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Sectorial study of technological progress and CO_2 emission: Insights from a developing economy

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ABSTRACT

Many studies have stated that technological progress is an important driver of carbon dioxide (CO_2) emissions and energy consumption. However, the sectorial differences in the relationship between CO_2 emission and technological progress have been understudied by scholars. This study attempts to fill such gap by empirically investigating the impact of technological progress on CO_2 emissions. A quantile regression method and balanced national data from Pakistan covering the period of 1991–2017 are used to establish relationships among the variables. The results and analysis reveal that the agriculture and services sectors have a negative impact on CO_2 emissions, whereas the construction, manufacturing, and transportation sectors greatly contribute to these emissions. The lower, medium, and upper-level emitters are used to understand the percentile conditions of each variable. A scenario analysis is also performed to forecast the reduction proportion of CO_2 emissions for the best understanding and policy implication in 2030, 2035, and 2040. The results of this study provide useful insights into the relationship between technological progress and CO_2 emissions and suggest different scenarios for reducing CO_2 emissions in the future that can support policy makers and planners.

Introduction

Climate change and global warming have seriously threatened ecosystems and human lives over the past few decades. Many scientists have concluded that global warming has sharply intensified due to the excessive CO_2 emissions caused by environmentally unfriendly economic and social activities (Nordhaus, 1991; Rafique and Rehman, 2017; Luukkanen et al., 2015). Over the past 20 million years, the amount of CO_2 emissions has reached critical levels (Pearson and Palmer, 2000), which have not received as much attention as it deserves. However, despite the increasing need to reduce CO_2 emissions, how to effectively reduce these emissions without compromising sustainable socioeconomic development, especially in developing nations, warrants further investigation (Abas et al., 2017; Shan et al., 2018). Therefore, researchers have gradually shifted their focus to determining the impact of technological development on environmental security and protection (Wang et al., 2019). Previous studies show that technological change can enhance economic flexibility, facilitate the adaption of economies to emission reductions, and ensure a swift development of new energy sources (Rafique and Rehman, 2017; Chappin & Dijkema, 2009). Although several researchers have revealed the link between technological advances and CO_2 emissions, the differential impact of technological advances on various economic sectors has not been thoroughly investigated (Shan et al., 2018; Wang et al., 2019). Therefore, much remains to be done in building a framework for technological advancement that may affect the CO_2 emissions of various economic sectors.

Although the global CO_2 emissions of Pakistan have increased by no more than 1% (0.8%), the Pakistani government has striven to address changes in climate by introducing adaptation methods and reducing greenhouse gas emissions (Lin and Ahmad, 2017). The transportation, energy, animal husbandry, agriculture, town planning, forestry, and other sectors are critical areas for interventions that aim to reduce the adversity of climate change. Over the past few years, Pakistan has experienced a historic energy crisis. The Pakistani energy sector is highly dependent on different energy sources, including natural gas (48.2%), oil (32.5%), hydropower (11%), coal (6%), nuclear power (1.7%), and liquefied petroleum gas (0.5%), all of which contribute to its 66.8

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million metric tons of energy supply (Pakistan Energy Yearbook, 2014). Nearly 20 years ago, Pakistan's electricity supply was mainly generated by hydropower. To promote economic development and industrialization, the Pakistan government implemented short- and medium-term policies to establish a thermal power plant that can meet the power supply needs of the country (Duan et al., 2016). However, these policies have seriously affected the energy security, environmental sustainability, balance of payments, and CO_2 emissions of the country.

Over the past decade, the growth of Pakistan's industry and technology has also experienced a significant imbalance, thereby providing a wealth of information for further econometric analysis. Pakistan has become an ideal place for research communities to examine the relationship between technological advancements and CO_2 emissions in different industrial and economic sectors. The research on the impact of technological and industrial developments in Pakistan can provide novel implications and insights that can help other developing countries reduce their CO_2 emissions without compromising their economic growth.

This study offers significant contributions to the literature. First, unlike previous studies that have only focused on the impact of overall technological advances on CO_2 emissions, this study comprehensively examines the relationship between technological advances and CO_2 emissions by considering the sectorial differences in the influence of technological advancements on CO_2 emissions (Munir and Ameer, 2018). Second, this study differs from previous studies that are conducted at the provincial or city levels in other countries (Shan et al., 2018; Wang et al., 2019) by forecasting CO_2 emissions from 2018 to 2040 for different sectors. This study also examines the CO_2 emission reductions in Pakistan from the perspective of multiple sectors and industries.

To determine the influencing factors of CO_2 emissions, this study applies the quantile regression model in analyzing those problems that extend to design-specific scenarios. This study attempts to fill the research gap by answering the following questions: (a) What are the key factors that influence energy-related changes in CO_2 emissions?; (b) How much do each of these factors influence CO_2 emissions?; (c) What would be the level of CO_2 emissions in the future (2018 to 2040) and how can such level be reduced?; and (d) What are the policy implications of reducing CO_2 emissions? This study is expected to be one of the pioneering works that provide an in-depth analysis of past, present, and future CO_2 emission trends and propose recommendations for reducing these emissions. By addressing these issues, this study can help the Pakistani government develop effective energy policies and accelerate activities that can boost the country's economic development.

The rest of this paper is organized as follows. Section 2 reviews the literature on the relationship between technological factors and CO_2 emissions. Section 3 presents the data sources and methods applied for the data analysis. Section 4 presents and discusses the empirical results in detail. Section 5 concludes the paper by presenting the policy implications.

2. Literature review

Given the dearth of authentic statistical data, previous studies have often used energy intensity as a representative of technological advances and an inverse indicator of energy efficiency (Du et al., 2012). By contrast, other researchers have revealed that technological advances adversely influence CO_2 emissions, which is consistent with the general view that technological advances can help reduce CO_2 emissions. For example, Poumanyvong and Kaneko examined 99 countries between 1975 and 2005 and found that energy intensity is positively associated with CO_2 emissions (Poumanyvong and Kaneko, 2010). Similar studies (Grepperud and Rasmussen, 2004; Martínez–Zarzoso and Maruotti, 2011; Shafiei and Salim, 2014; Sodri and Garniwa, 2016) found a positive association between energy intensity and CO_2 emissions. Chinese studies have produced similar findings, such as those of Du et al., who investigated 29 provinces in China and found a positive association between energy intensity and CO_2 emissions (Du et al., 2012). In addition, Wu et al. argued that technological advances play important roles in reducing particulate emissions (Wu et al., 2016).

However, several scholars have found a different relationship between technological advances and CO_2 emissions. For instance, Wang et al. (2012) found that the R&D results of energy-technology-related patent inventory measurement are representative of technological advancements (Wang et al., 2012) and found results are not supported. Similar results have been observed in other studies where only weak links between technology-based factors and CO_2 emissions are found (Wang et al., 2016; Wang et al., 2018). Conversely, several studies have supported the idea that technological advances may promote CO_2 emissions. For example, Wang et al. used the intensity of carbon emissions to reflect the effects of technological advancements on reducing CO_2 emissions in Guangdong Province and found that these two factors are negatively related (Wang et al., 2013). By contrast, an empirical study by Duarte et al. (2013) in 11 countries found that technology actors positively affect CO_2 emissions, especially in the UK and the US (Duarte, Mainar, & Sánchez–Chóliz, 2013). Wang et al. examined the four megacities of China and revealed a negative association between intensity of energy and CO_2 emissions, and these findings support the contentions of rebound effect theory (Wang et al., 2017). The rebound effect refers to the economic response triggered by the technological advances in improving energy efficiency, by the increasing demand to meet the increase in income caused by efficiency, or by the decline in the prices of products and services associated with energy (Sorrell and Dimitropoulos, 2008). In this regard, technological advances may be offset by energy-saving rebound effects and, in some cases, increase CO_2 emissions (Roy, 2000; Chai et al., 2016). The impact of technological advances is also anticipated to fluctuate significantly based on sectorial characteristics. The potential reductions in CO_2 emissions from different sectors and cities have been studied by Shan et al., who found that in general, the reduction in CO_2 emissions from heavy manufacturing is more significant than that in light manufacturing, high-tech manufacturing, construction, and services sectors (Shan et al., 2018). Grepperud and Rasmussen studied the Norwegian economy and found that only the metal sector produces a "backfire effect;" therefore, the energy savings are offset by the rebound effect (Grepperud and Rasmussen, 2004). However, despite these efforts, previous studies have not yet reached a clear consensus on the association between technological advancements and CO_2 emissions. In their empirical analysis, Sorrel and Steve attributed the competing explanations in the literature to the severe regional and sectorial heterogeneity of technological advancements, which has been rarely considered in contemporary academic thinking and trends (Sorrell and Steve, 2009).

