 emissions per capita, P is total population, URB is urbanization, A is economic activities or economic growth measured as RGDPP, EC is energy consumption per capita, T is technology innovation measured by the number of patents, and TO represents trade openness. The subscript i ($i = 1, 2,\ldots,N$) and t ($t = 1,2,\ldots,T$) represent cross sections and time periods respectively.

We use kg of oil equivalent per capita to measure EC following common practice in literature (Azam et al. 2015, Nasreen and Anwar 2014). The coefficient of EC is expected to be positive because it is the basic factor to increase emissions level (Lapinskienė et al. 2017; Shahbaz et al. 2012; Pao and Tsai 2010). Affluence is measured by RGDPP in constant 2010 US dollar. The RGDPP is a widely used indicator of economic activities in empirical studies and its impact on CO_2 emissions can be assumed positive because higher economic activities increase demand for energy and other natural resources that ultimately generate higher pollution emissions (Xu and Lin 2018; Shahbaz et al. 2013; Wang et al. 2011; Pao and Tsai 2010; Dietz and Rosa 1994). TO is measured as percentage of export and import value to GDP that is also a common routine in empirical studies. The impact of TO can be either positive or negative on CO_2 emissions (Azam et al. 2015; Nasir and Rehman 2011; Feridun et al. 2006). Some recent studies show that TO improves environmental quality by transferring clean technology into developing countries (Wang et al. 2015; Shahbaz et al. 2012; Frankel and Rose 2005). However, the actual impact of trade on pollution emissions depends on a country's environment policies. As discussed in the "Literature review" section, free trade may also shift pollution-intensive industries from home countries to developing ones where environmental regulations are relatively weaker which could have adverse effect on environment quality (McCarney and Adamowicz 2006; Antweiler et al. 2001). For technology innovation, we use number of patents following Sohag et al. (2015). A large body of empirical literature supports the number of patents to measure technology change in a country (Sohag et al. 2015; Ang 2011; Madsen et al. 2010). Sohag et al. (2015) used patent data to investigate the effect of technology innovation on EC. They argued that patents are the quantitative measure of technology innovation because they reflect the interest of organizations to explore new technologies. The impact of technology innovation on CO_2 emissions is expected to be negative because adoption of new technologies improves efficient use of energy and natural resources that result in fewer wastes and less environmental pollution (Park et al. 2017; Sohag et al. 2015; Wong et al. 2013).

We select 13 Asian countries for the estimation of empirical model on the basis of data availability. The countries included in the study are Bangladesh, India, China, Hong Kong, Indonesia, Iran, Japan, South Korea, Malaysia, Philippines, Sri Lanka, Thailand, and Turkey. Data on all the variables spanning 1985–2019 is taken from World Development Indicators.

Econometric Embedded Methodology

The basic concern of empirical analysis is the sign and size of the coefficients of technology change and trade openness, although the effects of the other variables also provide useful insights. The study utilizes panel cointegration and causality analysis to test the long-run relationship among the underlying variables. The standard procedure to test for cointegration is first to check stationary of the variables.

Panel cointegration tests

To examine cointegration among the variables, we apply Pedroni (1999, 2004)'s and Kao (1999)'s panel cointegration tests. Pedroni (1999)'s cointegration test is a powerful tool to test cointegration for both homogeneous and heterogeneous panels. The test equation can be written as

$$X_{i,t} = \propto_i + \gamma_i t + \theta_{1i} y_{1i,t} + \ldots + \theta_{mi} y_{mi,t} + u_{it} \quad (4)$$

In Eq. (4), it is assumed that x and y are $I(1)$. Furthermore, the individual intercept $\propto_i$ and the coefficients $\theta_{1i}, \theta_{2i}, \ldots, \theta_{mi}$ may vary across individual series in a panel. Pedroni (1999, 2004) suggested seven test statistics to check cointegration in heterogeneous panel. These different tests are corrected for bias due to endogenous variables and to deal with cross-sectional dependence by including time dummies. Mainly, these tests are classified into within dimension and between dimensions tests. The null hypothesis for all these tests is no cointegration H_0: $\gamma_i = 1$ (where $i = 1,2..,N$) against the alternative of cointegration but different for between and within dimensions. The alternative hypothesis for between dimension H_1: $\gamma_i < 1$ (where $i = 1,2..,N$) and for within dimension H_1: $\gamma_i = \gamma < 1$ (where $i = 1,2..,N$).