Paul and Bhattacharya performed a much-focused evaluation of India's aggregated CO_2 emissions and economic sectors from 1980 to 1996 and found that economic growth has the greatest impact on aggregated CO_2 emissions in major sectors, while the CO_2 emissions from the transportation sector are declining due to the increased effective fuel substitution and energy efficiency of this economic sector; they further argued that compared with the pollution coefficient, energy intensity has a relatively large impact on energy-related CO_2 emissions (Paul and Bhattacharya, 2004). Wang et al. examined the aggregated CO_2 emissions in China from 1957 to 2000 and found that energy intensity, substitution of fossil fuels, and penetration of renewable energy play important roles in reducing the aggregation of CO_2 emissions (Wang et al., 2005). Lise found in his analysis of the Turkish economy from 1980 to 2003 that economic expansion is the greatest influencing factor of CO_2 emissions, followed by the intensity of carbon and economic structures (Lise, 2006). Therefore, any empirical investigation cannot find any evidence to support the decoupling of economic growth during and carbon dioxide emissions. Liu et al. (2007) found that from 1998 to 2005, industrial activities and energy intensity show remarkable negative and positive effects on industrial CO_2 emissions in China (Liu et al., 2007). Ma and Stern instilled biomass in an extended Kaya identity, focusing on the decline and recovery of total carbon dioxide emissions since the mid-1990s in China and found that the positive impact of growth in pollution decreases over time (Ma and Stern, 2008). Ipek et al. (2009) subdivided the economy of Turkey into the industry, services, and agricultural sectors and then aggregated the energy consumed by these sectors into oil, solid fuels, electricity, and natural gas; they examined the impact of macroeconomic policies on CO_2 emissions by changing the industry share and by using diverse sources of energy between 1970 and 2006 and eventually revealed that the critical drivers of CO_2 emissions are associated with economic activities, while energy intensity has a major impact on reducing CO_2 emissions (İpek Tunç et al., 2009).

Some studies have examined the economic sectors of Pakistan from the environmental protection perspective. For instance, Yousuf et al. used baseline emission factors to determine the consumption of fossil fuels in the power sector and found that these factors can help in calculating emissions per MWh and identifying cleaning projects; they have also examined the potential of renewable and alternative energy sources in reducing CO_2 emissions (Yousuf et al., 2014). Khan et al. examined the association among energy consumption, air pollution, natural resource rents, and water resources and found that the impact of energy consumption and water resources on air pollution is positive in both the short and long term and that the impact of natural resource rents on air pollution is relatively small (Khan et al., 2016). Khan and Jamil found that the effects of economic activities are the strongest drivers of the changes in CO_2 emissions, followed by the effects in terms of structure and intensity (Khan and Jamil, 2015).

Ortolano et al. (2014) assessed the cleaning production practices of the leather and textile sector that meet the environmental standards of Pakistan. They selected 80 companies as samples and found that most of these companies have implemented clean production measures. The scale and engagement of companies with foreign client investments have inspired their acceptance of cleaner production practices and motivated their establishment of environmental management standards (Ortolano, Sanchez–Triana, Afzal, Ali, & Rebellón, 2014). Given that all provinces in Pakistan are building large coal-fired power plants, the CO_2 emissions of the country may increase after 2018. The World Bank reported that the CO_2 emissions of Pakistan exponentially increased between 1965 and 2008, but since then, the country has recognized this negative trend and began to reduce its load, thereby stabilizing its CO_2 emission rates (Abas et al., 2017). In 2013, the per capita emissions of Pakistan reached 168 million tons of CO_2 equivalent before falling to 0.7 in 2015 (Boden et al., 2009). Research on greenhouse gas emissions from SAARC countries reveals that in 2006 (Malik et al., 2012), the CO_2 emissions of Pakistan reached 200 million tons, which was predicted to increase to 482 million tons by 2018. The global transportation sector contributes 30 million tons of CO_2 emissions every year, which increased further in the following years due to the low price of oil in 2015/16. In the case of Pakistan, greenhouse gas emissions increase by 6% every year (18.5 Mt CO_2), and such percentage is likely to increase further as a result of the construction of coal-fired plants without carbon capture and storage facilities (Abas et al., 2017). Therefore, the high CO_2 emissions rates in the energy, construction, services, manufacturing, automotive, and agricultural sectors of Pakistan require further attention.

Some methodological limitations can also be observed in the literature. In many cases, researchers have used OLS methods to uncover the effects of technological advances but failed to justify whether or not heterogeneity can weaken the ability of these methods to interpret different sources in the context of Pakistan (Chandia et al., 2018; Farhani and Rejeb, 2012). To complement these shortcomings, this study examines the differences in the association between technological advancements and CO_2 emissions across several economic sectors between 1991 and 2017 in Pakistan. To capture the multiple technological advances in different sectors, technological factors are classified into five sectors, including agriculture, manufacturing, construction, services, and automobile transportation.

The quantile regression model has been used to determine the relationship between various technological advances and CO_2 emissions. Although many researchers have carried out fruitful studies on CO_2 emissions in different sectors, most of them have employed different methods, including the index decomposition method, econometric models, computable general equilibrium model, input–output method, system optimization method, and OLS method, to analyze the impact of driving forces on CO_2 emissions. Indeed, the effects of various factors on CO_2 emissions vary across different quantiles. The quantile regression has two significant advantages over traditional OLS. First, the random disturbance term of least squares regression is subject to the autonomous and identically distributed condition and is normally distributed. Under these conditions, the best estimate can be obtained from least squares. However, these assumptions are hardly satisfied in actual applications. No distributional assumptions are made by quantile regression. Therefore, the estimates of quantile regression are more robust than those of OLS regression. Second, quantile regression is suitable when the main location of the conditional distribution and tails varies along with the covariates. Given that CO_2 emissions significantly differ across various sectors, the quantile regression can reveal the effect of different variables on the distribution of CO_2 emissions (Xu et al., 2017). In addition, to understand the extent to which technological advances have buffered the association between carbon dioxide emissions and energy efficiency, and the extent to which various technological advances affect different sectors and transmitters. The results can be further used in especially designed scenarios to predict the future CO_2 emissions and reductions of Pakistan between 2018 and 2040.

3. Methods and data collection

3.1. Data source

Annual data from 1991 to 2017 for nine variables[1], including CO_2 emissions, GDP per capita, population density, energy intensity, agriculture value added, manufacturing sector, construction sector, services value added, and transport emission, are used in this study. Table 1 shows the number of the variables, sources of data, and means and standard deviations. All relevant data are collected from the World Development Indicators (WDI) database and the Pakistan Economic Survey.

3.2. Model description

The STRIPAT model extended from the original IPAT identity is applied to investigate the impact of technological progress on CO_2 emissions. Many researchers have used the STRIPAT model to investigate the association among CO_2 emissions, energy consumption, and urbanization (Du & Xia, 2018; Li & Lin, 2015). Another framework is Kaya identity, which has been criticized by scholars because of its unit flexibility (Dietz and Rosa, 1994). In previous studies, the STIRPAT model has been used to analyze the determinants of environmental pressure (Huo et al., 2015), whereas the IPAT identity has been used to describe those factors that trigger environmental changes (Chertow, 2001) as identified by Ehrlich and Holdren (1970). Many researchers have also applied the IPAT identity in environmental analysis (Ehrlich and Holdren, 1970; Jung et al., 2012; Xu and Lin, 2015; Zhao et al., 2018). This framework also measures the impact of

[1] The variables CO_2 emissions, GDP per capita, population density (PD), energy intensity (EI), agriculture value added (AVA), manufacturing sector (MS), construction sector (CS), services value added (SVA), and transport emission (TE) (given in Table 1) are used to measure the strength and effects.

Table 1
Description of variables.

Variables	Unit	Sources	Mean	Standard deviation
CO_2 Emission	Million tons.	World development indicators	129.04	39.02
GDP Per Capita PD	\$US People/km^2	Pakistan economic survey; WDI World development indicators	814.92 197.05	376.11 33.15
EI	Mtoe/\$US	World development indicators	0.08	0.09
AVA MS CS	% of GDP % of GDP % of GDP	World development indicators World development indicators World development indicators	23.05 14.17 21.28	1.24 1.17 1.73
SVA Automobiles (TE)	% of GDP % of total fuel combustion	World development indicators World development indicators	48.98 27.23	3.381.75

financial growth on the atmosphere (Lin and Sun, 2010; Wang et al., 2011; Xu and Lin, 2015). The related CO_2 emission factors and sources are presented in Table 1 along with population growth, affluence, and the impact of technology on the environment. The IPAT identity can be mathematically expressed as

$$I = P.\ A.\ T. \tag{1}$$

The IPAT identity (I = P. A. T) is often used as a basis for examining the role of economic activity in CO_2 emissions (Liu et al., 2014). In this model, I denotes environmental impact, P denotes population size, A denotes wealth of society, and T denotes technological progress, which is generally measured as the effect of environment per unit GDP. The sectorial indicators are used to estimate the data. Aside from its simplicity and other limitations, the IPAT identity has been criticized for its failure to adequately explain those factors that trigger environmental changes. According to Tursun et al. (2015), the IPAT identity is a mathematical formula that does not directly test how certain factors influence the environment (Xu and Lin, 2016). Wang and Zhao (2015) argued that the IPAT identity assumes that the elasticities of these factors are uniform. To address these limitations, on the basis of IPAT equation, Dietz and Rosa (1997) proposed the STIRPAT model, which is applied in this study. This model can be mathematically expressed as

$$I = \alpha P_i^a A_i^b T_i^c \varepsilon_i. \tag{2}$$

The STIRPAT model has been widely used in the literature in studying the drivers of environmental changes (Wei, 2011; Xu & Lin, 2016). Taking the natural logarithm form of all variables in Eq. (2), the STIRPAT model can be further presented as

$$lnI = ln\alpha + alnP + blnT + ln\varepsilon, \tag{3}$$

where I, P, A, and T are defined similarly as in the IPAT identity, a, b, and c represent the elasticity of I, P, A, and T, ε represents the residual error, and I represents the year. STRIPAT allows researchers to measure the proper decomposition of individual factors (Dietz and Rosa, 1994) and facilitates investigations into the multiple effects of technological progress. The STIRPAT model also helps identify the sectoral heterogeneity of technological progress by breaking down its impact on economic sectors, including agriculture, services, construction, manufacturing, and transportation. Xu and Lin (2015) and Talbi (2017) integrated energy-related variables into the STRIPAT model. A diagram and flowchart of the sectorial factors are presented in Fig. 1a. After the above extension and decomposition, the final form of the STIRPAT model (3) can be expressed as

$$\begin{aligned} lnCit = {} & \alpha + blnPDit + clnPGDPit + d1lnEIit + d2lnAVAit + d3lnCSit \\ & + d4lnMSit + d5lnSVAit + d6lnTEit + d7lnAVAit{*}lnEIit + d8lnCSit \\ & {*}lnEIit \\ & + d9lnMSit{*}lnEIit + d10lnSVAit{*}lnEIit + d11lnTEit{*}lnEIit + \varepsilon, \end{aligned} \tag{4}$$

where lnCit: natural logarithm of CO_2 emissions; lnPDit: natural logarithm of population density; lnPGDPit: natural logarithm of per capita GDP; lnEIit: natural logarithm of energy intensity; lnAGR it, lnCS it, lnMS it, lnSVA it, and lnTE it: natural logarithms of technological progress in the agriculture sector, construction sector, manufacturing sector, services value added, and transport emissions, respectively; lnAVA it*lnEI it, lnCS it*lnEI it, lnMS it*lnEI it, lnSVA it*lnEI it, and lnTE it *lnEI it: from the elasticity point of view, the interactions between various sectorial progress and energy intensity (EI), b, c, and d1–d7 indicate the corresponding elasticity in the economy of Pakistan.

The STIRPAT model estimates each coefficient as a parameter to address the problems of the IPAT model. In this model, each factor is allowed to be properly decomposed Dietz and Rosa, 1994). Eqs. (1) to ((3) are used to check the different factors that trigger environmental pollution (Xu and Lin, 2016). Different countries have already utilized this model, including China, OECD countries, South Korea, and the US (Cho and Sohn, 2018; Jung et al., 2012; Xu et al., 2014). The STIRPAT model employed in this study measures the relationship between CO_2 emissions and technological factors. Generally, this model has been widely used in examining the determinants of environmental changes, including energy consumption, economic growth, and technological awareness. Various economic sectors, including agriculture, construction, and transportation, and their subsectors are presented in Table 2. The ISIC classification of economic sectors is adopted to understand the fuel consumption and CO_2 emissions of their respective sub-sectors.

3.3. Quantile regression

Many studies have adopted regression techniques to determine the influencing factors of CO_2 emissions. Quantile regression (QR) is utilized in this paper to inspect the impact of CO_2 emissions on different variables. QR is an extended form of OLS introduced by Koenker and Bassett (1978). QR has several advantages over OLS. First, this method reveals the relationship at various points in the conditional distribution of the dependent variable and provides a comprehensive picture of dependence, including the asymmetric and nonlinear relationships among the explanatory variable(s) over the range of values of the dependent variable (Baur, 2013). QR analysis also allows the effects of explanatory variables (covariates) to differ across conditional quantiles. Second, the QR changes in the degree of dependence can be tested for each quantile of the distribution (Baur, 2013). Third, the QR model is more robust than OLS to non-normal errors, outliers in observations, skewness, and heterogeneity in the dependent variable (Zhu et al., 2016). Previous studies have adopted QR to identify the effects of different factors on increasing CO_2 emissions. For example, Wang et al. and Xu et al. used QR to determine the influencing variables of CO_2 emissions (Wang et al., 2019; Xu et al., 2017). QR also helps address those problems that may affect the accuracy of the estimates, including outliers, unobserved heteroscedasticity, and heteroscedasticity (Koenker, 2005; Koenker and Hallock, 2001; Wang et al., 2019). Therefore, this paper adopts QR to examine the relationships between technological progress and CO_2 emissions at different quantiles (such as 25%, 50%, and 75%). Eq. (4) measures the QR of the given variables.