Equation (4) is at first estimated by OLS method and then the relevant test is computed from the following statistics:

Within dimension statistics

1. Panel v-statistics: $Z_v \equiv T^2 N^{3/2}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\widehat{u}_{it-1}^{2}\right)^{-1}$
2. Panel ρ- statistics: $Z_\rho \equiv T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\widehat{u}_{it-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\left(\widehat{u}_{it-1}\Delta\widehat{u}_{it}-\widehat{\lambda}_i\right)$
3. Non-parametric panel t-statistics: $Z_t \equiv \left(\widetilde{\sigma}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\widehat{u}_{it-1}^{2}\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\left(\widehat{u}_{it-1}\Delta\widehat{u}_{it}-\widehat{\lambda}_i\right)$
4. Parametric panel t-statistics: $Z_t^{*} \equiv \left(\widetilde{s}_{N,T}^{*2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\widehat{u}_{it-1}^{2}\right)^{1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\kappa}_{11,i}^{-2}\widehat{u}_{it-1}\Delta\widehat{u}_{it}^{*}$

Between dimension statistics

1. Group ρ-statistics: $\widetilde{Z}_\rho \equiv TN^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\widehat{u}_{it-1}^{2}\right)^{-1}\sum_{t=1}^{T}\left(\widehat{u}_{it-1}\Delta\widehat{u}_{it}-\widehat{\lambda}_i\right)$
2. Non-parametric group t-statistics: $\widetilde{Z}_t \equiv N^{-1/2}\sum_{i=1}^{N}\left(\widehat{\sigma}_i^{2}\sum_{t=1}^{T}\widehat{u}_{it-1}^{2}\right)^{-1/2}\sum_{t=1}^{T}\left(\widehat{u}_{it-1}\Delta\widehat{u}_{it}-\widehat{\lambda}_i\right)$
3. Parametric group t-statistics: $\widetilde{Z}_t^{*} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\widetilde{s}^{*2}\widehat{u}_{it-1}^{2*}\right)^{-1/2}\sum_{t=1}^{N}\left(\widehat{u}_{it-1}^{*}\Delta\widehat{u}_{it}^{*}\right)$

where $\widehat{\lambda}_i = \frac{1}{2}\left(\widehat{\sigma}_i^{2}-\widehat{s}_i^{2}\right)$ and $\widetilde{s}_{N,T}^{*2} = \frac{1}{N}\sum_{i=1}^{N}\widetilde{s}^{*2}.$

To make the distribution of the calculated panel test statistics asymptotically normal, adjusted terms of mean and variance are applied as follows:

$$\frac{\varkappa N, T-\mu\sqrt{N}}{\sqrt{\mho}} \Rightarrow N(0,1) \tag{5}$$

where $\varkappa N$, T is the standardized form of the statistics with respect to N and T, and μ and $\mho$ are the moments functions of the underlying Brownian motion. Pedroni (1999) suggests that for smaller T, the group ADF test outperforms and has the best power followed by panel ADF while panel v and group ρ tests show poor performance.

Kao (1999) panel cointegration test is based on DF and ADF tests which include fixed effect or individual intercept in the initial equation but no deterministic trend. The test regression is as follows:

$$y_{it} = x_{it}\phi_i + \varphi_i + \xi_{it} \tag{6}$$

and $\xi_{it} = \rho\xi_{it-1} + \theta_{it}$. Both Pedroni (1999) and Kao (1999) tests assume the existence of a single cointegration vector, although Pedroni test permits heterogeneity across cross-sections.

Estimation of long run elasticity

If cointegration is found among the variables, the OLS estimator is not appropriate because it yields inconsistent and biased results. To deal with these weaknesses of traditional estimator, different models have been developed. For instance, Kao and Chiang (2000) suggest that the parametric dynamic OLS (DOLS) approach performs well in cointegrated panel. However, the major limitation of panel DOLS is that it ignores the cross-sectional heterogeneity in the alternative hypothesis. For this, Pedroni 2000, 2001proposed fully modified OLS (FMOLS) as an alternative estimator for cointegrated panel. It is a non-parametric approach which yields consistent results when sample size is small and also corrects for serial correlation and endogeneity. FMOLS has advantage over DOLS by allowing cross-sectional heterogeneity in the alternative hypothesis and provides asymptotically unbiased estimations (Lee and Chang 2008). Following Pedroni (2001), the panel FMOLS estimator can be expressed as