3.4. Technological progress on CO_2 emission in the various sectorial related framework

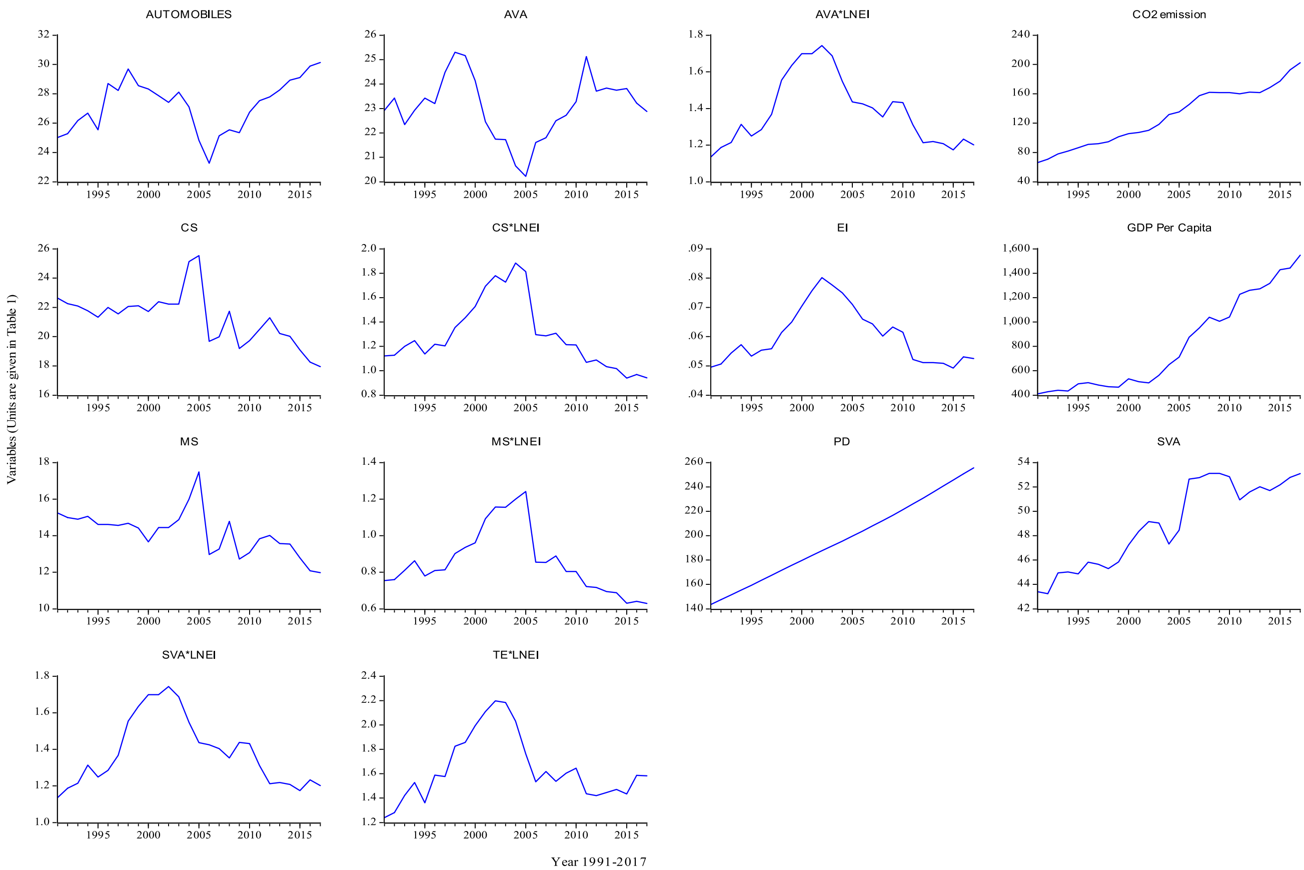

Fig. 1. Variations of all the individual variables during 1991-2017

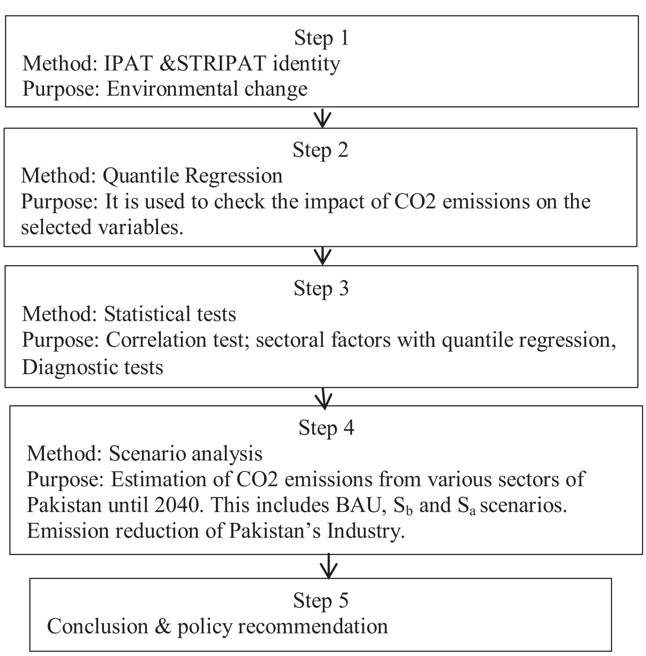

Fig. 1a. Flowchart of sectoral study for Pakistan

4. Results

This section presents the major findings of this study and performs some preliminary statistical tests. First, a correlation test is performed. Second, the test results for the effects of sectorial factors are evaluated by performing QR between CO_2 emissions and its driving forces. Third, a scenario analysis is performed to estimate the CO_2 emissions and emission reduction in different economic sectors of Pakistan. Finally, the variations in all individual variables between 1991 and 2017 are plotted in Graph 1.

4.1. Stationary test

To measure the stationarity of each variable, unit root tests are performed based on Fisher–ADF and Fisher–PP, which detect mutual unit cross-sections. Dickey and Fuller (1979) and Phillips and Perron (1988) introduced an individual unit root process where the null hypothesis (H_0) posits the existence of a unit root, whereas the alternative hypothesis (H_a) posits that the variables are stationary. Tests are practiced at the level and first difference while variables are log based and comprise a unit root at level but after the first variation, they become stationary at 1% level of significance. In addition, the normality without a natural log (ln) of all variables as measured by Jarque–Bera is 1.8108 with a p-value of 0.4044, whereas the normality with ln is 0.6281 with a p-value of 0.7304. The null hypothesis is only accepted with ln because the p-value exceeds 5%, thereby confirming the normality of the data. All factors and their outcomes are described in Table 3a.

4.2. Correlation and QR tests

To establish relationships among the selected variables, correlation tests are conducted for the sample period. The relationships are presented in Table 3. Although most of the coefficients are less than 0.9, the sectorial variables seem extremely correlated. A multicollinearity issue may also emerge due to the objective nature of the data, which may negatively influence the stability of the regression parameters. Only few variables in the analysis show a high correlation, which may

Table 2
Division of economic sectors.

Sector	ISIC code	Subsectors
Agriculture sector	1-5	Forestry, hunting, fishing, cultivation of crops and livestock production.
Manufacturing sector	15-37	Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. Gross value added at factor cost is used as the denominator.
Construction sector	10-45, 15-37	Mining, manufacturing, construction, electricity, water, and gas.
Services sector	50-99	Hotels, restaurants, government, financial, professional, personal services such as education, health care, and real estate services. Also included are imputed bank service charges, import duties, and any statistical discrepancies noted by national compilers as well as discrepancies arising from rescaling.
Automobiles	Category (1 A 3)	Combustion of fuel for all transport activity. Domestic aviation, domestic navigation, road, rail and pipeline transport.