$$\widehat{\beta}^{*}_{FM} = N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(y_{it}-\overline{y}\right)^{2}\right)^{-1}\left(\sum_{t=1}^{T}\left(y_{it}-\overline{y}\right)\right)z_{it}^{*}-T\widehat{\eta}_i \tag{7}$$

where $z_{it}^{*} = (z_{it}-\overline{z})-\frac{\widehat{L}_{21i}}{\widehat{L}_{22i}}\Delta y_{it}$, $\widehat{\eta}_i = \widehat{\Gamma}_{21i} + \widehat{\psi}_{21i}^{0}-\frac{\widehat{L}_{21i}}{\widehat{L}_{22i}}\left(\widehat{\Gamma}_{22i} + \widehat{\psi}_{22i}^{0}\right)$, and $\widehat{L}_i$ is a lower triangular decomposition of $\widehat{\psi}_i$. The associated t-statistics are given as

$$t_{\widehat{\beta}^{*}} = N^{-1/2}\sum_{i=1}^{N}t_{\widehat{\beta}^{*}}, i \tag{8}$$

where $t_{\widehat{\beta}^{*}}, i = \left(\widehat{\beta}_i^{*}-\beta_0\right)\left[\widehat{\psi}_{11i}^{-1}\sum_{t=1}^{T}(y_{it}-\overline{y})^{2}\right]^{1/2}$

Panel VECM analysis

The existence of cointegration also requires investigating the causality between the variables. For this, we apply panel VECM-based causality test to examine the direction of relationship. Following Lee and Chang (2008), we use a two-step procedure. In the first step, Eq. (3) is estimated by FMOLS estimator in order to obtain the residuals and in the second stage, this estimated residual (or error correction term by using lagged value) is used to estimate the individual error correction model which jointly form a vector. Specifically,

$$\begin{bmatrix} \Delta ln\, CE_{it} \\ \Delta ln\, EN_{it} \\ \Delta ln\, T_{it} \\ \Delta ln\, P_{it} \\ \Delta ln\, TO_{it} \\ \Delta ln\, A_{it} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \end{bmatrix} + \sum_{k-1}^{p} \begin{bmatrix} d_{11k} & d_{12k} & d_{13k} & d_{14k} & d_{15k} & d_{16k} \\ d_{21k} & d_{22k} & d_{23k} & d_{24k} & d_{25k} & d_{26k} \\ d_{31k} & d_{32k} & d_{33k} & d_{34k} & d_{35k} & d_{36k} \\ d_{41k} & d_{42k} & d_{43k} & d_{44k} & d_{45k} & d_{46k} \\ d_{51k} & d_{52k} & d_{53k} & d_{54k} & d_{55k} & d_{56k} \\ d_{61k} & d_{62k} & d_{63k} & d_{64k} & d_{65k} & d_{66k} \end{bmatrix} \times \begin{bmatrix} \Delta lnCE_{it-1} \\ \Delta lnEN_{it-1} \\ \Delta lnT_{it-1} \\ \Delta lnP_{it-1} \\ \Delta lnTO_{it-1} \\ \Delta lnA_{it-1} \end{bmatrix} \begin{bmatrix} \psi_1 \\ \psi_2 \\ \psi_3 \\ \psi_4 \\ \psi_5 \\ \psi_6 \end{bmatrix} ECT_{it-1} + \begin{bmatrix} \xi_{1it} \\ \xi_{2it} \\ \xi_{3it} \\ \xi_{4it} \\ \xi_{5it} \\ \xi_{6it} \end{bmatrix} \quad (9)$$

where ECT_{t-1} is the lagged error correction term used to detect long-run causality from independent variables to dependent variable. In Eq. (9), all the variables are treated as endogenous variables where each variable, in turn, becomes dependent variable for causality testing procedure. The significance of coefficient of ECT_{t-1} provides evidence of long-run causality because ECT_{t-1} causes the endogenous variables to converge toward long-run equilibrium due to variations in the exogenous variables. Short-run causality is detected using *F*-test of joint significance of the lagged first difference of independent variable.

Results and discussion

Unit root test

This study utilizes the Zivot–Andrews unit root test with structural break followed by Shahbaz et al. (2013) and Ertugrul et al. 2016. The results of the Zivot–Andrews test presented in Table 1 demonstrate that none of the variable is found stationary at level, while other statistics provide strong evidence that the series are stationary at first difference. The break dates also shown in Table 1 correspond to structural changes in the time series. The structural break period refers to several elements, for instance economic downfall, energy crises, fluctuations in business cycle, and changes in legislations and openness of markets.

Panel cointegration test results

To test the existence of long-run relationship among the variables, Pedroni (1999, 2004) panel cointegration test is applied with and without time effects. As discussed earlier in methodology section, Pedroni (1999, 2004) proposed a total of seven test statistics where four statistics tests are within dimension (panel) while three statistics tests between dimension (group) cointegration among the variables. Within-dimension estimator constructs the test statistics by pooling the autoregressive (AR) coefficients across individual countries during the unit root test process and thus restricts the first-order AR parameter to be similar across countries. On the other hand, between dimension estimators use average of individual AR for each cross-section to perform the test. The results of both types of tests are given in Table 2. The results clearly reject the null hypothesis of no cointegration in most cases, and we conclude that CO_2 emission, technology innovation, trade openness, and other control variables are cointegrated in our sample of 13 Asian countries for the period of 1995–2019.

Table 3 displays the results of Kao (1999)'s residual-based cointegration test results. The test statistics clearly reject the null hypothesis of no cointegration at less than 1% level of significance. The results confirm the Pedroni test statistics and strengthen the claim that a stable long-run relationship exists between the variables in selected Asian countries.

Long-run elasticity estimation

Table 4 displays the FMOLS estimation results at individual country and aggregate level where dependent variable is CO_2 emissions. The panel estimators are shown at the bottom of Table 4. In addition to heterogeneous FMOLS, we also report the results of the fixed-effects FMOLS estimator suggested by Mark and Sul (2003), using a sandwich form which allows for heterogeneous variance. The difference between the coefficients estimated from these two estimators is not very marked in terms of sign, size, and significance level.[1] The coefficients of *EC*, *A*, and *P* are found to have positive impact on CO_2 emissions, while technology and trade have negative impact on CO_2 emissions.

[1] Since both the heterogeneous and fixed-effects estimators provide almost similar results, so we focus only on heterogeneous estimator for discussion to conserve the space.

Table 1 Zivot–Andrews unit root test with structural break

Country	Regressors	Level	Time break	First difference	Time break
Bangladesh	CO_2	− 4.056	1991	− 4.933***	1993
	URB_{it}	− 6.619	1991	− 5.344***	1993
	P_{it}	− 5.516	1993	− 9.455**	1993
	A_{it}	− 7.978	1993	− 3.655**	1993
	EC_{it}	− 4.544	1993	− 5.433**	992
	T_{it}	− 7.913	1993	− 4.322**	1991
	TO_{it}	− 5.413	1993	− 5.648***	1991
India	CO_2	− 3.214	1993	− 5.214*	[illegible]
	URB_{it}	− 4.978	1992	− 7.412*	[illegible]
	P_{it}	− 5.433**	1992	− 6.344*	1992
	A_{it}	− 4.322	1992	− 5.516*	1991
	EC_{it}	− 5.648	1992	[illegible]	1990
	T_{it}	− 7.898	1991	[illegible]	1990
	TO_{it}	− 5.414	1991	[illegible]	1990
China	CO_2	− 7.433	1991	[illegible]	1991
	URB_{it}	− 5.214	1991	− 9.722**	1993
	P_{it}	− 7.412	[illegible]	− 3.566*	1993
	A_{it}	− 6.344	1993	− 4.988*	1993
	EC_{it}	− 6.233	[illegible]	− 6.455***	1993
	T_{it}	− 9.434*	1993	− 8.723***	2004
	TO_{it}	− 5.124	1993	− 6.478***	2004
Hong Kong	CO_2	− 8.977	1991	− 9.722**	1991
	URB_{it}	[illegible]	1991	− 5.688**	1991
	P_{it}	[illegible]	1991	− 6.868***	1991
	A_{it}	[illegible]	1991	− 6.344***	1991
	EC_{it}	− 6.868	1991	− 9.766**	1991
	T_{it}	− 6.344	1991	− 5.322**	1990
	TO_{it}	− 8.212**	1993	− 6.344**	1992
Indonesia	CO_2	− 7.322	1991	10.986**	
	URB_{it}	− 9.766*	1993	− 4.344*	1994
	P_{it}	− 5.322	1993	− 9.235*	1999
	A_{it}	− 6.344	1993	− 2.763*	1999
	EC_{it}	− 5.211	1993	− 1.357*	1999
	T_{it}	− 6.433	1993	− 9.877**	1999
	TO_{it}	− 3.245	1993	− 5.655*	1998
Iran	CO_2	− 4.335	1990	− 9.635*	1998
	URB_{it}	− 9.877	1990	− 3.465*	1991
	P_{it}	− 5.655	1990	− 6.987*	1991
	A_{it}	− 7.344**	1990	− 2.477***	1991
	EC_{it}	− 5.455**	1991	− 8.567***	1994
	T_{it}	− 7.866	1991	− 3.247***	1994
	TO_{it}	− 3.455	1992	− 9.346***	1994
Japan	CO_2	− 8.344	1996	− 1.652***	1990
	URB_{it}	− 8.455	1996	− 4.345**	1998
	P_{it}	− 9.635	1996	− 7.653**	1998
	A_{it}	− 3.465	1992	− 10.347***	1998
	EC_{it}	− 6.987	1992	− 2.466***	1998
	T_{it}	− 3.654	1992	− 2.433***	1998
	TO_{it}	− 2.456	1991	− 1.457***	1998