Note: ISIC code denotes the 2-digit industry code in the International Standard of Industrial Classification 2017.

be inconsistent with the actual situation and affect the model. In this case, cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) are applied to check whether the structural stability of the model lies within a specified range. The results in Figs. 2 to 3 indicate that the model parameters are significant. Other studies have applied CUSUM and CUSUMQ in analyzing the economic sectors of various countries. For example, Baloch and Suad applied these methods in investigating the transportation sector of Pakistan (Baloch and Suad, 2018), Raza and Shah applied these methods in examining the coal-related energy consumption of Pakistan (Raza and Shah, 2019), and Shahbaz et al. applied CUSUM and CUSUMQ in evaluating the energy demand in the US (Shahbaz et al., 2019).

EViews 10.0 is used for the QR of the model. According to Kim et al., QR can designate the entire conditional distribution of the dependent variables, such as CO_2 emissions (Kim et al., 2019). QR can also compensate for the limitations of OLS. Koenker and Bassett projected a quantile method, estimated the conditional quantiles of the dependent and independent variables, and obtained the regression model of all quantiles (Koenker and Bassett, 1978). Therefore, the variable estimates obtained by QR are more robust than those obtained by OLS (Xu et al., 2017). To study the effect of CO_2 emissions as a dependent variable (Y) which assume to be linearly dependent on independent variables (X). The τth conditional quantile function of Y is given as

$$Q_y(\tau|x) = \inf\{b|F_y(b|x) \geq \tau\} = \sum_k \beta_k(\tau)\, x_k = x'\beta(\tau), \tag{5}$$

where $F_y\,(b|x)$ is the conditional distribution function of Y given X, and $\beta(\tau)$ denotes the dependence relationship between vector X and the τth conditional quantile of Y. The values of $\beta(\tau)$ for τ is within [0,1], thereby highlighting the complete dependence structure of Y. The coefficients of $\beta(\tau)$ for the given τ are measured by minimizing the weighted absolute deviations Y and X.

The regression results are presented in Table 4. The experimental results provide a rich description of the response dynamics of CO_2 emissions to five technical factors. Each quantile adequately describes the distribution characteristics of CO_2 emissions at the low (25th), middle (50th), and high (75th) emission levels. In addition, QR can illustrate the marginal effect of explanatory variables on CO_2 emissions from different quantiles. Each quantile is employed to specify the effect of technological progress. The results of each model are relevant, and all sectors are considered the mean sites to reduce the effects of climate change in Pakistan. The effects of industry size on the explained variables do not show any significant difference. Therefore, all factors are estimated based on their real strength. The pseudo-R-square of the models exceeds 0.9, thereby indicating that these models explain over 90% of the driving mechanism of CO_2 emissions. For a comparative analysis, the estimates of the scenario analysis are presented in Table 5 and Fig. 2.

In terms of technological progress, lnSVA has a significant negative impact on CO_2 emissions. The coefficients of lnSVA are –0.2560, –0.1147, and –0.0169 at the 25th, 50th, and 75th percent quantiles, respectively. In other words, an increase in the technological progress of the service sector accounts for 0.25%, 0.11%, and 0.017% reductions in the CO_2 emissions in the low, middle, and high emission levels, respectively. Similarly, Wang et al. (2019) found that the technological progress in the construction and service sectors negatively influence CO_2 emissions. The coefficients of the agriculture sector (lnAVA) are –1.4844, –1.2216, and –0.1491 at the 25th, 50th, and 75th percentiles, respectively, thereby suggesting that each 5% increase in agriculture value added corresponds to 1.48%, 1.22%, and 0.15% reductions in CO_2 emissions in the low, middle, and high emission levels, respectively. Although the signs of the coefficients are negative at the 50th and 75th percentiles, the interaction term InSVA*EI does not satisfy the 1% level of confidence at the 25th and 50th percentiles. However, the coefficient is positive at the 25th percentile yet significant at the 1% level. Therefore, the technological progress in the service sector performs poorly in promoting energy efficiency. For the interaction term lnAVA*EI, all coefficients are negative yet fail to meet a fixed level of

Table 3
Correlation test.

Variables	CO_2	PD	PGDP	EI	AVA	CS	MS	SVA	TE	AVA*EI	CS*EI	MS*EI	SVA*EI	TE*EI
CO_2	1.000													
PD	0.985	1.000												
PGDP	0.949	0.959	1.000											
EI	-0.223	-0.259	0.380	1.000										
AVA	-0.749	-0.819	0.443	-0.742	1.000									
CS	0.694	0.714	0.689	-0.723	0.653	1.000								
MS	0.614	0.634	0.667	-0.786	0.536	0.966	1.000							
SVA	-0.537	0.830	0.704	-0.750	-0.643	0.644	0.661	1.000						
TE	0.233	0.332	0.223	-0.236	0.518	-0.264	-0.321	0.084	1.000					
AVA*EI	-0.211	-0.254	-0.281	-0.994	-0.222	0.199	0.217	-0.211	-0.287	1.000				
CS*EI	-0.120	-0.153	-0.163	0.985	-0.064	-0.002	0.023	-0.189	-0.190	0.975	1.000			
MS*EI	-0.094	-0.131	-0.163	0.980	-0.056	-0.024	-0.011	-0.098	-0.171	0.969	0.9985	1.000		
SVA*EI	-0.328	-0.360	-0.147	0.993	-0.104	0.239	0.259	-0.338	-0.242	0.987	0.9663	0.959	1.000	
TE*EI	-0.248	-0.295	-0.379	0.992	-0.181	0.198	0.223	-0.235	-0.352	0.994	0.9721	0.965	0.988	1.00

Note: All the variables are taken as a natural logarithm.

Table 3a
Unit root test of individual variables.

Unit root Method	Fisher-ADF	Fisher-PP
LNCO$_2$ ΔLNCO$_2$	-1.019378 (0.7302) -3.148213 (0.0357)***	-1.474481 (0.5303) -3.095089 (0.0399)***
LNPD ΔLNPD	-1.427145 (0.5504) -4.919011 (0.0007)***	-5.515129 (0.0001) -2.256447 (0.0192)***
LNPGDP ΔLNPGDP	0.345572 (0.9762) -4.332605 (0.0024)***	0.298864 (0.9736) -4.312868 (0.0025)***
LNEI ΔLNEI	-3.481704 (0.0173) -8.119509 (0.0000)***	-4.877540 (0.0006) -19.31612 (0.0001)***
LNAVA ΔLNAVA	-1.722812 (0.4086) -4.381899 (0.0021)***	-1.931283 (0.3136) -4.381899 (0.0021)***
LNCS ΔLNCS	-1.857877 (0.3458) -6.171556 (0.0000)***	-1.770388 (0.3860) -8.422342 (0.0000)***
LNMS ΔLNMS	-2.336002 (0.1689) 6.191169 (0.0000)***	-2.321562 (0.1730)-11.56950 (0.0000)***
LNSVA ΔLNSVA	-1.289063 (0.6190) -4.687106 (0.0011)***	-1.267196 (0.6289 -4.731896 (0.0009)***
LNTE ΔLNTE	-1.582482 (0.4770) 5.237452 (0.0003)***	-1.595472 (0.4706)-5.237452 (0.0003)***
LNAVA*LNEI ΔLNAVA*LNEI	-4.684280 (0.0010) -8.014552 (0.0000)***	-4.684280 (0.0010)-16.16265 (0.0001)***
LNCS*LNEI ΔLNCS*LNEI	-5.230685 (0.0002) -5.498573 (0.0002)***	-5.314957 (0.0002)-20.43149 (0.0001)***
LNMS*LNEI ΔLNMS*LNEI	-5.296329 (0.0002) -8.116084 (0.0000)***	-5.416128 (0.0002)-20.47145 (0.0001)***
LNSVA*LNEI ΔLNSVA*LNEI	-3.089499 (0.0404) -8.134041 (0.0000)***	-4.552485 (0.0013)-19.79315 (0.0001)***
LNTE*LNEI ΔLNTE*LNEI	-3.291452 (0.0263) -8.178941 (0.0000)***	-4.766194 (0.0008)-19.77799 (0.0001)***

H_0: unit root. Δ is the first difference. *** specifies statistical significance at the 1% level. All the variables are stationary at first difference because the p-value is <5%. So the null hypothesis is rejected.