Table 1 (continued)

Country	Regressors	Level	Time break	First difference	Time break
South Korea	CO_2	− 3.725	1999	− 3.455*	2001
	URB_{it}	− 2.455	1999	− 2.455*	2001
	P_{it}	− 3.455	1997	− 4.346*	2000
	A_{it}	− 2.455	1997	− 6.435*	2000
	EC_{it}	− 4.344	1997	− 2.477**	1990
	T_{it}	− 6.455	1997	− 8.567***	[illegible]
	TO_{it}	− 2.467	1997	9.346***	1990
Malaysia	CO_2	− 4.346	2000	− 9.766***	[illegible]
	URB_{it}	− 6.435	2000	− 5.322**	[illegible]
	P_{it}	− 2.477	1999	− 6.344**	[illegible]
	A_{it}	− 8.567	1999	[illegible]	1994
	EC_{it}	− 3.247	1999	[illegible]	1994
	T_{it}	− 2.433	1999	[illegible]	1994
	TO_{it}	− 1.457	1999	[illegible]	1994
Philippines	CO_2	− 2.206	2003	[illegible]	1990
	URB_{it}	− 4.987	2003	− 3.755*	1990
	P_{it}	− 4.764	[illegible]	− 2.788*	2000
	A_{it}	− 4.346	[illegible]	− 3.877*	2000
	EC_{it}	− 3.236	[illegible]	− 4.925***	1998
	T_{it}	− 2.875	2001	− 3.555**	1998
	TO_{it}	− 2.98	[illegible]	− 6.435***	1998
Sri Lanka	CO_2	− 4.94	1999	− 3.572*	1991
	URB_{it}	[illegible]	1994	− 5.763*	1991
	P_{it}	[illegible]	1994	− 9.349*	1991
	A_{it}	[illegible]	1991	− 9.348***	1990
	EC_{it}	− 2.144	1991	− 2.984**	1990
	[illegible]	− 7.546	1991	− 4.764***	1990
	[illegible]	− 3.677	1991	− 4.346***	1990
Thailand	CO_2	− 3.987	2003	− 2.788**	2003
	URB_{it}	− 4.98	1995	− 3.877**	2003
	P_{it}	− 3.244	1995	− 1.984***	2003
	A_{it}	− 3.755	2000	− 2.766*	2003
	EC_{it}	− 2.788	2000	− 3.982*	2001
	T_{it}	− 3.877	2000	− 2.834***	2002
	TO_{it}	− 4.925	2000	− 1.985***	2002
Turkey	CO_2	− 3.555	2004	− 2.873**	1996
	URB_{it}	− 6.435	2006	− 3.247*	1996
	P_{it}	− 2.445	2000	− 2.433*	1995
	A_{it}	− 1.988	2000	− 1.457*	1995
	EC_{it}	− 7.455	2000	− 2.987***	1995
	T_{it}	− 9.455	1999	− 4.23***	1995
	TO_{it}	− 7.555	1999	− 4.987***	1995

*, **, ***represent statistical significance at 10%, 5%, and 1% level

The coefficient of *EC* is positive and significance at 1% level, implying that a 1% rise in *EC* leads to a 0.711% increase in CO_2 emissions per capita in our sample of Asian countries. At individual level, *EC* has a significantly positive impact on CO_2 emissions per capita in all the selected countries. The results provide strong evidence that greater energy consumption tends to increase CO_2 emissions in our sample of Asian countries. The coefficient of urbanization is positive and

Table 2 Pedroni cointegration test

Test	No time effects Statistics	Fixed time effects p value	Statistics	p value
Panel υ-statistics	0.605	0.473	− 1.086	0.861
Panel σ-statistic	2.059	0.980	3.377	0.999
Panel $\rho\rho$-statistic	− 2.311	0.010	− 1.795	0.036
Panel *adf*-statistic	− 5.786	0.000	− 5.172	0.000
Group σ-statistic	2.886	0.998	3.853	0.998
Group $\rho\rho$-statistic	− 4.061	0.000	− 6.263	0.000
Group *adf*-statistic	− 5.913	0.000	− 5.740	0.000

Lag length selection is based on the SIC criteria. We adopted Newey–West automatic bandwidth with quadratic spectral kernel

significant for all countries except Hong Kong and Thailand. The positive coefficient shows that an increase in urbanization leads to increase CO_2 emissions in Asian countries. Our results are similar with Poumanyvong and Kaneko (2010), Bekhet and Othman (2017), and Pata (2018). The finding is contradictive with Sharma (2011) and Ali et al. (2019). The coefficient associated with technology innovation is highly significant and negative, implying that a rise in technology innovation by 1% leads to decrease of CO_2 emissions per capita by about 0.024% in the long run. In case of individual countries, technology coefficient is negative and significant in China, Hong Kong, Indonesia, Iran, Japan, Malaysia, Philippines, and Turkey whereas negative and insignificant in Bangladesh, India, and Sri Lanka. Almost all the countries in our sample show negative coefficient of technology innovation except Korea and Thailand. The negative coefficient of technology suggests that a rise in technology innovation leads to reduce CO_2 emissions in selected Asian countries. The coefficient of trade openness is negative and significant at 5% level for the panel of our selected countries. The estimated elasticity of trade openness is − 0.025, implying that a 1% increase in trade openness is associated with a 0.025% decrease in CO_2 emissions per capita. At country level, the coefficient of trade openness bears negative sign in Bangladesh, China, India, Iran, Philippines, Thailand, and Turkey, more than half of our sample countries. These findings support the idea that through technology spillover effects, trade openness can reduce CO_2 emissions in these Asian countries. However, trade openness is also found to have positive impact on CO_2 emissions in six countries namely Hong Kong, Indonesia, Japan, Korea, Malaysia, and Sri Lanka. These country-specific results might be due to the rebound effects of trade-facilitated technology change on energy consumption and thus on CO_2 emissions as reported by Sohag et al. (2015) in case of Malaysia. Another possible reason behind the positive coefficient of trade could be the country-specific factors like weaker environmental standards and subsidized energy prices as argued by Wan et al. (2015), Antweiler et al. (2001), and McCarney and Adamowicz (2006). However, when combined with panel estimation, we can conclude that overall trade openness has inverse impact on CO_2 emissions.

Table 3 Kao's residual-based cointegration test results

	Lag length	t-statistics	p value
ADF	7	− 3.703	0.0001

Lag length selection is based on the SIC criteria

To conclude, the country-specific and panel cointegration results suggest that there exists a cointegrated relationship between *EC*, *TO*, technology change, and other variables in our sample of Asian countries. Moreover, technology and trade have potential to combat energy CO_2 emissions in the long run.

Panel causality analysis

The existence of the cointegration among emissions, energy, trade, technology, and other variables suggests that there must be Granger causality in at least one direction. For this, we apply a panel VECM causality test to identify the direction of relationship among the variables. To compute panel VECM, we consider 3 lags based on FPE, AIC, and HQ criteria, given in Table 5.

Short-run and long-run causality results are given in Table 6. We find that the coefficient of ECT_{t-1} is significant and negative at 1% level of significance when CO_2 emission is assigned as dependent variable. The coefficient of ECT_{t-1} is − 0.0158 which indicates that the speed of adjustment toward full equilibrium is 1.58% in a year. The results confirm the existence of long-run Granger causality from energy consumption, technology change, trade openness, and other variables to CO_2 emissions.