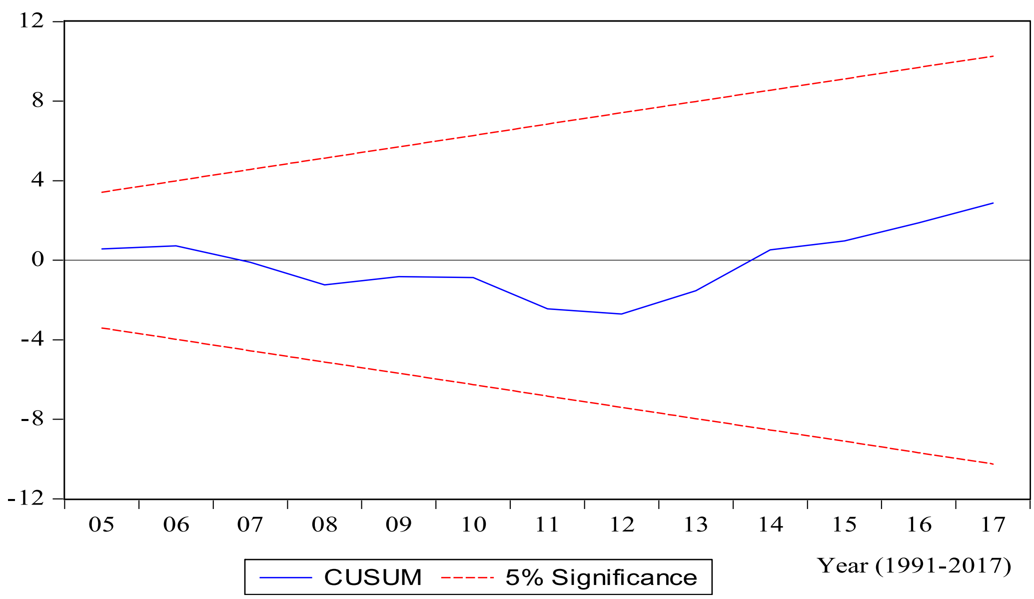

Fig. 2. CUSUM test for stability.

confidence. These coefficients are significant at 11%, 1%, and 5% in all emission levels. In this case, the technological progress of the agriculture sector cannot efficiently reduce CO_2 emissions due to energy efficiency concerns. In general, the agricultural sector accounts for 14% to 30% of the global greenhouse gas emissions due to its intensive use of fossil fuels (Reynolds and Wenzlau, 2012). Using fuel-driven agricultural equipment, pumping irrigation, raising livestock in indoor facilities, and applying nitrogen-rich fertilizers also contribute to such high emission levels. However, the Food and Agriculture Organization argued that the agricultural sector has great potential to reduce its emissions by 80% to 88% (Reynolds and Wenzlau, 2012). As a result, many agricultural activities, such as irrigation, should be powered by renewable energy sources to reduce the CO_2 emissions of the entire agriculture sector. Models related to the transportation, manufacturing, and construction sectors show a positive relationship. Overall, the EI coefficients are positive and increase the CO_2 emissions in the low, middle, and high emission levels. For the interaction term lnCS*EI, the coefficients are 5.60, 4.83, and 7.09 at the 25th, 50th, and 75th percentiles, respectively, thereby suggesting that a 12% increase in the technological progress of the construction sector contributes to a 5.60%, 4.83%, and 7.04% increase in the low, middle, and high emission levels, respectively. In sum, the construction sector performs poorly in controlling its CO_2 emissions. The interaction term lnMS*EI reveals the positive coefficients listed in Table 4. The manufacturing sector performs poorly in terms of technological progress, which increases the CO_2 emissions of this sector by 1.32%, 2.06%, and 3.50% in the low, middle, and upper emission levels.

The industrial sector has a huge impact on national energy use, CO_2 emissions, and environmental systems. Many studies (Liu et al., 2007; Ouyang and Lin, 2015; Xie et al., 2016; Xu and Lin, 2015) identify industrial activity and energy intensity as major contributors to increasing and reducing industrial CO_2 emissions, respectively.

The transportation sector of Pakistan has been classified as very dangerous due to its contributions to environmental change (Lin and Raza, 2019). The coefficients of this sector are 1.12, 2.35, and 0.51 at the 25th, 50th, and 75th percentiles, which indicate that every 13%, 12%, and 10% change in the CO_2 emissions of this sector contributes 1.12%, 2.35%, and 0.51% to the CO_2 emissions increase in the low, middle, and upper emission levels, respectively. These findings can be ascribed to the fact that the transportation sector is the largest consumer of fossil fuels in Pakistan. For the term lnTE*EI, all coefficients are positive and equal to 10.51, 3.80, and 7.37 at the three quantiles, thereby suggesting that every 12%, 11%, and 10% increase in the emissions of this sector increases the CO_2 emissions in the low, middle, and high emission levels by 10.51%, 3.80%, and 7.37%, respectively. Wang et al. (2011) argued that the effects of per capita economic

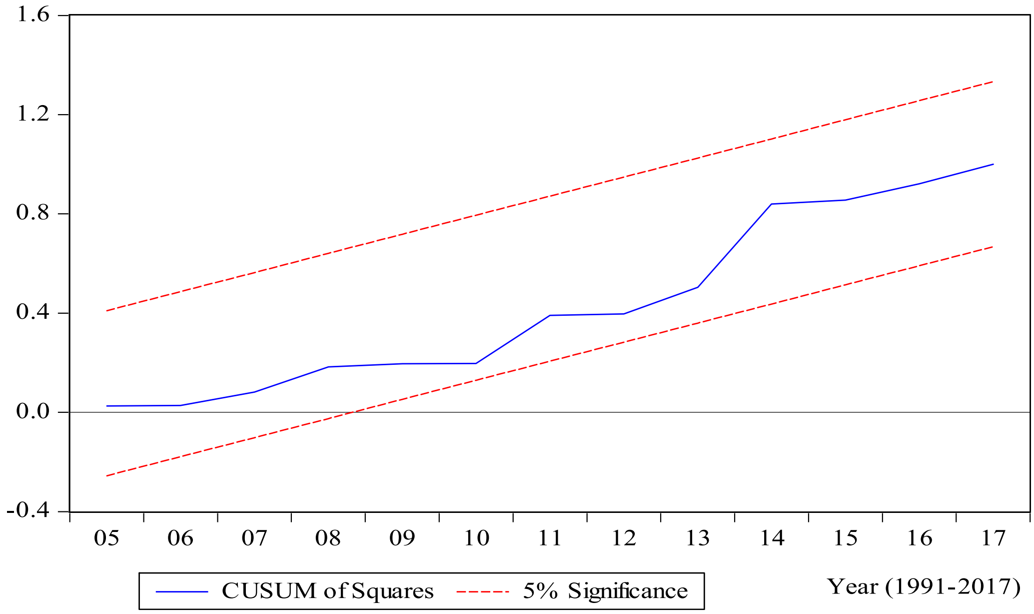

Fig. 3. CUSUMQ test for stability.

activity and transportation mode conversion are the main drivers of the increasing CO_2 emissions and that the effect of transportation intensity is the main force that drives China's transportation sector to reduce its CO_2 emissions (Wang et al., 2011). Similarly, the power, transport, forestry, agriculture and livestock, town planning, and manufacturing sectors are the mean sites to alleviate the impacts of climate in Pakistan (Yousuf et al., 2014).