When energy consumption is taken as dependent variable, the coefficient of ECT_{t-1} is negative and significant at the 1% level, indicating that energy consumption responds to long-run equilibrium. It explores that *EC* has long-run causality

Table 4 Fully modified OLS results (ln *CE*: dependent variable)

Country groupings	ln URB_{it}	ln EN_{it}	ln T_{it}	ln TO_{it}	ln P_{it}	ln A_{it}
Bangladesh	3.022** (0.120)	1.865* (0.337)	−0.011 (0.043)	−0.048 (0.091)	1.135* (0.257)	−0.514** (0.241)
China	1.862* (0.067)	1.279* (0.072)	−0.069** (0.0347)	−0.009 (0.028)	1.292 (0.803)	0.381* (0.102)
Hong Kong	−1.165** (0.076)	0.637* (0.022)	−0.125* (0.005)	1.147* (0.032)	5.066* (0.149)	−1.37* (0.045)
India	0.971*** (0.087)	2.041* (0.119)	−0.011 (0.013)	−0.007 (0.032)	1.743* (0.109)	−0.881* (0.091)
Indonesia	0.876* (0.065)	1.761* (0.101)	−0.191* (0.021)	0.145* (0.034)	−1.691* (0.188)	1.181* (0.082)
Iran	0.801* (0.254)	0.786* (0.059)	−0.012** (0.005)	−0.092* (0.013)	0.686* (0.131)	0.165* (0.061)
Japan	0.020*** (0.081)	1.752* (0.014)	−1.086* (0.007)	0.219* (0.003)	−8.769* (0.075)	0.738[illegible]014)
Korea	0.336*** (0.987)	0.812* (0.129)	0.059 (0.039)	0.101 (0.052)	0.528 (1.204)	−0.326 ([illegible])
Malaysia	0.110* (0.233)	0.615** (0.263)	−0.174* (0.027)	0.293* (0.084)	−1.093* (0.387)	1.375* (0.287)
Philippines	0.047*** (0.058)	2.495* (0.101)	−0.037** (0.015)	−0.154* (0.046)	1.189* (0.136)	[illegible]105 (0.133)
Sri Lanka	0.233* (0.457)	0.701** (0.257)	−0.019 (0.051)	0.486* (0.124)	−11.57[illegible]* (2.372)	1.054* (0.359)
Thailand	−0.983* (0.455)	1.229* (0.089)	0.028* (0.007)	−0.242* (0.036)	4.[illegible]06* ([illegible]89)	0.037 (0.068)
Turkey	0.055* (0.344)	1.233* (0.075)	−0.014* (0.005)	−0.055* (0.019)	0.1[illegible]* (0.068)	−0.226* (0.053)
Panel results						
Heterogeneous estimator	0.877*** (0.355)	0.711* (0.022)	−0.024* (0.006)	−0.025** (0.012)	[illegible]662* (0.034)	0.258* (0.018)
Fixed effects estimator	0.432*** (0.070)	0.724* (0.012)	−0.035* (0.019)	−0.021[illegible]007)	0.[illegible]6* (0.018)	0.269* (0.008)

Std. errors are given in parentheses. * and ** level of significance at 1% and 5%, respectively. We a[illegible] qua[illegible]tic spectral kernel and Andrews automatic bandwidth selection method following Wang and Wu (2012) methodology

* and ** level of significance at 1% and 5%, respectively

with all other variables. The significance and negative ECT_{t-1} in case of technology change panel VECM equation shows that all selected variables cause technology innovation in our sample countries. Similarly, trade openness showed long-run causality with all other variables. The feedback relationship between technology and trade suggests that trade openness Granger causes technology and in result, technology change leads to higher trade. These findings are consistent with Wan et al. (2015), Grether et al. (2007), and Frankel and Rose (2005) and support the idea that trade facilitates technology spillover from other countries to Asia that ultimately reduces pollution emissions. Moreover, unidirectional Granger causality is found from RGDPP to CO_2 emissions but the same is not true from opposite direction. This implies that any effort to reduce CO_2 emissions would not affect the pace of economic growth in Asian countries. The long-run causal relationship is found bidirectional between CO_2 emissions and energy consumption, CO_2 emissions and technology, and CO_2 emissions and trade. With respect to short-run causality, the results are, however, not so strong. Among our variables of interest, only technology Granger causes energy consumption at 10% level of significance but the same is not true from the opposite direction. The overall results imply that all the four variables (*CE*, *EC*, *T*, and *TO*) dynamically interact to restore long-run equilibrium whenever there is a deviation from the cointegration relationship. It is also important to note here that the long-term impact of technology and trade are likely to be more significant, both because it takes time for trade-