Alkhathlan and Javid (2015) obtained similar findings in Saudi Arabia (Alkhathlan and Javid, 2015). Overall, the global transportation sector generates 7.34 billion tons of CO_2, which accounts for 23% of all CO_2 emissions around the world. According to IEA (2008), the global CO_2 emissions of the transportation sector is expected to reach 18 gigatons by 2050. Pakistan's economic growth, population growth, and urbanization continue to accelerate, and private cars, passenger transport, domestic aviation, and freight all produce CO_2 emissions (Peng et al., 2015). Along with the increasing emissions of the transportation sector and the continued acknowledgement of the importance of energy conservation and environmental protection, reducing CO_2 emissions has become a primary concern in Pakistan.

Table 5
Estimation of CO_2 emissions in different sectors of Pakistan (million tons).

Year	2030	2035	2040
Scenario a	272.01	302.01	335.02
Business as usual	253.50	278.50	306.01
Scenario b	236.98	257.01	278.01

4.3. CUSUM and CUSUMQ tests

The results of the CUSUM and CUSUMQ tests are presented in Figs. 2 and 3, respectively. The lines fall at the 5% critical bound for both cases, thereby indicating that the model parameters are stable and that its findings hold relevant policy implications.

4.4. Scenario analysis

The CO_2 emissions of the five major economic sectors of Pakistan under different scenarios are then projected as shown in Table 5 and Fig. 4. Many researchers have performed scenario analysis to predict CO_2 emissions and their reduction potential (Du and Lin, 2018; Ouyang

Table 4
Estimation results: the effects of sectorial factors with quantile regressions.

Dependent variables Models	Quantiles		
	25%	50%	75%
$lnCO_2$	-166.4880 (0.053)**	-97.4876 (0.0864)**	-88.1271 (0.1021)*
lnPD	-36.0643 (0.1212)*	-40.9649 (0.1207)*	-16.0834 (0.1256)*
lnPGDP	131.6944 (0.1445)*	128.4272 (0.1866)*	164.3520 (0.1244)*
lnEI	0.8951 (0.21)	0.6271 (0.19)	0.5824 (0.10)*
LnAVA	-1.4844 (0.0516)**	-1.2216 (0.0803)**	-0.1491 (0.0531)**
LnCS	1.6645 (0.7369)	3.5305 (0.0415)***	2.5588 (0.0502)**
LnMS	0.4913 (0.1263)	0.7741 (0.1140)	1.3255 (0.1918)
LnSVA	-0.2560 (0.0370)***	-0.1147 (0.0138)***	-0.0169 (0.0253)***
LnTE	1.1236 (0.1330)	2.3507 (0.1210)	0.5058 (0.1033)*
ln(AVA*EI)	0.9973 (0.1173)	-0.2351 (0.0131)***	-0.0826 (0.0571)**
Ln(CS*EI)	5.5979 (0.1172)	4.8337 (0.2246)	7.0390 (0.1987)
ln(MS*EI)	1.3197 (0.1361)	2.0558 (0.1490)	3.5016 (0.1201)
Ln(SVA*EI)	1.3020 (0.1078)*	-1.2139 (0.316)	-0.9627 (0.150)
Ln(TE*EI)	10.5154 (0.1273)	3.8024 (0.1145)	7.3733 (0.1038)*
Pseudo R-squared	0.942	0.936	0.927

Note: *p shows significant at 10%, **p significant at 5% and ***p shows significant at 1%. p is the probability.

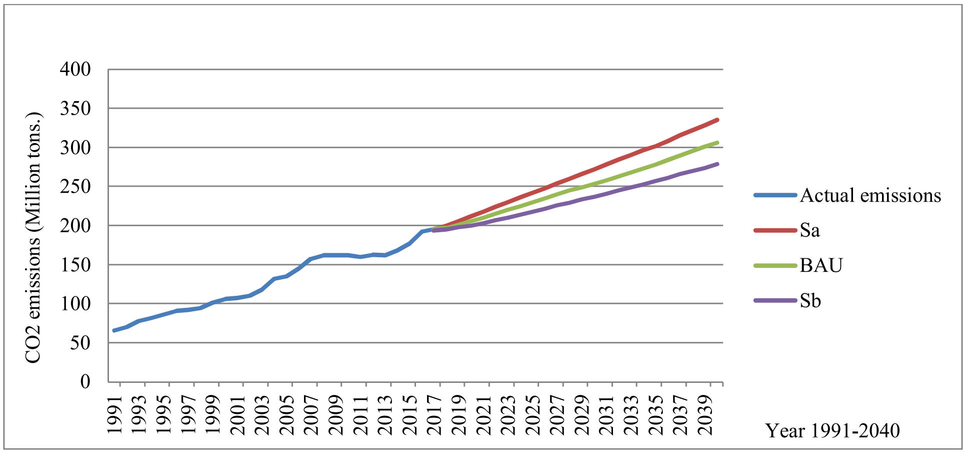

Fig. 4. Scenario analysis of actual and estimated fossil fuel-related emissions from 1991-2040.

and Lin, 2015; Xie et al., 2016). The intervals 2030, 2035, and 2040 are used in the scenario analysis given that Pakistan has already pledged to reduce its CO_2 emissions by 2025 in its intended nationally determined contributions submitted to the United Nations. The employed scenarios include the business as usual (BAU) or moderate scenario, scenario "a" or the benchmark scenario, and scenario "b" or the advanced scenario. The following assumptions are held in the scenario analysis:

1. the growth rate for the sample period of 191-2017 is taken as the base case scenario;
2. BAU is taken as the moderate scenario and the baseline to determine the trend during this period;
3. scenario "a" is taken as the highest emission scenario where the growth (g) of BAU is > 5%; and
4. scenario "b" is taken as the lowest emission scenario where the g of BAU is < 5%.

Through these scenarios, the CO_2 emissions and energy-related utilization in Pakistan can be compared. Pakistan is a developing economy that requires improvement in its technological and environmental aspects. The benchmark scenario measures the unrestrained emissions in a free environment, whereas the advanced scenario is based on the policies and recommendations of the authors.

The economy of a country continuous to grow through the contributions of its various sectors, which harmful emissions can be controlled by applying the relevant technologies and policies. The advanced scenario represents the maximum emission reduction scenario as a result of the regulations successfully implemented by the government. By 2030, the CO_2 emissions of Pakistan are projected to reach 253.5, 272.0142, and 236.698 Mt in the moderate, benchmark, and advanced scenarios, respectively. By 2035, the benchmark and moderate scenarios will have 302.001 Mt and 257 Mt of CO_2 emissions, respectively. By 2040, CO_2 emissions will reach 335.002 Mt and 278.011 Mt in the benchmark and advanced scenarios, respectively. The industrial carbon emission reduction potential and proportion of total emissions in these scenarios are shown in Tables 5 and 6. In general, the economic sectors of Pakistan are likely to reduce their CO_2 emissions in the future. Compared with the benchmark scenario, the CO_2 emissions will increase by 18.51, 23.501, and 29.002 Mt in 2030, 2035, and 2040 with corresponding proportions of 13.6%, 15.1%, and 16.75%, respectively. These emissions will also decrease by 16.52, 21.5, and 27.989 Mt in these same intervals with corresponding proportions of 11.85%, 12.85%, and 13.95%, respectively. The CO_2 reduction efforts of Pakistan's economic sectors are important in achieving the country's carbon reduction targets. The forecast results of the advanced scenario also highlight the huge potential for Pakistan's economic sectors to reduce their CO_2 emissions. If Pakistan makes the necessary investments and follows the advanced scenario, then the country can achieve both economic and environmental sustainability.

Table 6
Emission reduction of Pakistan's Industry.

Year	Scenario 'a'	Scenario 'b'		
	Emission increase	Proportion (%)	Emission reduction	Proportion (%)
2030	18.51	13.60	16.52	11.85
2035	23.51	15.10	21.49	12.85
2040	29.01	16.75	28.00	13.95

Note: Proportion is calculated at 5% change in emissions.

5. Discussion

This section discusses the main findings of this work in relation to the literature and presents their policy implications.

5.1. Discussion of the main findings

The technological progress in the service sector has a negative impact on CO_2 emissions. Industrial and energy-intensive sectors play important roles in developing economies. Some studies (Abdelaziz et al., 2011; Falavigna et al., 2013; Ji, 2017; Shan et al., 2018) have measured environmental efficiency by using sectorial information and found a significant change in environmental achievements. By contrast, maximum production is measured based on the energy consumption of those economic sectors that contribute to climate change. The majority of the previous studies reveal a positive association between the production sector and CO_2 emissions (Hammond and Jones, 2008; Pérez-Lombard et al., 2008). Similarly, due to the rapid urbanization that triggers the excessive growth of the construction, production, manufacturing, transportation, and services sectors, these sectors have become major emitters of CO_2 in developing countries (Ouyang and Lin, 2015; Wang et al., 2017), including Pakistan. The service sector has performed poorly in improving its energy efficiency. The findings of this work agrees with those of previous studies on OECD countries (Mulder et al., 2014) and China (Wang and Liu, 2019), where only a slight decline in energy intensity was observed in the service sector. The service sector also demonstrates a solid relationship with other sectors (Alcantara et al., 2009; Butnar et al., 2011). Therefore, the rapid development of modern economic sectors (including the service sector) can reduce CO_2 emissions by affecting the other production activities in the collective economy. Given its reduced share of energy, the service sector of Pakistan has sufficient incentives to invest in energy conservation. Mulder et al. suggested that the energy cost of the service sector as a proportion of its total production costs is relatively low (Mulder et al., 2014), thereby highlighting the underperformance of this sector in terms of improving its energy efficiency.

The technological progress in the agriculture sector (lnAVA) shows a negative effect on CO_2 emissions, but this sector performs well in terms of energy efficiency. Falavigna et al. used a DEA model to estimate the ecological efficiency of the Italian agriculture sector and found a significant change in environmental achievements (Falavigna et al., 2013). Rafiq and Rehman studied 53 countries, including 23 high- and 30 low–medium-income countries, examined the impact of wealth, population, and technology by using the STIRPAT model, and estimated the CO_2 emissions in these countries by using the EKC hypothesis (Rafiq and Rehman, 2017). They found that the agriculture and service sectors have important roles in reducing pollution triggered by industrialization and recommended that the industrial sector should coordinate with climate specialists to reduce its CO_2 emissions (Rafique and Rehman, 2017).

The technological progress in the construction sector has a positive impact on its CO_2 emissions. However, only few empirical studies have directly examined the impact of technological progress on the construction sector (Grepperud and Rasmussen, 2004; Mulder et al., 2014). lnCS affects energy intensity, especially in the high emission level. Pakistan has undergone rapid urbanization as reflected in its large-scale construction of various infrastructures, including houses, commercial buildings, and roads. The construction sector consumes a significant amount of energy, with the construction, operation, and maintenance of buildings accounting for 40% to 50% of the global energy consumption and anthropogenic greenhouse gas emissions (Miller et al., 2015; Su and Moaniba, 2017).

The technological progress in the manufacturing sector (lnMS) shows a positive association with CO2 emissions, which can be reduced by implementing structural reforms and conducting knowledge transfers. The technological knowledge transfer can improve the capabilities of technology beneficiaries by changing the design and improving their extant technologies, which in turn promote a domestic manufacturing of equipment with improved functionality and fewer emissions. India and China are leading countries that have successfully upgraded their technological capabilities through knowledge transfer (Lewis, 2007). Therefore, the manufacturing sector of Pakistan needs to focus on achieving a structural transformation.

The emissions of the transportation sector (lnTE) of Pakistan show a strong, positive relationship with the country's CO_2 emissions. As discussed above, the transportation sector has become one of the largest consumers of oil in Pakistan. The energy consumption of the construction, manufacturing, and transportation sectors continue to increase along with their urbanization and technological progress. The growth in cement output, non-metallic mineral products sector, industrial activities, and domestic demand have also increased the emissions of the transportation sector of other countries (Ouyang and Lin, 2015; Xu et al., 2012). Zhang et al. (2018) also verified the contribution of this sector to climate change mitigation. Urban transport can create environmental issues, such as air and sound pollution, which are highly local in nature. The global air pollution has reached alarming levels due to the dramatic increase in urban traffic. In Pakistan, petroleum products are widely consumed in the transportation sector (Imran, 2010). Overall, all the diagnostic tests shows the significant results such as impact of CO2 emissions on independent variables, quantiles at various percentages (i.e. 25%, 50%, 75%), correlation, stationary, and emission reduction potential during the period. Therefore, alternative cleaner energy resources, such as solar and wind energy, should be used to overcome the emissions problem.

6. Conclusions and policy recommendations

This study examines the effects of the agriculture, manufacturing, construction, services, and transportation sectors on the CO_2 emissions in Pakistan. A QR method and a balanced national dataset covering the years 1991 to 2017 are used to establish relationships among the variables. This sectoral study also promotes awareness regarding the effects of technological progress on CO_2 emissions. The historical growth of CO_2 emissions is projected by performing a scenario analysis. The agriculture and service sectors are revealed to have negative impacts on CO_2 emissions, whereas the construction, manufacturing, and transportation sectors greatly contribute to increasing these emissions. Low, middle, and high emission levels are used to understand the percentile conditions of each variable (Table 4). Tables 5 and 6 present the predicted CO_2 emission reductions and corresponding proportions for 2030, 2035, and 2040.

This paper provides some policy recommendations for mitigating the impact of CO_2 emissions from the different economic sectors of Pakistan. First, for environmental policies, the agriculture, automobile manufacturing, and construction sectors, which are largely dependent on fossil fuels, should rely on renewable energy sources instead of primary energy sources, such as oil, coal, and gas. Second, the government should develop environment-friendly policies and frameworks to encourage the automobile manufacturing sector to design fuel- and energy-efficient vehicles, which can be achieved by attracting international investments, expertise, and green technologies. These measures and policy frameworks can also help strengthen management capacity, promote public awareness regarding energy efficiency and conservation, and encourage green productivity in the transportation sector. Therefore, technological innovations and structural adjustment should be introduced to the automobile manufacturing sector. Third, energy-efficiency- and renewable-energy-related model change policies should be introduced. Pakistan has no mandatory target for vehicle CO_2 emissions (only for other types of emissions). The economic and geographic challenges in improving public transportation, cargo, and urban transport should be considered to help reduce CO_2 emissions. Fourth, economic growth can be stalled by CO_2 emissions. This problem can be addressed by controlling the air pollutant emissions from various sectors (Zhang et al., 2018) and by using renewable energy sources. The government should also encourage the use of clean energy sources and technologies and motivate the vehicle manufacturing sector to use clean fuels. Finally, the goal of environmental sustainability can be achieved by adopting and implementing viable strategies at the project and organizational levels and at all phases, including the planning, designing, and implementing projects that are particularly relevant to the construction sector. To this end, the government should develop a construction policy that encourages the social and environmental sustainability of the construction sector, and an assessment model should be designed based on reliable and sustainable sources (Ma et al., 2018). Achieving sustainable development has become a priority for developing and developed countries around the world; this objective can be achieved by implementing various measures for promoting green economic growth, reducing poverty, and facilitating social and environmental improvements (Sikdar, 2003). The construction sector should follow the basic principles of sustainable development and adopt green technologies to reduce its reliance on major sources of pollution.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2019.119862.

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