Table 5 VAR based lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
1	2868.458	8560.338	1.05e−16	−19.765	−19.228	−19.551
2	3075.330	394.939	3.18e−17	−20.961	−19.96326*	−20.561
3	3158.400	155.103	2.29e−17*	−21.291*	−19.832	−20.705*
4	3187.689	53.458	2.40e−17	−21.242	−19.325	−20.474
5	3216.496	51.368	2.53e−17	−21.192	−18.814	−20.239
6	3248.411	55.573*	2.62e−17	−21.163	−18.325	−20.026
7	3266.906	31.428	2.97e−17	−21.041	−17.743	−19.719
8	3297.269	50.322	3.11e−17	−21.001	−17.243	−19.495

*Lag order selected by the criterion (each test at 5% level)

Table 6 VECM based Granger causality analysis

Dependent variable	Direction of causality Short run (*F*-statistics) Δln*CO*	Δln*EC*	Long run Δln*T*	Δln*TO*	Δln*P*	Δln*A*	Δln *URB*	ECT_{t-1}
Δ ln *CO*	_	1.332	0.956	0.273	4.123*	2.439***	1.233	− 0.158*
Δ ln *EC*	0.362	_	1.711	0.458	9.627*	1.178	0.236	− 0.135*
Δ ln *T*	1.227	2.385***	_	0.175	12.101*	1.851	3.141	− 0.141*
Δ ln *TO*	0.708	0.511	0.172	_	0.291	5.342*	0.055	− 0.114*
Δ ln *P*	0.888	0.938	0.247	2.248	_	0.541	1.267	− 0.004
Δ ln *A*	0.074	0.435	0.526	0.764	3.481**	_	0.054	0.011
Δ ln *URB*	0.063	1.755	0.235	2.256	3.234	0.097	_	0.002**

* and ** significance at 1% and 5% level, respectively

facilitated technology to diffuse through industry and because higher prices may induce new technology for several years (Popp 2001).

Conclusion

To control pollution emissions without hampering economic growth has been the major concern of policymakers in every corner of the world. Previous studies have highlighted that urbanization, technology innovation, and trade openness have potential to combat environmental pollution while maintaining stable economic growth. Thus, the study is an effort to investigate the dynamics of urbanization, technology innovation, trade openness, and CO_2 emissions by controlling for several important variables, i.e., energy consumption, economic growth, and population size. For this, we use STIRPAT function to specify our empirical model by using panel data of 13 Asian countries over the period of 1985–2019. For empirical analysis, we adopt Pedroni and Kao panel cointegration approaches and fully modified OLS (FMOLS) for long-run elasticity estimation. We also specify a panel VECM model based on FMOLS estimation to examine the direction of causality among the variables in Asian countries.

Empirical results obtained from Pedroni and Kao cointegration techniques provide strong evidence to believe that there exists stable long-run relationship among the variables. The results of FMOLS reveal a positive relationship between urbanization, energy consumption, and CO_2 emissions whereas a negative impact of trade and technology on CO_2 emissions is observed. The causality analysis confirms the presence of feedback causality between energy consumption and emissions, trade and emissions, technology, and emissions in the selected sample of Asian countries. In other words, causality results imply that all these four variables (*CE*, *EC*, *T*, and *O*) dynamically interact to restore long-run equilibrium whenever there is a deviation from the cointegration relationship.

The empirical findings suggest that technology and trade play important role in reducing CO_2 emissions. These findings are very much in line with the latest report of Asia Energy Outlook ([illegible] 2017), which suggests that technology innovation must be combined with technology transfer to support emission reduction efforts globally. The negative coefficient of technology change indicates that meeting the objective of pollution reduction without reducing economic growth is possible through adopting new technologies. The government needs to allocate more resources to R&D activities to generate new innovations. The negative coefficient of trade openness advocates the *gain from trade theory* and suggests that higher openness facilitates technology transfer and reduces pollution emissions. Moreover, Asian economies need to increase the scale of trade openness to get the benefit of advanced technologies from other developed countries of the world. However, the country level mixed results of trade also require more careful thought while regulating trade flows and designing a comprehensive technology, trade, and environmental policy to achieve sustainable economic development.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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